

ABSTRACT

Title of Dissertation: THE SPATIAL STRUCTURE OF
OPPORTUNITY
AND THE LOCATION DYNAMICS OF
HOUSING MOBILITY PROGRAMS

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In recent decades, federal housing policy has increasingly relied on housing vouchers that facilitate greater mobility among low income families and allow them to move into “high opportunity” neighborhoods. As housing policy has embraced this goal, however, a number of questions remain in the development of more equitable policy; among them, three are particularly poignant. First, how can the spatial dimensions of opportunity be measured and visualized? Can valid measurements of spatial opportunity be constructed, and if so, how? Second, how can housing mobility programs help low-income families access communities of opportunity? Finally, how do housing voucher recipients of different races sort into neighborhoods, and how can housing policies use these behavioral insights to generate more equitable outcomes?

In this dissertation, I address each of these questions in turn through three empirical studies; in the first, I construct a conceptually and statistically valid measurement

model of spatial opportunity using data from the Baltimore metropolitan region. I use this model to explain why current techniques are awed, and how modern quantitative methods can help introduce flexibility into opportunity analyses, leading to better, more nuanced policy prescriptions. In the second study, I develop a multilevel model to assess the longitudinal success of housing voucher programs in the Baltimore region. Using 10 years of data from Baltimore's voucher programs, I examine how residential trajectories differed among household who received different types of housing assistance. I find that stark differences exist between recipients of different types of vouchers, and also among different racial groups. In the third study, I use a series of disaggregate discrete choice models to study the residential sorting patterns of Baltimore's voucher holders. I find that voucher holders are sensitive to both dwelling unit characteristics, and neighborhood characteristics, but that the strongest sorting factor, by far, is neighborhood racial composition. Together, these studies show how the geography of opportunity can be measured and displayed, how black and white housing voucher recipients have starkly different access to the types of spatial capital that facilitates socioeconomic mobility, and how voucher programs can be redesigned to help foster racial and spatial equity.

THE SPATIAL STRUCTURE OF OPPORTUNITY AND THE LOCATION
DYNAMICS OF HOUSING MOBILITY PROGRAMS

by

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Chapter 1

The Geography of Opportunity (Redux)

During the last decade, social equity has become a major focus of large-scale metropolitan planning. Fostered by administrative efforts like the Partnership for Sustainable Communities¹, cities and metro areas across the country are seeking new tools and analytical devices to address sustainability and urban inequality. The theoretical foundation for many of these devices is what has been called the Geography of Opportunity, defined as “the array of markets, institutions, social and administrative systems, and networks that potentially offer resources promoting socioeconomic advancement.” (Galster et al. 1999, p.99). This concept has made a powerful impact in planning circles, creating a new emphasis on the socio-spatial implications of housing policy, and motivating regions to develop new frameworks for evaluating equity (Briggs & Wilson 2005).

Among the tools being widely adopted is a technique called opportunity

mapping, in which the characteristics of a region's neighborhoods are quantified and combined into an index representing the area's social and physical health and its impact on the residents who live there. These maps can then be used to assist policymaking, for instance, by prioritizing affordable housing investments in high opportunity areas. The construction of these opportunity maps has developed into something of a cottage industry, led by the Kirwan Institute at the Ohio State University who pioneered the technique in the early 2000s and has since conducted over a dozen such exercises for communities across the U.S. (Reece & Gambhir 2008).

Although opportunity mapping has been an invaluable tool for helping cities and regions better understand their existing socioeconomic geography, it suffers from a number of shortcomings. For one, the maps use an inconsistent collection of 'opportunity indicators,' many of which have a tenuous connection to the social science literature on individual outcomes. Further, many of the indicators for which there is the greatest evidence of impact, such as collective efficacy, or residential stability are consistently omitted or overlooked. Another major conceptual problem is that opportunity maps fail to differentiate the importance or contribution of different neighborhood contextual features for different individual outcomes. For instance, is school quality as important as exposure to violence? Is improving physical health more important than providing an escape from income poverty?

Some of these are normative questions that have no objective answer; others are difficult questions that have challenged social scientists for many years, yet a large and quickly growing literature offers some possible answers. While policymakers often speak of the geography of opportunity, scholars from so-

ciology, criminology, public health, community psychology, and social epidemiology commonly use the term ‘neighborhood effects’ to refer to the ways that the contextual attributes of local communities shape the lives of their residents. In the past two decades research on neighborhood effects has exploded and volumes of information have been published regarding the ways that spatial inequality is reproduced through the resources, externalities, and socialization processes inherent in different communities.

The purpose of this review is to improve the process of opportunity mapping by creating a better connection to the scientific literature on the impact of neighborhoods. It sets out to answer the following questions:

- What do we know about neighborhood effects and their impact on individual wellbeing?
- How have different research strategies shaped scholarly understanding of neighborhood effects over time?
- What hurdles still remain in the quest to understand neighborhood effects?
- And finally, how can some of these obstacles be overcome using the latest methodological and computational resources available?

The literature review is structured as follows: I provide a brief background on the theoretical underpinnings of neighborhood effects research, and its empirical traditions. I then examine the residential mobility studies that provide the backbone of neighborhood effects research, with particular focus on the Moving to Opportunity program and its impact on the field. This leads to a natural discussion of the methodological challenges facing researchers of neighborhood context, and the persistence of such challenges

in the literature. Finally, I discuss the current state neighborhood effects research and the gaps that remain.

1.1 History and Development of Neighborhood Effects Research

In the early 20th century, urban sociologists from the Chicago School introduced and popularized the notion of urban ecology. The original idea was based on the evolutionary processes of competition and succession, and although it has evolved over the years, its premise is that context is a crucial component of socialization that shapes the behaviors and outcomes of individuals (Park et al. 1925). Certainly people have free will, agency, and inherited biological tendencies—but they are also influenced profoundly by conditions of the social and physical environment like family structure, interpersonal interaction, and institutional resources. Yet despite its historic academic tradition, ecological research was not a popular topic in the academic literature until recent decades.

During the social turbulence of the 1960s, researchers began to debate the sources of persistent inequality and the possibility of spatial influences. In 1968, economist John Kain first proposed the well known spatial mismatch hypothesis (Kain 1968; Kain 1992). He posited that the migration of jobs away from central cities created a disconnect between the abilities of the labor force and the skill requirements of proximate jobs. Put simply, the movement of low skill jobs into the suburbs left many low skill workers in urban areas without access to viable employment.

Two decades later, sociologist William Julius Wilson took up Kain's mantle once again, arguing in his seminal work, *The Truly Disadvantaged*, that macroeconomic shifts including de-industrialization and employment decentralization sent a chain reaction echoing through the social world (Wilson 1987). Not only had whites and jobs left inner cities, Wilson argued, but the black middle class had begun its exodus as well, creating severe social and economic isolation for those that remained behind. Wilson, thus, expanded upon Kain's theory to include important aspects of social processes—the lack of positive role models and social networks exacerbated greatly the dynamic of hard-to-reach jobs.

Wilson's book was groundbreaking and inspired scholars across the urban disciplines to investigate the ways that structural forces in spatial context contribute to the socioeconomic prospects of individuals, particularly for racial minorities and the poor (Sampson 2008). By the early 1990s, these ideas had already made a lasting impression across the social sciences and a wave of interest in neighborhood effects began; In 1993 Douglas Massey and Nancy Denton published their book, *American Apartheid*, in which they argued that persistent (and intentional) racial segregation was a primary driver of urban inequality, and in 1995 Galster and Killen proposed a conceptual model called “the geography of opportunity” to help articulate the multiple dimensions of spatial disadvantage facing the urban poor (Galster & Killen 1995; Massey & Denton 1993).

At the same time that these theoretical contributions were advancing, empirical research began to support the notion that neighborhoods could substantially enhance (or impede) individual welfare. Although Galster and Killen's

model was compelling, much of the existing research at the time was based on aggregate measures and observational studies that were unable to rule out the possibility of selection bias, the notion that high achieving individuals were simply sorting themselves into higher status neighborhoods. Thus, concerns about endogeneity, and an inability to control for it, meant that researchers were unable to make causal inferences about the effects of neighborhoods on individuals.

To overcome issues of selection bias, researchers began to exploit data from residential mobility programs in which participants used housing vouchers to relocate to new neighborhoods. Theoretically, these programs would allow researchers to isolate the effects of neighborhoods on individuals by controlling for the unobserved household characteristics. Among the first to explore these data were James Rosenbaum and his colleagues, who studied the Gautreaux program in Chicago (Rosenbaum 1995).

The Gautreaux program began when a housing activist named Dorothy Gautreaux initiated a class action lawsuit against the Chicago Housing Authority (CHA) and the U.S. Department of Housing and Urban Development (HUD) in 1966. She argued that the two administrative bodies “engaged in ‘systematic and illegal segregation’ ” that violated the equal protection clause of the constitution (Keels et al. 2005). Two years later, in 1968, the Fair Housing Act was enacted, providing additional legal support to Gautreaux’s case and others like hers that would come after. In 1976 the Supreme Court ruled in favor of the plaintiffs and the ‘Gautreaux program’ was created as a court ordered remedy. The program provided housing vouchers to low income families, most of which were headed by single black females. Families

were arbitrarily assigned to move into either the white suburbs outside the city or remain in the predominantly black neighborhoods inside Chicago. Although assignment was not truly random, a natural comparison was created between participants who moved to the suburbs and those who remained within the city of Chicago, thus providing an important test of the impact of integrated and affluent neighborhoods.

Rosenbaum's early research on the Gautreaux participants showed large improvements in employment among adults, especially those who were unemployed before the move (Rosenbaum 1995; Rosenbaum & DeLuca 2008). The results also revealed important (and large) educational improvements among youth. As Rosenbaum and DeLuca explain, "Gautreaux children who moved to the suburbs were more likely than city movers to graduate from high school, attend college, attend four-year versus two-year colleges, and (if they were not in college) to be employed and to have jobs with better pay and benefits" (Rosenbaum & DeLuca 2008, p.655). Later research confirmed these results, and also suggested that moves to high-income integrated neighborhoods were associated with less time on welfare (Mendenhall et al. 2006).

1.2 The MTO Enigma

The Gautreaux studies were cited widely as strong evidence that neighborhood effects were real, robust, and large in magnitude. But they also drew criticism. Gautreaux was more rigorous than any study that had come before in terms of controlling for individual characteristics, but it was not a truly randomized experiment; households retained the choice to move into differ-

ent neighborhoods and thus researchers still could not rule out the possibility of selection bias.

As a direct result, the social science and public policy communities resolved to conduct a large-scale social experiment that would randomly assign housing vouchers to public housing residents for the explicit purpose of testing neighborhood effects with methodological rigor. The experiment, called Moving to Opportunity for Fair Housing, was conducted in five U.S. metros, Baltimore, Boston, Chicago, Los Angeles and New York and ran from 1994 to 2010. Nearly 5000 families participated in the program, each of which was assigned to one of three groups: a treatment group that was assigned a housing voucher that could only be used in a census tract with a poverty rate below 10%. A second group (section 8) received an unrestricted housing voucher that could be used in any location, and a third group (control) did not receive a housing voucher but instead remained in public housing (Sanbonmatsu et al. 2004; Orr et al. 2003; Ludwig et al. 2008). Households were tracked throughout the duration of the program and three surveys were conducted, including a baseline conducted prior to randomization, an interim conducted five to seven years after randomization, and a final conducted at the conclusion of the program. The comprehensive surveys included questions pertaining to health, neighborhood perceptions, victimization, socioeconomic status, and education, among others. MTO, therefore, was viewed as a comprehensive dataset with all the necessary information to understand the impact of neighborhood effects on a variety of outcomes.

Unlike Gautreaux, the initial results from MTO were somewhat humbling. Families in the treatment group reported significant improvements in safety

and housing quality, which resulted in improved mental health among adults and young girls, yet no significant educational or employment outcomes emerged (Ludwig et al. 2012a; Ludwig et al. 2013; Burdick-Will et al. 2011; Kling et al. 2007). The disappointing results from MTO led many to believe that neighborhood context was not as important as was once believed—at least for socioeconomic outcomes. Positive results from the Gautreaux program were written off as selection bias and neighborhoods were thought to improve health and safety but not employment or education. These beliefs were facilitated by a widely cited report by the National Bureau of Economic Research (the principal investigator of the MTO program) that proclaimed boldly no neighborhood effects on education or employment could be found.

In the mid and late 2000s, however, scholars began to question the validity of MTO’s ability to discern neighborhood effects. A number of studies began to surface suggesting that MTO did not actually provide a significant change in neighborhood structures for families in the experimental group. In other words, the MTO treatment did not generate a large enough ‘neighborhood dose’ for several reasons (Rosenbaum & Zuberi 2010; Burdick-Will et al. 2011).

A major critique rests on the fact that MTO was designed to test the neighborhood impacts of poverty and social class rather than race and segregation, meaning that many families moved to lower poverty neighborhoods that remained predominantly black (Clampet-Lundquist & Massey 2008; Sampson 2008; Burdick-Will et al. 2011). Additionally, even though families in the treatment group moved to lower poverty neighborhoods, they tended to be declining neighborhoods that saw substantial increases in poverty as the pro-

gram continued, and many families never moved very far in the first place, remaining largely within the same school districts and municipal service districts (DeLuca & Rosenblatt 2010; Burdick-Will et al. 2011). Further, many families in the experimental group only stayed in their initial placements for one year (a requirement of the program) before moving back to neighborhoods with high levels of poverty (Kingsley & Pettit 2008; Peter Rosenblatt & Deluca 2012a).

Taken together, this evidence suggests that the MTO treatment effect (on those who leased up) was not a substantial dose of different contextual conditions on poor families. In other words, it may be unreasonable to expect significant changes in education or socioeconomic outcomes because families did not experience significantly different neighborhood conditions, especially when considering cumulative exposure. As others have noted, MTO was an experiment that tested the impact of a policy that offered offering housing vouchers to low-income families rather than one that tested the impact of neighborhood context on individual outcomes.

Thus began a long and hotly contested debate in the literature about the efficacy of MTO and the presence of neighborhood effects. Eventually, a kind of feud developed among quantitative researchers studying neighborhood effects. The culmination of this feud occurred in 2008 in which a special issue of the *American Journal of Sociology* was convened to discuss the outcomes of MTO and allow researchers from either side of the debate to weigh in (Sampson 2008; Ludwig et al. 2008; Clampet-Lundquist & Massey 2008). On one side of the debate, Jens Ludwig and his colleagues fiercely defended the methodological rigor of MTO, and the hallowed ground of ex-

perimental design. They argued that because MTO failed to find significant neighborhood effects on education or economic self-sufficiency, other non-experimental studies of neighborhood effects that did find such impacts were essentially flawed and their findings rendered invalid. On the other side of the debate, Massey and Clampett-Lundquist argued that the design of MTO itself was flawed, and despite its experimental rigor, its outcomes were not truly representative of neighborhood effects due because MTO treatments were non-uniform. For many years this feud continued between the ‘observationalists’ and the ‘experimentalists’ each arguing that the other faction misunderstood critical methodological and/or substantive issues.

In 2011, however, a detente began to emerge. In the interest of advancing the knowledge of neighborhood effects, authors from each side of the debate agreed to collaborate on a single paper in which they would compare the results of MTO (experimental), Gautreaux (quasi-experimental) and PHDCN (observational) to help identify the sources of disparate findings (Burdick-Will et al. 2011). After much analysis, the authors found that the results from these three studies with different research designs did, in fact, converge, and concluded that experimental design was not, necessarily, the superior method for studying neighborhood effects.

1.3 A Quantifiable Challenge

Although the MTO study generated controversy in the social science community (in addition to contested findings) it nonetheless offered important insights into the study of neighborhood effects. If nothing else, the experi-

ence of MTO provided greater knowledge about the methodological issues surrounding neighborhood effects studies and the types of research designs that should be considered in the future. Clearly, part of the reason for the disparate findings in neighborhood effects research is due to a lack of formal and widely adopted methodology for measuring the impact of context on individuals, and indeed, Galster & Hedman (2013) find that differences in methodological approaches account for a significant amount of the variability in measures of neighborhood effect outcomes. Since large scale social experiments—particularly those involving the distribution of housing vouchers—are prohibitively difficult and expensive to design and administer, it is critically important to design rigorous studies of neighborhood effects using non-experimental methods.

To overcome the issues of measurement and selection bias in contextual studies, scholars have advocated several approaches. G. Galster (2008b), for example, proposes a general econometric model specification that attempts to isolate the effects of neighborhood while holding constant other influences. In his model, “the outcome of interest (O) observed at time t for individual i residing in neighborhood j in metropolitan area k can be expressed:

$$O_{it} = \alpha + \beta[P_{it}] + \gamma[P_i] + \varphi[UP_{it}] + \delta[UP_i] + \theta[N_{jt}] + \mu[M_{kt}] + \varepsilon$$

O_{it} = employment status or income (model dependent) for individual i at time t

$[P_t]$ = observed personal characteristics that can vary over time (e.g., marital

or fertility status, educational attainment)

$[P]$ = observed personal characteristics that do not vary over time (e.g., year and country of birth)

$[UP_t]$ = unobserved personal characteristics that can vary over time (e.g., psychological states, interpersonal networks and relationships)

$[N_t]$ = observed characteristics of neighborhood where individual resides during t

$[M_t]$ = observed characteristics of metropolitan area in which individual resides during t (e.g., area unemployment rates)

ε = a random error term

i = individual

j = neighborhood

k = metropolitan area

t = time period (typically a year)”

Yet as Galster himself notes, even this thoughtful specification does not overcome a number of challenges facing researchers who would seek to estimate the equation. These challenges include defining the appropriate scale of neighborhood, identifying and measuring the mechanisms by which neighborhoods influence individuals, establishing the intensity and duration of exposure to neighborhoods, minimizing bias from omitted variables, and endogenous relationships that exist between individual characteristics and neighborhood characteristics.

Each of these challenges is unique, and researchers have offered attempts to address one or more of them during the course of particular research projects. Jacob et al. (2009), for example, advocate an instrumental variable

approach to control for selection bias and endogeneity; Hedman et al. (2013) use a multilevel regression with a longitudinal specification to account for cumulative exposure to neighborhood disadvantage, finding that children's exposure to impoverished neighborhoods significantly impacts their earnings later in life.

Measuring neighborhood constructs is among the most difficult of the challenges identified by Galster. Indeed, appropriate measurement is a constant challenge in the social sciences and among its many disciplines, a number of techniques have been developed to overcome this impediment. In psychology, for example, there is a relatively well-established science for building objective measurements that are not directly observable. These techniques are called psychometrics and entail, for example, the use of IQ tests, targeted survey responses, and other methods.

In urban studies, however, comparatively rigorous methods have been lacking. To address this issue, Raudenbush & Sampson (1999) proposed the notion of 'ecometrics,' patterned after psychometrics but oriented toward ecological measurements rather than individual measurements. In short, ecometrics uses survey response data and applies structural equation models to identify and measure neighborhood social constructs that are independent of individual responses and perception. These ecometric measures can then be used in conjunction with multilevel model specifications to assess neighborhood effects. This, theoretically, allows independent variables at the neighborhood level to estimate dependent variables at the individual level while controlling for a host of individual characteristics.

While each of these examples outlined above helps elucidate one or two of

the methodological issues raised by G. Galster (2008b), none of the studies identified have attempted to address all of them. Nor have any of the studies identified above proposed solutions to omitted variable bias (for which science, in general, has found no solution except for experimental design). Furthermore, two of Galster’s challenges have received relatively little attention, namely defining the appropriate scale of measurement and identifying the mechanisms of neighborhood effects. These two issues will be explored further in the following section.

1.4 Lessons Learned and New Directions

Despite confusion during the MTO Enigma, the empirical record on neighborhood effects has proven robust. The social science community, it seems, has settled the debate that neighborhoods do matter for cognitive, educational, and socioeconomic outcomes—and the most recent and rigorous evidence from multiple studies confirms this position (Massey 2015). Sampson et al. (2008), for example, find robust impacts of concentrated disadvantage⁴ on the verbal abilities of young black children—and that these impacts persist throughout the life course. Continuing his work on collective efficacy, Robert Sampson has validated several of his previous work using updated data from the Project on Human Development in Chicago Neighborhoods in his 2012 book, *Great American City: Chicago and the Enduring Neighborhood Effect*. He also demonstrates the significant benefit that non-profit organizations provide to residents, and the impact of spatial interdependence (Sampson 2012).

Following his mentor’s assertion that selection bias is itself a neighborhood effect, Sharkey (2013) has demonstrated convincingly that concentrated disadvantage manifests throughout generations; his recent book *Stuck In Place* uses data from the Panel Study of Income Dynamics to detail the longitudinal impacts of neighborhood effects, finding that children who grow up in poverty are significantly more likely to live in impoverished neighborhoods (and be poor themselves) once reaching adulthood.

George Galster, meanwhile, has exploited data from a natural experiment in Denver, Colorado in which public housing residents were randomly allocated to new neighborhoods. Using a combination of quasi-experimental methods and instrumental variables, Galster and his team show that concentrated disadvantage has a significant and large effect on young children’s educational outcomes and school performance (Galster & Santiago 2015; Galster et al. 2015).

Perhaps most intriguingly, additional follow-up research on the Moving to Opportunity experiment has revealed important neighborhood effects that were masked during the first waves of research. Raj Chetty and his team at Harvard (comprising the “Equality of Opportunity Project”) have found causal evidence that moving to low-poverty census tract at young age (i.e. less than 13 years old) increases earnings in adulthood by 30% (Chetty et al. 2015). They demonstrate further, that the earlier the intervention (i.e. the younger the children were when they moved) the more pronounced the socioeconomic effect later in life. These findings are incredibly important contributions to the scholarly landscape of neighborhood effects for two reasons: first, they show that the one study which has always cast doubt

in the minds of methodological purists (MTO) converges with most other empirical studies; using rigorous experimental design, it is now clear that neighborhoods do, in fact, affect socioeconomic outcomes. Second, Chetty and his colleagues have shown (like other studies) that neighborhood effects are cumulative and interventions are particularly important for young children. These findings help re-frame the neighborhood effects discussion into a life course perspective which is closer to the social psychological roots in which many of the early empirical studies were based (Leventhal & Brooks-Gunn 2000; Fauth et al. 2005; Leventhal et al. 2005; Brooks-Gunn et al. 1993).

Taken together, these studies combine with the existing body of neighborhood effects research to tell a powerful story: neighborhood contexts matter critically, for a variety of reasons including socioeconomic mobility, and especially so for youth. It seems clear that the answer to the question “do neighborhoods matter?” has been answered with a resounding “yes”. For researchers interested in urban contexts, then, this is no longer an appropriate question. Indeed, recently, Sharkey & J. W. Faber (2014) have argued “that any attempt to reduce the literature to a single answer about whether neighborhoods matter is misguided.” Thus, they “call for a more flexible study of context effects in which theory, measurement, and methods are more closely aligned with the specific mechanisms and social processes under study,” and they call for attention to a new set of questions: “Where, When, Why, and For Whom Do Residential Contexts Matter”?

To help address these questions, two of the important challenges posed by Galster seem particularly relevant: defining the appropriate scale of neigh-

neighborhood and identifying the mechanisms through which neighborhoods impact individuals. By leveraging big data, computational resources and the latest techniques in quantitative analysis, it is possible to shed light on these issues. Most studies of neighborhood effects entail the use of administrative data, typically collected at the census tract level as proxies for neighborhood measurements. As many have pointed out (e.g. Sampson et al. 2002a; G. Galster 2008b; Galster 2012), these measurements are adequate at best, though they are ubiquitous because they are easy to obtain and they comport reasonably with the notion of ‘neighborhood’. More importantly, there have rarely been data sources available at geographic scales smaller than census tracts. This is no longer true. Increasingly, microdata are available for many types of urban phenomena, and, also increasingly, they are publicly available, either through open data portals or data mining techniques. Examples of such sources include parcel data on land use characteristics, urban amenity locations (e.g. OpenStreetMap), systematic observational data (e.g. data mining through google street view), and sentiment analysis conducted through geolocated twitter data (O’Brien et al. 2013; Bader et al. 2015).

It is also possible to combine these data with publicly available data on urban transport networks like the General Transit Feed Specification (GTFS), a data format for the public dissemination of transit data or the OpenStreetMap road network, a kind of Wikipedia for maps. Using free and open source software, these data sources can be combined and leveraged to create more realistic representations of urban areas that have more grounding in behavioral theory. Using these techniques, it is possible to define ‘neighborhood’ as the area reachable within a specified commute time via a

particular mode of travel. A neighborhood, so defined, would then consist of the social processes, and physical/administrative resources to which an individual is exposed (within a specified amount of time/distance). Using this neighborhood framework, it is then possible to conduct investigations into the mechanisms through which neighborhoods affect individuals. Contextual researchers could then conduct analyses on each of the proposed mechanisms of neighborhood effects through a process of deductive reasoning (moving beyond simple measures of concentrated disadvantage into more nuanced measures of processes/resources) in which different mechanisms are systematically tested and validated or eliminated.

Chapter 2

The Cartography of Opportunity

2.1 Introduction

Two decades ago Galster and Killen coined the term “geography of opportunity” in a seminal article published in this journal (Galster & Killen 1995). Since then, the spatial pattern of factors that shape the structure of opportunity in metropolitan regions has been an important topic of public policy and lively subject of research. Conceptually, the notion of spatial opportunity is both simple and intuitive: neighborhoods, as unique packages of resources, institutions, and socializing agents, are likely to have a powerful influence on the welfare and life chances of their residents. In sociology, there is a long tradition of scholarship on spatial opportunity structures, the impacts of which are called neighborhood effects. In the last few decades, however, interest in these topics has burgeoned, and the geography of opportunity has

attracted the interest of researchers from across the social and behavioral sciences. Today, the term geography of opportunity is widely used even in popular media, and closing the spatial opportunity gap is a well understood goal of sustainable urban development. What is less well understood, however, is how “opportunity” should be defined, how it should be measured, and how those measures can help close the opportunity gap through spatial policy interventions. Despite these ambiguities, achieving spatial equality of opportunity has become an acutely important agenda, particularly in the fields of housing policy, community development, and equity planning, and it has motivated calls for strategic neighborhood investments, residential mobility programs, or both.

To this end, many attempts have been made to visualize the geography of opportunity and quite literally plot it on a map. Recently, these *opportunity maps* have not only become increasingly common, but their preparation has been encouraged and facilitated by the US Department of Housing and Urban Development (HUD). In many respects, this is overwhelmingly positive, and the increasing prominence of opportunity mapping represents a useful and important step forward for equity planning. Maps are powerful vehicles for revealing spatial patterns in social structure. Like any data visualization technique, however, maps can be misleading or misinterpreted if their underlying assumptions are not met or critically examined. For these reasons, the institutionalization of opportunity mapping portends a need to examine critically the foundations that underlie the construction of opportunity maps, and their application in planning and public policy. A closer look at the conceptual foundations and analytical methods that underlie these exercises offers important lessons not just for the practice of opportunity mapping

but also for the implementation of fair housing policy, regional planning, and equity planning in general.

In the following essay, I examine the practice of opportunity mapping from both theoretical and methodological perspectives, highlighting several weaknesses of the common methods. Following, I outline an improved theoretical framework based on Galster's (2012) categorization of the mechanisms of neighborhood effects. Using data from the Baltimore metropolitan region, I then use confirmatory factor analysis to specify a measurement model that verifies the construct validity of the proposed theoretical framework. The model provides estimates of four latent variables that may be conceived as the essential dimensions of spatial opportunity: Social-Interactive, Environmental, Geographic, and Institutional. Finally, I develop a typology of neighborhood opportunity by applying an unsupervised machine learning algorithm to the four dimensions of opportunity. The results suggest that the practice of opportunity mapping can be improved substantially through (1) a better connection to the empirical literature on neighborhood effects, (2) a multivariate statistical framework, and (3) more direct relevance to public policy interventions.

I begin with the premise that opportunity maps are intended to display the spatial variation in structures that influence a variety of socioeconomic outcomes, regardless of personal circumstance. This assertion has two important implications. First, opportunity mapping is distinct from vulnerability mapping. The former is concerned with identifying social, physical, and environmental attributes that affect a hypothetical household that resides in a particular neighborhood. The latter is concerned with identifying particular

subpopulations who are at increased risk to external shocks due to their own precarious circumstance. A map of poverty concentration could serve either of these purposes: an impoverished family is at a greater risk of homelessness in the event of a major recession; an impoverished neighborhood imposes a negative externality on all neighborhood residents, whether they are personally below the poverty line or not. A map showing the concentration of homeowners holding high-cost loans is an example of a vulnerability map, *not* an opportunity map. *Ceteris paribus*, there is no reason to assume that a family living in a neighborhood will be affected by the share of its neighbors paying high interest rates on their mortgages. In practice, these two concepts are often conflated, leading to an erratic and unjustified collection of indicators intended to measure “opportunity”.

The second implication flows from the first: there should be some plausible connection that explains why the spatial structures measured affect socioeconomic outcomes. For example, a neighborhood with high rates of unemployment has less opportunity because the population in that neighborhood is less connected to the labor market and may have relatively little information about potential employment opportunities that may be passed on to job seekers in the neighborhood. For this reason, there is a natural connection between the practice of opportunity mapping and the literature on neighborhood effects—the body of research designed to uncover the causal effects of spatial structure on key socioeconomic outcomes.

Following this premise, I argue that traditional opportunity mapping exercises are often flawed in their theoretical and methodological conceptions. These flaws make opportunity maps difficult to interpret, and limit their util-

ity in the formulation of housing policy. To address these issues, I outline an alternative methodology based on structural equation modeling, and I present an empirical example demonstrating the conceptual superiority over traditional methods. Finally, I use a simple machine learning algorithm to show how neighborhoods may be classified into a typology useful for planners and policymakers, skirting the typical issues that arise in the presentation and display of opportunity maps.

2.2 The Geography of Opportunity & The Mechanisms of Neighborhood Effects

Among social scientists it is now widely accepted that neighborhoods influence a wide variety of socioeconomic outcomes. In a recent and comprehensive review of the literature, Galster and Sharkey (forthcoming) identify compelling evidence of neighborhood effects on outcomes that include cognitive and behavioral development, educational performance and attainment, teen fertility, physical and mental health, labor force participation and earnings, and crime. Additional effects have been found related to outcomes as diverse as obesity (Diez Roux AV et al. 2006), violence (Sampson et al. 2005), crime (Kling et al. 2005), high school graduation (Wodtke et al. 2011), children's test scores (Burdick-Will et al. 2011), college attendance rates (Chetty et al. 2015), earnings (Chetty et al. 2015), intergenerational mobility (Chetty & Hendren 2015), mental health (Sanbonmatsu et al. 2004; Ludwig et al. 2012b), physical activity (Kaczynski & Henderson 2007), cognition (Sharkey 2011; Sampson et al. 2008), infant health (Yang & Chou

2015), mortality (Anderson 2015), employment (Galster et al. 2015), and many others.

Some of these studies use similar explanatory variables, but many examine the effect of a particular key variable such as poverty, walkability, or ambient pollution. The challenge for researchers seeking to construct opportunity indices is to synthesize these results into a common formula that represents the most important neighborhood influences on the most important outcomes of interest. Overcoming such a challenge requires first the specification of a particular outcome (e.g. economic mobility), second the identification of appropriate causal neighborhood mechanisms that contribute to the outcome, and third the application of appropriate weights to each mechanism. In formal terms, this is equivalent to the equation given by G. Galster (2008a), in which an outcome of interest O observed at time t for individual i residing in neighborhood j in metropolitan area k can be expressed:

(1)

$$O_{it} = \alpha + \beta[P_{it}] + \gamma[P_i] + \varphi[UP_{it}] + \delta[UP_i] + \theta[N_{jt}] + \mu[M_{kt}] + \varepsilon$$

where

O_{it} = employment status or income (model dependent) for individual i at time t

$[P_t]$ = observed personal characteristics that can vary over time (e.g., marital or fertility status, educational attainment)

$[P]$ = observed personal characteristics that do not vary over time (e.g., year and country of birth)

$[UP_t]$ = unobserved personal characteristics that can vary over time (e.g., psychological states, interpersonal networks and relationships) $[UP]$ = unobserved personal characteristics that do not vary over time (e.g. IQ, prior experience) $[N_t]$ = observed characteristics of neighborhood where individual resides during t

$[M_t]$ = observed characteristics of metropolitan area in which individual resides during t (e.g., area unemployment rates)

ε = a random error term

i = individual

j = neighborhood

k = metropolitan area

t = time period (typically a year)

This equation (henceforth Galster's equation) is a useful vehicle for describing the challenges and assumptions underlying opportunity mapping methodology and will be used throughout the paper. The challenge for opportunity mappers is, thus, to identify the vector(s) of spatial attributes (terms M and N) that contribute to a variety of outcomes (O), and to develop a valid framework for applying weights to these indicators (i.e. the parameters θ and μ). This is a tall order since there exists no study to date that permits the estimation of Galster's equation (and there is unlikely to ever be one) (G. Galster 2008a). Empirically, it is also impossible to determine whether some outcomes (O 's) are more important than others (is cognition, for example, more important than employment?) and philosophically, these issues will draw diverse opinions. Furthermore, there may be important path-dependencies among outcomes; cognition, for example, is likely to impact educational performance, which is in turn likely to impact employment

prospects.

2.2.0.1 Identifying Outcomes and Indicators

With respect to the voluminous literature on neighborhood effects, several authors have offered opinions on which variables might best represent the vectors N and M . Chetty & Hendren (2015), for instance, hold that “Low-income children are most likely to succeed in counties that have less **concentrated poverty, less income inequality, better schools, a larger share of two-parent families, and lower crime rates**. Boys’ outcomes vary more across areas than girls, and boys have **especially poor outcomes in highly-segregated areas**”. These sentiments are largely shared by Massey (2015), who argues that “The social scientific evidence thus yields several firm conclusions. First, the combination of **racial segregation, class segregation, and high rates of minority poverty** mechanically combine to produce neighborhoods of concentrated disadvantage. Second, exposure to concentrated disadvantage reduces human wellbeing along multiple dimensions, with powerful negative effects on health, cognition, education, employment, and earnings” (Massey 2015).

With respect to housing policy, the realm in which much of the research on spatial opportunity has been conducted, authors have argued that “both common sense and a growing body of research evidence teach us that living in a racially isolated, high poverty community undermines a family’s wellbeing and life chances, yet conversely, we know much less about how to define the “opportunity rich” neighborhoods to which we should be helping families move. We suggest that, instead of simple proxies, such as a neighborhood’s

racial composition or poverty rate, destination neighborhoods should be targeted on the basis of concrete opportunities, such as **community safety, quality schools, or access to skill-appropriate jobs**” (Briggs & Turner 2006, p.28). Others, meanwhile, have argued that “The neighborhood effects literature stresses that residential mobility may affect individuals by giving them access to better **community resources, schools, labor markets, and immediate neighbors, and moving them away from segregated enclaves and the negative influences in their prior neighborhoods**” (Rosenbaum & Zuberi 2010, p.31) (emphasis added).

Synthesizing these results, Galster (2010) argues that while “the listings of potential mechanisms differ in labeling and categorizations, there is a broad consensus about how the underlying causal paths are thought to operate in theory. Unfortunately, there are few tentative conclusions, let alone any consensus, about which mechanisms demonstrate the strongest empirical support” (p.1). In other words, the empirical record provides guidance on the vectors that comprise N and M (or at least the mechanisms underlying them), but little to no guidance on the appropriate magnitudes of each θ and μ . Continuing his comprehensive review, Galster finds empirical evidence for 15 independent causal pathways through which neighborhoods affect different socioeconomic outcomes, which he organizes into four categories: social-interactive, environmental, geographic, and institutional. These categories are largely identical to those outlined by Sampson et al. (2002b), except that Galster includes an environmental category whereas Sampson et al differentiate two types of social-interactive categories; this difference merely reflects the fact that Sampson et al review only the sociological literature while Galster also incorporates epidemiological perspectives. The categories

are also similar to those outlined by Ellen & Turner (1997), and Leventhal & Brooks-Gunn (2000). Given the strength with which these categories are represented in the literature, it is natural that they should be reflected well in the opportunity mapping methodology. In practice, however, this is rarely the case.

2.3 The Practice of Opportunity Mapping

The practice of opportunity mapping has several intellectual roots. As a technical exercise, opportunity mapping builds on techniques developed for suitability analysis by Ian McHarg (Collins et al. 2001). Ostensibly, opportunity mapping involves the identification of areas well suited to promote social mobility by combining GIS layers of various social, economic, and environmental variables. More conceptually, the practice builds on equity mapping developed by Toulmin (1988) and Truelove (1993) and applied by Talen (1998) and Talen & Anselin (1998). This body of research defines equity in terms of proximity or access to various public facilities or neighborhood attributes. The current practice of opportunity mapping, however, draws from John Powell's opportunity-based housing model, and was developed in the context of fair housing litigation (Powell 2003). Specifically, in the case of *Thompson v HUD*, John A. Powell testified as follows (Powell 2005):

The segregation of African American public housing residents isolates them from the opportunities that are critical to quality of life, health, stability, and social advancement. The safe and

stable neighborhoods, successful schools and employment opportunities generally available to Whites in the greater Baltimore region have been denied to African American public housing residents in the City of Baltimore. To remedy this segregation two objectives must be met: 1) the remedy must give African American public housing residents the opportunity to live in racially integrated areas in the Baltimore region and 2) the remedy must affirmatively connect African American public housing residents to high opportunity neighborhoods in the Baltimore region.

powell then introduced opportunity maps that included measures in three categories—economic opportunity and mobility, educational opportunity, and neighborhood health—aggregated into an overall opportunity index, and showed that minorities and public housing developments were (and are) disproportionately concentrated in low opportunity areas.

powell's testimony was persuasive and helped lead to a ruling in favor of the plaintiff class and the creation of a regional housing mobility program designed explicitly to help connect families with high-opportunity neighborhoods. In recent years, opportunity mapping exercises have been conducted in metropolitan areas across the nation including Seattle, Austin, Minneapolis, Chicago, Baltimore, Boston, and many other places, and these maps have moved well beyond the realm of fair housing litigation into much broader usage including the development of regional housing, transportation, and economic development policies. Much of the work has been conducted by the Kirwan Institute, whose process has become somewhat standardized: (1) Select variables that measure the presence or lack of opportunity, (2) Collect

data and assign values to common geographic units, (3) Normalize the data and assign to subcategories, (4) Compute a composite opportunity index, (5) Create thematic maps, (6) Overlay with other variables of interest (Reece & Gambhir 2008). This methodology appears logical and straightforward upon first inspection, however, it also involves a number of subjective decisions and computational tasks at each step in the process that significantly influence the results of the analysis yet are neither discussed in the literature nor widely understood.

2.4 Critique

Despite the widespread and increasingly common use of opportunity maps in the development of urban policy, there exists no published discussion among researchers or practitioners that examines the utility and soundness of the technique. This is an important omission in the literature. According to Giovannini et al. (2005, p.14), “composite indicators are much like mathematical or computational models. As such, their construction owes more to the craftsmanship of the modeller than to universally accepted scientific rules for encoding. With regard to models, the justification for a composite indicator lies in its fitness for the intended purpose and in peer acceptance”. Absent the discussion and peer acceptance described by Giovannini et al. (2005), the opportunity metrics in common use should be treated with skepticism. Indeed, upon review of the data and methods used to develop most opportunity maps, it is clear that a number of critical flaws exist that limit the utility of opportunity mapping in its current form.

2.4.0.0.1 Indicator Selection and Categorization The list below represents the indicators and categories used most commonly in these exercises (Kirwan Institute for the Study of Race and Ethnicity 2013):

I. Education Indicators

- Adult education attainment
- Promotion Rates
- Graduation rates
- School Proficiency Index
- Student poverty rates
- Student teacher ratio
- High Quality Teachers

II. Economic Indicators

- Economic climate (change in number of jobs)
- Employment competition (ratio of jobs to labor force within a certain miles)
- Proximity to employment
- Job growth trends
- Population on public assistance
- Unemployment rate

III. Housing and Neighborhood Indicators

- Affordable housing
- Foreclosure rate

- High-cost loan rate
- Housing cost burden
- Home ownership
- Housing vacancy
- Mortgage denials
- Population change 1990-2000
- Poverty rates
- Property appreciation and tax base
- Property values
- Sub-prime loans
- Subsidized housing

IV. Transportation and Mobility Indicators

- Access to automobile
- Mean commute time
- Public transit access
- Transit cost
- Transit dependency
- Transportation cost
- Walkability

V. Health and Environmental Indicators

- Amount of toxic waste release
- Crime index
- Grocery stores

- Parks and open space
- Proximity to toxic waste release sites

Each of the variables identified above is useful for understanding the spatial distribution of inequality. Their categorization and aggregation, however, calls into question the construct validity of each purported subindex: are education, economy, housing and neighborhood, transportation and mobility, and health and environment truly the subdimensions of opportunity? Are the indicators grouped into those categories valid measures of those subdimensions? And is it justified to assume each indicator and each category contributes equally to the geography of opportunity? The answer to all of these questions is “probably not”.

What is striking about the variables and categories outline above is the complete omission of a category pertaining to social structure. Indeed, this is even more egregious as several authors have argued that “if neighborhood effects on child outcomes exist, presumably they are constituted from social processes that involve collective aspects of community life” (Sampson et al. 1999, p.634; Mayer & Jencks 1989). The empirical record appears to confirm this view, and there is strong evidence that at least *some* aspect of social interactive mechanisms contributes to a variety of socioeconomic outcomes (Galster 2012). In some cases, social variables are misappropriated into other categories; adult educational attainment, for instance, is often categorized into an “educational” group, which ostensibly measures the educational opportunities in a neighborhood (Reece & Gambhir 2008; Kirwan Institute for the Study of Race and Ethnicity 2013). Conceptually, however, educational opportunities are a dimension of institutions—not people—and adult educa-

tional attainment does not measure institutional capacity. Even as a proxy, educational attainment is a poor indicator of school quality; in Baltimore, for example, there are several neighborhoods near the City's inner harbor in which the population is young, affluent, and well educated—and these neighborhoods are served by some of the lowest-performing schools in the state of Maryland.

Other times, social variables such as poverty are grouped into an ambiguous “neighborhood quality” category which also contains variables related to the housing stock, such as vacancy rates and home values (Reece & Gambhir 2008). Because these variables measure multiple unrelated phenomena, it is wholly unclear what this category measures, how it should be interpreted, and how it provides useful information to policymakers. This does not suggest that any of the indicators in this category are necessarily misguided in their own right, but that their combination into a single metric has no theoretical justification and no direct utility.

Instead of focusing on social indicators, opportunity mapping exercises seem to place undue importance on the location of jobs—an ode to the pervasive notion of spatial mismatch (Kain 1968; Kain 1992). This is despite the fact that “there is considerable statistical evidence that this spatial mismatch is of less importance to economic outcomes than the social-interactive dimensions of neighborhoods” (Galster 2010, p.14). The employment category also reveals another problem in that indicators are often grouped into their topical domain rather than their underlying data-generating process. This strategy leads to unemployment rates and access to jobs grouped into the same category, which is problematic because the *pathways* through which

unemployment and access to jobs affect socioeconomic mobility are entirely distinct. Furthermore, in many cases, unemployment and job accessibility are almost perfectly correlated in the opposite direction: central cities have large concentrations of unemployed people *and* the best access to jobs (Chaple 2014). Averaging these two indicators together results only in noise.

2.4.0.0.2 Normalization, Weighting, and Aggregation Returning to Galster's equation, it is natural to frame opportunity mapping through the lens of a linear regression equation; first an outcome variable (opportunity) is defined, then explanatory variables are identified and combined to yield an estimate of the outcome. This regression metaphor is useful for discussing the implicit assumptions that underlie the current practice of opportunity mapping and the potential drawbacks they introduce. I argue that the most important assumptions that should be treated with caution are the identification of coefficients, possible non-linearity of effects, and interactions among variables.

While there appears to be some agreement among researchers about the types of neighborhood structures that contribute to spatial inequality, there is little guidance from the literature regarding *how much* each structure contributes to the pattern. Since the mechanisms that drive neighborhood effects remain very much elusive, it is extremely difficult to quantify the relative contribution of each potential source (Galster 2010; G. Galster 2008a). For this reason, explanatory variables in an opportunity index are treated as equal, independent, and linear in effect. In the absence of any alternative theoretical framework, these are reasonable simplifying assumptions. In many cases, however, these assumptions may be untrue, which could lead to

misinterpretation of opportunity metrics and faulty policy prescriptions.

Indeed, in some cases, there is already evidence that these assumptions are violated. Galster et al. (2000), for instance, have argued that “when a neighborhood reaches a critical value of a certain indicator, it may trigger more rapid changes in that neighborhood’s environment,” and that neighborhood poverty rate is one such indicator that has a non-linear relationship with other quality of life indicators such as unemployment and vacancy rate. In the face of this evidence, it is questionable whether poverty (which follows a log-linear distribution) should be treated as a linear variable in opportunity indices or whether its inclusion warrants some other transformation. This consideration is likely to apply for other variables as well. In a similar vein, it is reasonable to assume that each of the opportunity indicators may have a more nuanced relationship with a particular outcome. It would seem unlikely that each of the variables identified above have the exact same significance and magnitude associated with a particular outcome. In other words, in the context of Galster’s equation, it is unreasonable to assume that each θ and μ are equal and invariant across opportunity indicators.

One possible solution is to develop weights for each indicator using alternative methods that could include surveys/crowdsourcing or an alternative statistical model. With respect to the former, researchers must rely on stated preferences about the types of opportunities that matter and the types of resources people believe contribute to that particular type of opportunity. This method introduces bias relative to the composition of the sample, their knowledge, and their desires. With respect to the latter, researchers must assume that an alternative model carries the appropriate information they wish

to distill. One potentially valuable method is the use of decomposition techniques like factor analysis and principal components analysis, which project collections of correlated variables onto a smaller subset of representative factors or components. This technique helps solve the problem of weighting individual indicators within categories but does not overcome the issue of weighting different dimensions of opportunity relative to one another. In other words, factor analysis can help estimate a reduced set of variables that represent meaningful sub-dimensions of opportunity, but does not provide a framework for understanding how those estimated variables should be aggregated into a single univariate metric.

Finally, the research discussed above highlights at least three important heterogeneities with respect to neighborhood effects on particular subpopulations: race, gender, and age (Sharkey & J. Faber 2014). Younger people and minorities are more prone to neighborhood effects in general; girls experience a larger effect on their mental health, and boys experience a larger effect on their education, employment, and criminality (Chetty & Hendren 2015; Galster et al. 2015; Sanbonmatsu et al. 2004). Returning to Galster's equation, these findings imply that the P terms are not only significant, but that depending on the values they take, also change the values of θ and μ . In the face of these findings, the design of a universal index of opportunity may be problematic. If there is heterogeneity in the way that neighborhood effects are experienced, then there may need to be heterogeneity in the types of metrics that are collected and combined. The typology approach described in later sections addresses this issue by introducing flexibility in the way that opportunity metrics are combined and displayed.

2.4.0.0.3 Geographic Assignment Apart from the difficulty of conceptualizing measures of opportunity, a number of technical challenges remain concerning the quantification and representation of space, particularly when different data sources refer to different underlying data models (e.g. point, line, polygon, raster). When computing a spatial opportunity index an analyst must combine multiple, unrelated data, nearly all of which are measured along different scales and units. To overcome this issue, data must be standardized according to a common geographical unit that is representative of a neighborhood, and converted to a consistent measure. In practice, this nearly always involves collecting data by census tract, and standardizing the data to z-scores. Census tracts are usually chosen as the geographic unit of analysis because they offer the finest geographic precision for which data are widely available.

The drawbacks associated with using census tracts as a proxy for neighborhoods are many and have been well articulated by others (Sampson et al. 2002b; Walter & Wang 2016). Census tracts vary in size and may or may not correspond well with a resident’s notion of neighborhood. Second, using only the data contained within a single census tract ignores the possibility of spatial spillover and the influence of adjacent or outlying neighborhoods (Sampson et al. 1999; Dietz 2002; Sampson 2012; Anselin 2013). Third, data that are important but unavailable at the census tract level, like those defined by an alternative geography, (e.g. zip-codes), or disaggregate microdata (i.e. point locations) require additional transformation, introducing an additional source of error. With respect to polygons-to-polygon conversions, this error represents the well known “modifiable areal unit problem” (MAUP). With respect to point-to-polygon conversions, there are many pos-

sible sources of error depending on how the conversion is performed.

The simplest way to deal with point data, is to simply aggregate all the points within a single tract, and assume that locations with multiple locations have better access. Indeed, this is a common technique in opportunity mapping (Kirwan Institute for the Study of Race and Ethnicity 2013) This is an undesirable method, however, for a number of reasons. First, many tracts would not have a score at all simply because they did not contain any points. This is problematic because tracts could still have good access to one or more points even if those points do not fall within the tract itself. Second, this method fails to account for the difference in tract size, and will provide a bias toward larger tracts.

Another technique for transforming point locations into tract scores is to calculate a measure of kernel density. Kernel density estimators are common among statistical and GIS and software packages, and are typically applied when performing cluster analyses (e.g. the study of crime). In the context of spatial analysis, kernel estimators split a study region into a raster grid, then for each grid cell, search for any points that fall within a specified distance of the originating cell. Points within the search radius are then applied to a distance decay function so that nearby points have a larger effect than those further away. The result is a crude estimate of spatial exposure; since the score given to each cell in the raster is a distance-weighted sum to a given resource, it can be conceptualized as Euclidian-based accessibility measure. Grid scores can then be averaged for each census tract to provide an overall measure. This method is better than simply aggregating points to tracts because it incorporates the influence of points that lie outside the tract bound-

aries. It is also preferable to simple buffer-based methods (e.g. aggregating all points that lie within a 1-mile radius of the tract) because it treats space as continuous rather than discrete, and does not assume a constant effect within the buffer. Despite these strength, kernel density methods also suffers some drawbacks. For one, both the size of the grid cells and the search radius must be specified by the analyst, which requires some theoretical foundation for decision making. Second, although a kernel density calculation can be used to estimate access or exposure to a resource, it ignores the impacts of infrastructure connectivity and travel times. Thus, it may be a good choice for estimating the impact of resources that are unrestricted by transport networks (e.g. pollution radiating from a smokestack) but is less desirable for measuring access to amenities like jobs.

A third option is to incorporate locational amenities into a transportation model. For many point-based indicators this may be the most desirable method because it provides the most reliable measure of accessibility, accounting for transportation infrastructure and commute times. This method also provides the potential benefit of disaggregating among modes of travel, for instance, to compute measures of accessibility by transit, which can add an additional layer of sophistication. Since many opportunity analyses are conducted at the metropolitan region, and many metropolitan planning organizations (MPOs) develop travel models, incorporating travel models into opportunity analyses seems like a natural fit. For many spatial variables of interest, this method should be chosen above others when there is an available travel model, though it is not without some disadvantages. One drawback worth noting is that travel models frequently rely on transportation analysis zones (TAZs) or other alternative geographic units like statewide modeling

zones (SMZs). Rarely do these types of models incorporate census tracts, so the conversion of model zones to census tracts can introduce error (i.e. the modifiable areal unit problem). Furthermore, accessibility-based measures still require theoretical specification on the analyst's part with respect to the search radius and the travel cost function used to parameterize the measure.

What is clear from this discussion is not that some methods are inherently more preferable than others, but that a sound rationale is required for a series of subjective decisions and that developing indicators of opportunity is less a formulaic exercise than an iterative one in which many alternatives are tested with respect to their theoretical soundness and analytical performance.

2.4.0.0.4 Visualization In the common practice of opportunity mapping, each spatial indicator is z-transformed, then aggregated into a scale, which typically ranges from around -3 to 3. For the purposes of visualization, this scale is then collapsed into a five-level index with each quintile representing a different echelon of opportunity. From a visual perspective, this is a convenient transformation; maps based on quantiles produce equal shares of each color and typically produce identifiable patterns and appealing aesthetics. From an analytical perspective, however, maps based on quantiles of any number can be misleading because they intentionally break data into a uniform distribution. Each quantile contains the same number of observations as every other, regardless of the shape of the underlying data's distribution. This means that extreme outliers may be classified into the same quantile as observations that are relatively common in the data but happen to fall near the top or bottom of the distribution. Furthermore, when data are highly clustered, quantile breaks may create artificial differentiation among obser-

vations that have similar or even the exact same values. This creates the visual distortion that meaningful differences exist in the data when, in truth, none exist at all. Conventionally, opportunity maps are displayed using five quintiles, which comports nicely to a familiar likert-like interpretation, but it is not clear why the data should be divided into five quintiles rather than three or seven or ten divisions.

Again, this is an area with few hard guidelines. As Christopher Ingraham explained in a short article for the Washington Post’s Wonkblog, “Visualizing data is as much an art as a science. And seemingly tiny design decisions—where to set a color threshold, how many thresholds to set, etc.—can radically alter how numbers are displayed and perceived by readers” (Ingraham 2016). Rather than force these choices upon an analyst, one alternative is to use a clustering algorithm to divide neighborhoods into discrete categories based on the structure of their underlying data. These techniques help remove subjectivity from the analysis, using a data-driven approach that defines clusters of neighborhoods by maximizing the variation between clusters and minimizing the variation within them. Such an approach is discussed in later sections.

2.5 A Measurement Model of Opportunity Structure

Given the conceptual and technical measurement issues outlined above, it is clear that opportunity is a difficult concept to operationalize, let alone measure and visualize. One way to address this problem is to treat the quantification of opportunity as a measurement error problem. Through

a liberal interpretation, this may be viewed as an extension of econometrics, a methodology concerned with developing measures of neighborhood social ecology (Raudenbush & Sampson 1999; Mujahid et al. 2007; O'Brien et al. 2013). In this framework, opportunity and its subdimensions are viewed as latent variables that cannot be measured directly, but can be estimated by modeling the covariation among the indicators through which they manifest. As with any measurement model, however, opportunity metrics require a sound theoretical framework for organizing and specifying relationships among variables. As described above, a major weakness of opportunity analyses to date has been the lack of a sound framework for organizing indicators into categories of metrics. To address this issue, I argue that the literature on neighborhood effects offers a sound organizing framework for classifying subdimensions of opportunity. Specifically, I propose that neighborhood indicators should be categorized according to the four mechanisms of neighborhood effects outlined by Galster (2012): social-interactive, environmental, geographic, and institutional. These categories are well supported by the empirical literature, and are theoretically grounded in causal processes that generate socioeconomic outcomes. Following the outline of this framework, I use confirmatory factor analysis to verify the construct validity of the proposed approach by showing that indicators load on the theoretically-defined factors in the expected patterns and that the measurement model is valid with respect to overall model fit indices. This gives both theoretical and empirical justification to the notion that the selected indicators measure what they purport to measure, and that four resulting metrics are reasonable estimates of each theorized dimension.

Both exploratory factor analysis (EFA) and principal components analysis

(PCA) are becoming increasingly common in urban research although neither approach is truly widespread. Ewing et al. (2003), for example, uses PCA to develop a measure of urban sprawl, and Nosoohi & Zeinal-Hamadani (2011) use EFA to study measures of welfare and development in Iran. In the context of opportunity mapping, other researchers have advocated for similar data-reduction techniques in the computation of opportunity metrics. Walter & Wang (2016), for example, suggest the use of geographically weighted principal components analysis (GWPCA). They do not, however describe their theoretical framework for categorizing indicators into groups, nor do they provide any argument as to why their measurements are causally related to important socioeconomic outcomes. Indeed, their only rationale for choosing indicators is “accounting for and considering the variables used in all previous studies” (Walter & Wang 2016). Thus, although they provide suggestions for enhancing the methodological rigor of opportunity analyses, they do not demonstrate that their approach has any greater level of construct validity than traditional approaches. In other words, they do not report whether their indicators load on components in the expected fashion and whether those components capture enough variation to be viewed as valid composite indicators. In many cases, this seems unlikely, at least when applied to a diverse range of metropolitan areas. Access to primary care physicians and the percentage of area coverage by parks and green space, for example, which are classified under the “Healthy Environment” category are unlikely to load on a single factor, with physician access likely biased towards urban areas and green space likely biased toward suburban and exurban areas. When these indicators do not load strongly on a single component, it is unclear how the results of GWPCA should be interpreted and is unlikely

that the first component may serve as a composite metric for the category. Furthermore, Walter & Wang (2016) fall victim to the same categorization issues that plague traditional approaches by conflating institutional measures like school proficiency and early childhood neighborhood participation alongside social-interactive measures like poverty and labor market engagement. Although these indicators may be highly correlated and may well load on a single component, they are quite distinct from a conceptual perspective.

By contrast, confirmatory factor analysis (CFA) approaches based on structural equation modeling are comparatively rare in urban research. One notable exception is Bagley & Mokhtarian (2001), who use confirmatory factor analysis to study the effects of neighborhood conditions on travel behavior. CFA differs significantly from EFA and PCA approaches because it requires the specification of an a priori theoretical model. For this reason, CFA is often used for the purposes of construct validity because it demonstrates that observed data conform to the particular theory imposed by the researcher. In the context of opportunity mapping, this makes CFA a particularly attractive approach because it facilitates the evaluation of the particular theoretical frame used to devise opportunity metrics. Another benefit of the CFA approach is that indicators can be specified to load on distinct but correlated latent variables (e.g. assigning educational attainment to an institutional dimension rather than a social dimension) rather than simply mining the data for common covariance, as is the case with EFA. The preceding section describes the theoretical framework and the data sources used to construct such a model.

2.5.1 DATA

2.5.1.0.1 Institutional Institutional variables are designed to capture “actions by those typically not residing in the given neighborhood who control important institutional resources located there and/or points of interface between neighborhood residents and vital markets” (Galster 2012). Although institutional data comprises more than educational systems, schools are a primary vehicle through which institutional capital and institutional opportunity is transmitted. Furthermore, schools are perhaps the only type of institution that facilitates evaluation of *quality* in some form. For this reason, variables in the institutional category are designed to capture multiple dimensions of school quality and include the share of highly qualified teachers¹, the share of Students achieving a passing grade on state administered exams, performance on Advanced Placement exams, SAT scores, and high school dropout rates. These data are collected from the Maryland State Department of Education which provides annual statistics for each school in the state of Maryland.

Maryland State Assessments (MSA), administered every year to students in grades 3 through 8, and High School Assessments (HSAs) are administered in grades 9-11. For this analysis, subject scores for each school are averaged into an overall measure of students who score passing grades on the exams. Individual school measures are then assigned to census tracts by collecting

¹To be classified as a “highly qualified” teacher, MSDE requires that instructors in core academic subject areas must: Hold at least a bachelor’s degree from a regionally accredited institution of higher education (IHE); hold a valid Standard Professional Certificate or Advanced Professional Certificate or Resident Teacher Certificate in the subject area they are teaching; and satisfy additional requirements associated with specific teaching levels and experience. For additional information, see http://www.marylandpublicschools.org/msde/programs/esea/docs/TQ_Regulations/general_definition.htm

catchment areas from each jurisdiction in the Baltimore region, matching each school with its catchment area, then geocoding each tract to the applicable catchment area. The best fitting model is achieved by incorporating a nested structure in which separate factors are estimated for high school and elementary school. These two factors are combined with two measures of middle school quality (highly qualified teachers and standardized test achievement) to yield the overall institutional factor².

2.5.1.0.2 Geographic Geographic variables are designed to capture aspects of neighborhoods that affect residents' life-courses "purely because of the neighborhood's location relative to larger-scale political and economic forces," and encompass the subdimensions of spatial mismatch and public services (Galster 2012). Operationally, these are dimensions of the built environment, particularly accessibility to necessary goods and services. For the purpose of this analysis, geographic variables include jobs accessible by walk and transit, access to healthcare facilities, access to public institutions, and access to social organizations.

Job location data is collected from the U.S. Census Longitudinal Employment-Household Dynamics (LEHD) via the LEHD Origin-Destination Employment Statistics (LODES) database. The LODES database records the location of jobs, annually, at the census block level. Although the current analysis is limited to the Baltimore Metropolitan region, it is necessary to collect and analyze LODES data for the entire state of Maryland, as well as portions of Washington D.C., Virginia, West

²a middle school factor is not estimated because it only includes two distinct data points

Virginia, Pennsylvania, and Delaware to reflect the fact that, while families must reside in the Baltimore region, they still have access to jobs in nearby counties and states. I use total jobs accessible rather than low/mid-skill jobs because, in Maryland, there is very little spatial differentiation among jobs of differing skill levels.

Healthcare facility data is collected from the 2013 Maryland Quarterly Census of Employment and Wages (QCEW), a database of employment records updated quarterly by the Maryland Department of Labor, Licensing, and Regulation (DLLR). The QCEW database contains information on the location, employment levels, and industrial classification for each employer in the state. Social organizations (e.g. philanthropies and non-profits), public institutions (like schools and universities) and applicable healthcare facilities were identified from the QCEW data. Healthcare facilities were selected using the following NAICS codes:

- 6211: Offices of Physicians
- 6214: Outpatient Care Centers
- 6219: Other Ambulatory Healthcare Services
- 6221: General Medical and Surgical Hospitals

Because the key variables in the geographic category are *destinations*, (i.e. locations that require travel to and from a household's residence) computing access to these destinations requires data on transportation infrastructure that facilitates such travel (i.e. pedestrian, transit, and automobile networks). Data for walk networks is collected from OpenStreetMap (OSM), a world-wide, open source repository for spatial data. In many urban areas, OSM is the most comprehensive and up-to-date source of roadway, bikeway, and

pedestrian infrastructure. Data for transit networks is provided by the Maryland Transit Administration and the Central Maryland Regional Transit Agency in the form of General Transit Feed Specifications (GTFS). GTFS data is published by these agencies on a regular basis and includes information on bus and rail transit stops, frequencies, and schedules.

Accessibility (sometimes called “cumulative opportunity”) measures the ease with which a person can consume a resource located in space. Typically, accessibility is used to measure how many jobs are available to a person living in a particular residential area, though it can also be applied to any type of origin or destination. There are many measures of accessibility, most of which are variations on the seminal work of Hansen (1959). In simple terms, accessibility for a given location can be calculated as the weighted sum of all activities that can be reached within some specified cost. Formally, accessibility A_i can be expressed by

(2)

$$A_i(C) = \sum_j a_j f(c_{ij})$$

Where:

a_j is the quantity of some resource at location j obtainable within a generalized cost parameter C

c_{ij} is the generalized cost of travel between origin i and destination j

$f(c_{ij})$ is an impedance function that quantifies the disutility of the travel

In regional science and urban economics literature, $f(c_{ij})$ is typically a linear or exponential decay function, yielding what is often called a gravity model. Gravity equations of this type are commonly used in econometric location

choice models to help explain why certain sets of amenities (like jobs) “pull” households into locating in a certain area.

In this analysis, the cost parameter C is fixed at a threshold of 60 minutes, meaning that only activities that can be reached within a 60 minute commute will be included in the measure. The cost of travel c_{ij} (i.e. time) varies by mode, with automobiles often covering longer distances than walk/transit in shorter periods of time, except in cases of extreme congestion. For job accessibility, the impedance function is fixed at 1, meaning that the accessibility measure represents simply the total sum of jobs that can be reached within 60 minutes. For healthcare and occupational training a linear decay function is applied that weights nearer activities higher those which are further away. Automobile accessibility is computed via the MSTM; walk accessibility is computed via the Pandana software library for the python programming language³; transit accessibility is computed using the TransportAnalyst software platform⁴.

2.5.1.0.3 Environmental Environmental variables are designed to capture the “natural and human-made attributes of the local space that may affect directly the mental and/or physical health of residents without affecting their behaviors” (Galster 2012). Unfortunately, there are relatively few data sources that can provide such variables at the necessary scale, so this category includes only three: a crime victimization index (which captures the social environment), proximity to designated toxic release sites (which captures the ambient physical environment), and the share of vacant hous-

³<http://udst.github.io/pandana/>

⁴<https://github.com/conveyal/analyst-server>

ing units (a measure of physical disorder). Additional variables that could be incorporated into future analyses might include lead contamination in the water, access to parks and open space, or signs of physical disorder collected through systematic social observation (Bader et al. 2015; O'Brien et al. 2013).

In lieu of actual crime statistics, which are unavailable for the region (except Baltimore City) a Crime risk index is used. The crime risk index is developed by Applied Geographic Solutions⁵, and uses data from the FBI Uniform Crime Reports (available at the county level) combined with data from local jurisdictions to model crime risk down to the census tract level. To be sure, this is a weakness of the current analysis. Reported crime would be a better measure of a negative environmental externality, and modeled data are likely to be confounded by the sociodemographic data with which it is estimated.

Toxic release sites are collected from the Environmental Protection Agency's (EPA) Toxic Release Inventory Program⁶, which publishes an annual database of toxic chemical and pollution emitting locations. To quantify the toxic effect of environmental pollution, it is necessary to estimate exposure to such pollutants. Although data provides the point sources of pollution emitting locations, the myriad factors that may influence particulate dispersal (e.g. wind speeds, weather patterns, atmospheric pressure, etc) estimating the precise level of exposure to pollutants is challenging. Following some simple assumptions, however, it is possible to estimate a reasonable approximation using standard spatial analysis procedures.

⁵http://www.appliedgeographic.com/MethodologyStatements_2015/CrimeRisk2015A.pdf

⁶<http://www2.epa.gov/toxics-release-inventory-tri-program>

Kernel Density Estimation (KDE) is a statistical technique used to produce a smooth density surface of point events over space (Xie & Yan 2008). In spatial analyses, kernel density estimators are used commonly to identify “hot spots” of point occurrences, like crimes or traffic accidents. The estimators work by splitting a study area into a regular grid, then specifying a search radius over which the density kernel will be calculated. In the context of toxic release sites, the use of KDE helps incorporate the effects of multiple, overlapping sites in close proximity. For this analysis, a search radius of five miles is specified, which suggests that each toxic release site could have harmful effects of to five miles away, and that the effects decrease with distance according to a quadratic decay function. Tracts are assigned the average value of the grid cells that fall inside them. KDE is performed using ArcGIS (version 10.2) via the Kernel Density tool.

2.5.1.0.4 Social-Interactive Social-Interactive variables measure the attributes of people living in each neighborhood, and are designed to capture the “social processes endogenous to neighborhoods,” which may include social capital, collective efficacy, collective socialization, and parental mediation among others (Galster 2012). These include a number of variables commonly used to measure concentrated affluence and concentrated disadvantage including owner occupancy rate, income, share of residents with a high school diploma or greater, poverty rate, unemployment rate, and welfare receipt (Sampson et al. 1999; DiPasquale & Glaeser 1999; Sampson et al. 2008; Hedman et al. 2013). Although these variables are unable to tap directly the social processes that affect socioeconomic outcomes, they have been shown to correlate strongly with these social structures and thus

can be viewed as important proxy measures (Sampson et al. 1999). This is consistent with the notion of a measurement model in that each variable is viewed as an imperfect measurement of the underlying construct.

Naturally, some of these variables will be positively related to social opportunity (e.g. educational attainment) while others will be negatively related (e.g. unemployment). Models were tested that included a nested structure that included sub-dimensions of concentrated affluence and concentrated disadvantage, however the non-nested model yielded a better fit. All variables are collected from the 2010 Census American Community Survey (ACS) via the Neighborhood Change Database (NCDB) provided by Geolytics Inc. As with other categories, the variables selected here represent only a small portion of those that might be included under ideal circumstances. Better data would tap resident perceptions of social cohesion and control through direct survey measures, and might also include information about membership in community organizations, voluntary associations and neighborhood activism (Sampson et al. 1999). The omission of these data sources does not imply their lack of importance, but rather their difficulty in collection (Walter & Wang 2016).

2.5.2 RESULTS

To identify the four dimensions of opportunity outlined above, I construct a confirmatory factor analysis, occasionally referred to as a measurement model in the structural equation modeling literature. The model is estimated using the lavaan package in the R statistical language (Rosseel 2012; R Development Core Team 2011). The results confirm the emergence of

the hypothesized factors, and the indicators load strongly in the expected fashion.⁷

Table 2.1: Factor Loadings

Factor	Indicator	Loading	Std. Err	Std. Loading
social	income	1.000	0.000	0.884
social	edu_diploma	0.915	0.034	0.808
social	owner_occupied_housing	0.840	0.035	0.743
social	poverty	-0.994	0.031	-0.879
social	unemployment	-0.798	0.037	-0.705
social	welfare	-0.764	0.038	-0.675
geographic	walk_score	1.000	0.000	0.870
geographic	density_public_institutions	1.113	0.028	0.968
geographic	density_social_orgs	1.103	0.028	0.960
geographic	jobs_transit	0.907	0.034	0.789
geographic	access_healthcare	1.011	0.031	0.879
HS	hs_performance	1.000	0.000	0.977
HS	ap_scores	0.957	0.016	0.936
HS	sat_score	1.023	0.009	1.000
HS	teachers_high	0.771	0.027	0.753
ES	reading_3rd	1.000	0.000	0.928
ES	math_3rd	0.958	0.025	0.890
ES	reading_5th	1.003	0.024	0.931
ES	math_5th	0.977	0.025	0.907

⁷Note that because all three variables in the environmental dimension are *negative*, it should be assumed that this represents the inverse of opportunity. In other words, crime, toxic exposure, and vacancy are allowed to load positively on the environmental factor, and the inverse of the environmental factor is taken to be a measure of opportunity.

Factor	Indicator	Loading	Std. Err	Std. Loading
institutional	HS	1.000	0.000	0.914
institutional	ES	0.939	0.032	0.902
institutional	ms_performance	0.990	0.030	0.884
institutional	teachers_middle	0.883	0.033	0.788
environmental	toxic	1.000	0.000	0.570
environmental	crime	1.266	0.089	0.721
environmental	vacancy	1.275	0.089	0.727

The relationship between the four latent variables, measured quantitatively by their correlation (Table 2) and visually by their maps (Figures 3-6) is substantial. Given the high degree of correlation among the latent factors, a better model might be obtained by allowing cross loadings or specifying only one or two factors. While such a strategy might facilitate a better fitting model, however, each of the factors measures a distinctly different construct and are estimated using data from different sources they are treated as distinct.

Table 2.2: Model Fit Indices

Fit Index	Value
SRMR	0.048
IFI	0.903
CFI	0.903
NFI	0.892
TLI	0.890
RMSEA	0.107

Fit Index	Value
Chi Square	2093.331

There are no hard guidelines for determining whether CFA represents an adequate model fit. Most authors suggest that a model with an incremental fit index (e.g. IFI, CFI or TLI) higher than 0.9 represents an adequate fit while indices greater than 0.95 represent a good fit. Absolute fit indices, such as the Square Root Mean Residual (SRMR) should be below 0.8 and ideally below 0.5, whereas the Root Mean Square Error of Approximation (RMSEA) should ideally be below .10. These criteria are merely guidelines, however. To illustrate, in a field in which previous models generate CFI values of .70 only, a CFI value of .85 represents progress and thus should be acceptable (Bollen 1989). Indeed, Marsh et al. (2004) argue that even in psychometrics in which factor models are common and measurement items are relatively standardized, “there is some evidence to suggest that even the old cutoff values (e.g., RNI and TLI > .90) are overly demanding in relation to a normative criterion of appropriateness based on the best existing psychological instruments. Hence, the new, more demanding cutoff values proposed by Hu and Bentler (1998, 1999) appear to be largely unobtainable in appropriate practice” (Marsh et al. 2004, p.326). Following this advice, the model presented here appears to be adequate, though not perfect. Although many of the incremental indices are modest, they meet the suggested minimum criteria and there exist no similar models in the literature with which to compare them. The SRMR reports a good fit and the RMSEA sits on the edge.

The four variables estimated by the model are presented as maps in figures 3-6 below. Following the standard convention, maps are shown in quintiles, with green colors representing higher levels of opportunity, purple colors representing lower levels, and white representing the average.

What is immediately clear is that the social, environmental, and institutional dimensions of opportunity are all highly related to one another; high opportunity tends to be in outer suburbs with most of the disadvantaged neighborhoods clustered in Baltimore City. The one exception to this trend is the geographic dimension of opportunity, which reflects the fact that agglomeration economies and infrastructure provision still favor the City strongly.

Table 2.3: Latent variable Correlation

	social	geographic	institutional	environmental
social	1	-0.78	0.90	0.88
geographic		1	-0.82	-0.95
institutional			1	0.95
environmental				1

For opportunity mapping applications that require the construction of a single univariate index, such as the analysis of disparate impact in fair housing, analysts are left with few alternatives than to simply average the four components together. This process yields the composite opportunity map presented below.

Again, the composite map may be useful for certain applications, but it does little to provide guidance for interventions that seek to shape the geography

of opportunity because it does not provide an indication of why a particular neighborhood has a particular score. For this reason, it may be useful to create an alternative map (or series thereof) which permits greater flexibility in interpretation.

2.6 A Typology of Spatial Opportunity

As an alternative to the composite opportunity index, it may be useful to develop a typology of neighborhoods based on the empirical clustering of opportunity sub-dimensions. This can be accomplished by applying any of several clustering algorithms common to data science and machine learning. Again, this technique, as applied to opportunity data is not entirely novel. A similar approach is applied by Walter & Wang (2016). In their work, however, they use discriminant analysis (which categorizes neighborhoods horizontally) to develop a typology that categorizes neighborhoods along a vertical continuum (e.g. high to low). In my view, this removes the benefit provided by clustering algorithms, which is that the resulting categories need not be ranked in an ordinal hierarchy. An illustrative example is given by Spielman & Singleton (2015) who use cluster analysis applied to U.S. Census data to develop a geodemographic typology. Their typology is descriptive rather than normative and allows them to move away from the “variables paradigm” which seeks to describe neighborhoods along a singular continuum. Instead, they apply “a contextual mode of analysis, [in which] neighborhood-to-neighborhood differences are conceptualized as changes of type, not increments to variables” (Spielman & Singleton 2015, p.1004).

In the context of opportunity mapping, this is an especially useful paradigm shift for three reasons. First, it recognizes that the *utility* garnered by each dimension of opportunity is heterogeneous across households and aggregation may, therefore, obscure more information than it reveals; as discussed above, young children likely benefit far more from the institutional dimension (e.g. school quality) than the geographic dimension (e.g. access to jobs) (Sharkey & J. Faber 2014). Second, it removes the need to develop a system for weighting each of the four opportunity dimensions relative to one another. In other words, this removes the necessity of assigning arbitrary values of θ . Third, it provides guidance for policymakers seeking to improve the opportunity level in a given community. A single univariate scale, ranging from high to low can be useful for some policy applications, such as proving disparate impact in the siting of public housing. For other applications, however, such as community development, a univariate scale is less useful. In these cases, policy analysts require information about *why* a particular location has a low opportunity score and what might be done to improve it.

To illustrate this idea, I construct a neighborhood typology by applying a clustering algorithm to the four latent variables estimated in the previous section. One particular benefit of this strategy is that clusters do not contain a pre-defined number of neighborhoods; unlike dividing the composite index into quintiles, each cluster contains a unique number of tracts, defined by their empirical relationship. The cluster analysis identifies five distinct neighborhood types, which vary in their levels of opportunity measures. Formally, this is a gaussian finite mixture model fitted by an expectation-maximization (EM) algorithm performed using the Mclust package for the R statistical language (Fraley et al. 2012). The algorithm tests a variety of different cluster

specifications and selects (a) the optimal number of clusters and (b) the assignment of each tract to the optimal cluster based on Bayesian Information Criteria (BIC) (Fraley & Raftery 2002).

The cluster means are presented in the table below. Clusters one and two (which together comprise about 50% of the census tracts) are strong on environmental, social, and institutional measures, with cluster one performing slightly better. Both clusters are lower than average on the geographic dimension. Cluster three is near the regional average on most measures, with geographic measures slightly better and others slightly worse. Clusters four and five have higher than average geographic measures but lower than average on all others. Cluster five appears to be particularly disadvantaged, with extremely low social, institutional and environmental scores.

Table 2.4: Cluster Means

cluster	n	proportion	social	geographic	institutional	environmental
1	152	0.224	0.825	-0.933	0.924	0.624
2	199	0.309	0.354	-0.312	0.390	0.235
3	143	0.223	-0.240	0.185	-0.190	-0.108
4	115	0.174	-0.760	0.950	-1.040	-0.684
5	47	0.069	-1.601	1.494	-1.513	-1.030

The map generated by the cluster analysis reveals similar macro-level patterns to the composite index, but the interpretation of each neighborhood is more nuanced. It would be convenient to label clusters one and two as high opportunity, cluster three as moderate opportunity, and clusters four and five as low opportunity, but this normative interpretation ignores the

tradeoffs these neighborhoods embody. For a household with young children, clusters one and two offer vital resources for development: good schools, supportive social environments, and safe clean air. If this household is transit dependent, however, clusters one and two may not be viable options at all because they lack important access to services captured by the geographic dimension. For this household, utility may be maximized by a neighborhood somewhere in cluster three (or possibly four); in these neighborhoods, it is possible to find a decent school and still maintain decent access to goods and services served by transit.

From a policy perspective, the cluster approach also yields important entry points for particular policy prescriptions. Cluster five desperately needs investment in its institutional infrastructure, and improving the schools may result in positive externalities in the social dimension. Clusters four and five are important candidates for inclusionary zoning and affordable housing policies to ensure that all people have access to the good schools and safe neighborhoods they offer. Cluster four may be ripe for investments in public transportation to help bridge “last mile” connections between homes and workplaces. Adding more data to the cluster analysis can further improve the policy relevance of the results. The inclusion of housing market conditions, for example could differentiate neighborhoods in cluster three—those with improving markets might focus on preserving affordable housing before displacement becomes a concern whereas those with declining markets would be strong candidates for capital injections like block grants.

2.7 Conclusions

Cartography—the making of maps—is among the oldest and best techniques for data visualization. According to the famed data visualization expert Edward Tufte, “No other method for the display of statistical information is so powerful” (Tufte 1983). But like the statistics that underlie them, data maps can mislead as well as inform. This paper is designed to elucidate the difficulty inherent in designing opportunity maps. While the paper identifies a number of crucial pitfalls common in the current state of practice, it also identifies a number of strategies for overcoming these issues and developing better, more useful metrics and visualizations.

The foundation of this work is a measurement model used to estimate four latent sub-dimensions of opportunity. The model presented here should not be interpreted as the perfect implementation of a spatial opportunity analysis, but rather an example of a general methodology that can and should be extended by additional data and research. This methodology includes a theoretical framework for selecting indicators and dividing them into categories, a measurement strategy that facilitates the evaluation of construct validity, and a visualization strategy that provides more relevance for policymakers.

Despite the solutions proposed in this paper, however, the practice of opportunity mapping still faces a number of serious challenges. As with any quantitative analysis, opportunity mapping is not a purely technical exercise and requires that a series of important subjective decisions be made by an analyst. The only way to validate these decisions is for opportunity analyses to be conducted transparently and vetted by the research community. Beyond the subjectivity of analysts, challenges still remain. Although confir-

matory factor analysis and structural equation modeling can help estimate the sub-dimensions of opportunity, more research is necessary to help determine how these dimensions relate to one another and how they combine to produce the socioeconomic outcomes of greatest interest. As the empirical record on neighborhood effects expands, these challenges should wane.

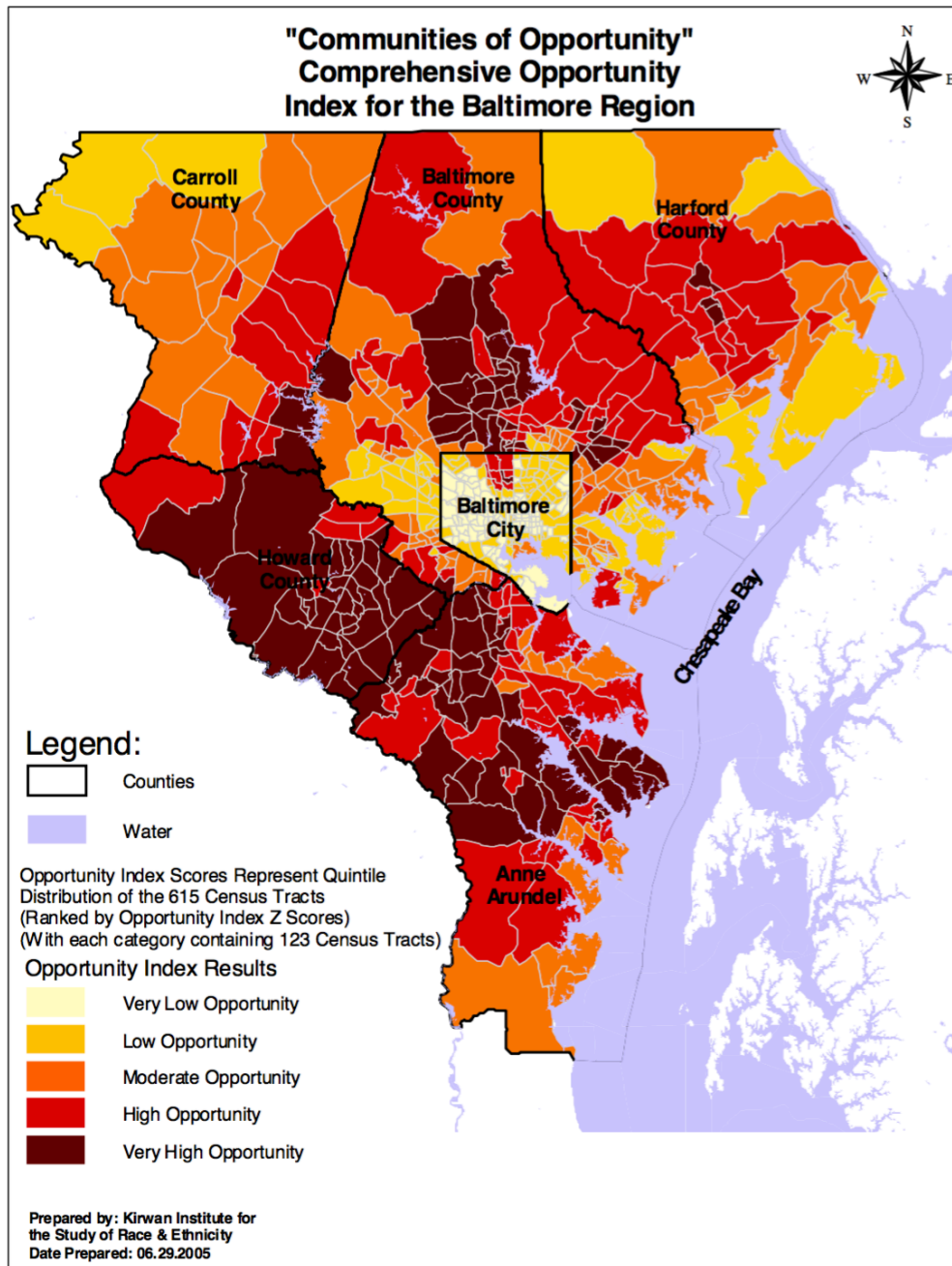


Figure 2.1: Thompson v. HUD Opportunity Map

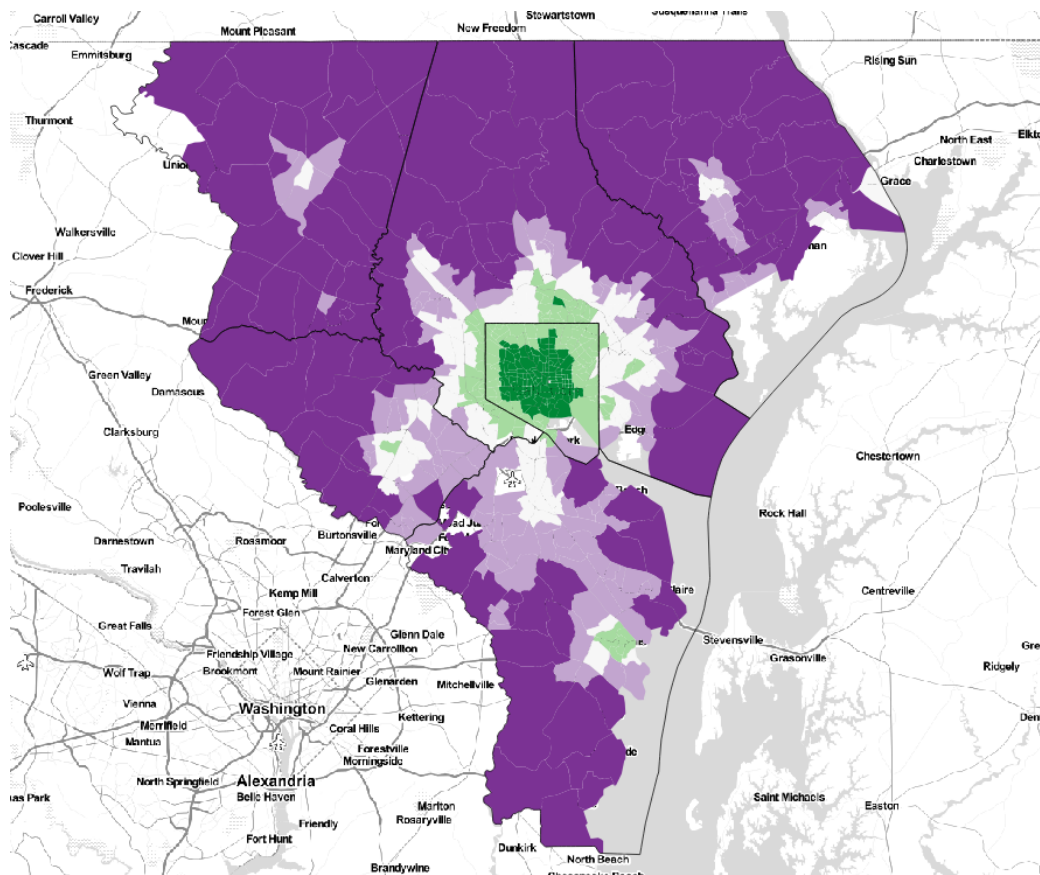


Figure 2.5: Geographic Map

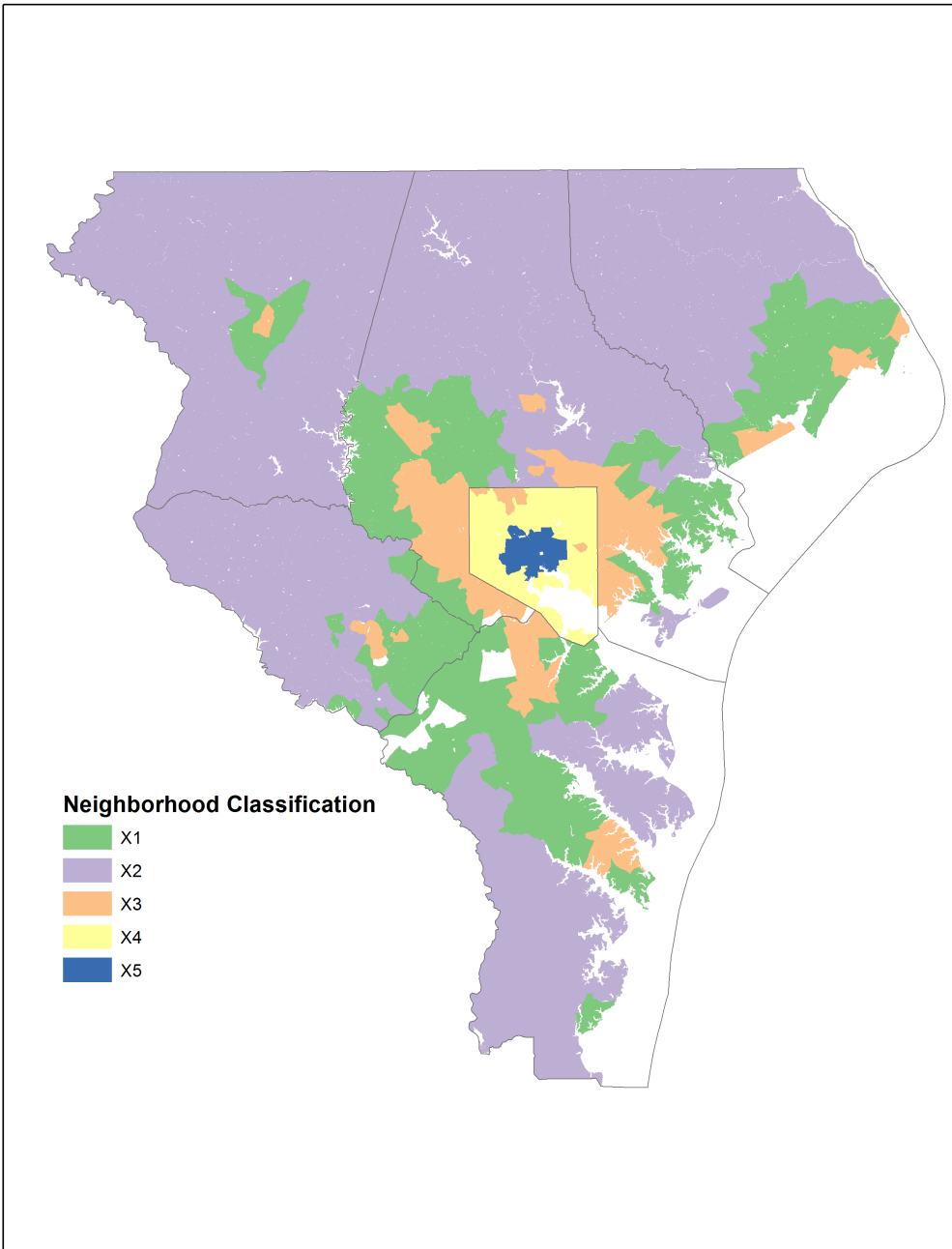


Figure 2.7: Opportunity Typology

Chapter 3

Who Moves to Opportunity? Spatial Returns to Housing Assistance and the Effect of Specialized Mobility Programs

3.1 Introduction

Since the passage of the Fair Housing Act in 1968, the federal government has faced a legal mandate to mitigate racial and economic segregation. In the past year, this mandate has been strengthened thanks to the Affirmatively Furthering Fair Housing (AFFH) rule, which requires that the U.S. Department of Housing and Urban Development (HUD) use proactive means to equalize the geography of opportunity. Over the last several decades courts have ruled in several cases that HUD and various local housing authorities

have failed to achieve this goal. In response to these cases, a number of specialized housing mobility programs have been designed to provide vouchers that help low income families relocate to “communities of opportunity.” The most well known of these programs is the Gautreaux program that helped African-American families in Chicago’s inner city move to predominantly white suburbs with overwhelmingly positive results. In Baltimore, a similar program was launched in 2003 in response to the *Thompson v. HUD* fair housing case. The Baltimore Housing Mobility Program (BHMP)

In the following paper, I examine the residential trajectories of housing choice voucher holders in the Baltimore metropolitan region. For decades, the Baltimore region has been a laboratory for housing mobility policies, having participated in the Moving to Opportunity experiment during the 1990s and 2000s, and hosting its own unique mobility program from 2003 to present. In addition to its voucher programs, Baltimore is notorious for its legacy of segregation and racial inequality. It was the first city in the United States to enact a racial zoning ordinance, the legacy of which can still be seen today. More recently, the 2015 death of Freddie Gray in police custody and the resulting public unrest brought issues of the region’s racial and spatial inequality to the front pages of the media, and a 2016 investigation by the U.S. Justice Department found widespread civil rights violations on behalf of the Baltimore police department. With this history as the backdrop, this paper uses a longitudinal multilevel model to study how different household characteristics and different types of vouchers influence whether a household moves into a high-opportunity neighborhood.

I proceed by constructing a series of spatial opportunity indices. I then ex-

amine the average neighborhood opportunity scores for each of Baltimore's voucher programs and describe how these levels changed over time. This descriptive analysis yields important insights into the structural differences, both between voucher programs and individual households. Following this descriptive analysis, I construct a longitudinal models of locational attainment, in which household characteristics are used to predict the opportunity scores of the neighborhood in which it is located. These models are used to study whether certain types of vouchers, and certain types of households generate greater locational returns. The findings from these models can be used to design more successful mobility programs, and to understand whether certain types of households face additional barriers toward their use of housing vouchers in high-opportunity neighborhoods.

3.2 Background

3.2.1 FAIR HOUSING THROUGH RESIDENTIAL MOBILITY

For several decades, fair housing policy in the United States has been deeply intertwined with the notion that socio-spatial context—the resources embedded in residential neighborhoods—has a profound effect on the welfare and life chances of residents. The historical antecedents of this lens reach to the 1960s, the passage of the Fair Housing Act, and the deleterious ills of racial and economic segregation. In the realm of housing policy, experts have long recognized that residential contexts can affect the socioeconomic prospects of their residents. In part for this reason, fair housing policy in the United States has always been a turbulent and contentious domain. Fair housing

policy was born in the 1960s in the wake of the civil rights movement, a period that featured a growing counterculture, racially concentrated poverty, and violent civic unrest. In response, the Civil Rights Act was passed in 1964, and shortly thereafter President Johnson signed the Civil Rights Act of 1968, including Title VIII, better known as the Fair Housing Act. The Fair Housing Act banned discrimination in the housing market on the basis of race, color, religion, and national origin and established the principle that HUD must administer its programs in ways that “*affirmatively further fair housing*” (National Fair Housing Alliance 2009).

Since its passage, the Fair Housing Act has been amended on multiple occasions, served as the foundation for key fair housing legal actions, and shaped the substance and administration of multiple HUD housing programs. It has also served as the basis for lawsuits against HUD and local public housing authorities for concentrating public and subsidized housing in low-income, minority neighborhoods. Because neighborhoods with concentrations of low-income minorities provide fewer opportunities than more affluent white neighborhoods, litigants have successfully argued that placing subsidized housing in these neighborhoods does not affirmatively further fair housing and thus violates the Fair Housing Act.

In addition to several critical court cases, the specific strategies for affirmatively furthering fair housing have been shaped by two major policy experiments: the Gautreaux program, and the Moving to Opportunity (MTO) experiment. The Gautreaux (quasi) experiment occurred as part of a court-ordered legal settlement in 1976 to redress purported racial discrimination by the Chicago Housing Authority (CHA) (Rosenbaum & Deluca 2008). The

settlement resulted in the establishment of a residential mobility program for low-income black families to relocate to new neighborhoods, and encouraged them to move to predominantly white suburbs. The program (named Gautreaux after the original plaintiff) continues to be one of the most important sources of information on residential mobility and neighborhood effects. Although the Gautreaux program was voluntary, and participants were not randomly selected, initial results were startlingly positive, and studies showed large and significant gains in employment and education for parents and children who moved to white, suburban neighborhoods (Rosenbaum & Deluca 2008; Mendenhall et al. 2006)

The promising results of the Gautreaux program prompted HUD to launch a more comprehensive and rigorous study of the effects of offering families housing vouchers to move to higher opportunity neighborhoods. The Moving to Opportunity (MTO) experiment was authorized by Congress in 1992. Participants in the program came from extremely poor neighborhoods in Baltimore, New York, Chicago, Los Angeles, and Boston and were randomly assigned to one of three groups: (1) an experimental group that received housing counseling and a restricted voucher that could only be used in census tracts with low poverty rates (less than 10%, using 1990 data); (2) a second group that received regular Section 8 vouchers with no restrictions, and (3) a third control group that remained in public housing. The short and mid term results from MTO were modest, a marked difference from Gautreaux that would begin a near decade-long debate over the quantitative approaches used to identify neighborhood effects. The interim and final program evaluations (conducted 4-7 and 10-15 years after randomization, respectively) reported that MTO movers in the experimental group

experienced no significant gains in long-term employment, earnings, or educational outcomes (Orr et al. 2003; Sanbonmatsu et al. 2011). Further, the majority of MTO movers stayed in the central city rather than relocating to nearby suburbs. Often, this meant that movers' new neighborhoods were largely similar to their original neighborhoods (save for lower poverty rates). Many families stayed in the same school districts, and in predominantly black neighborhoods (DeLuca & Rosenblatt 2010; Briggs et al. 2010). These initial findings cast some doubt on the presence of neighborhood effects through the latter portion of the 2000s. The most recent evidence, however, using long-term data has been overwhelmingly positive. Recent research by Chetty et al. (2015) has shown that there are significant employment benefits for children who moved to low poverty neighborhoods, especially those that move at a very young age. These findings underscore the importance of housing mobility programs as a method for combatting persistent racial and spatial inequality. When low-income families are given the chance to move into better neighborhoods, they experience important changes in social, environmental, and institutional contexts that result in better socioeconomic outcomes.

3.2.2 SEGREGATION AND THE SPATIAL STRUCTURE OF OPPORTUNITY IN BALTIMORE

The history of racial segregation (and the resulting inequality) in Baltimore is long and well-documented. It was the first city in the United States to enact a racial zoning ordinance that made segregation, officially, the law of the land. In 1917, when racial zoning ruled unconstitutional, racial covenants

were enacted in their place to maintain the spatial order, and in 1948 when racial covenants were outlawed, redlining persisted a method for excluding African Americans from certain neighborhoods (Pietila 2010). Although redlining was outlawed with the passage of the Fair Housing act, exclusionary practices persisted, leading the urban historian Hirsch (2003) to surmise that “although one may detect the workings of the private market and choice in the rise, growth, and maintenance of residential segregation in Baltimore as elsewhere, those forces simply did not produce the enduring degree of racial separation evident by the 1980s. That outcome took a team effort that included the public’s representatives (local and national), authority, and powers—and the hands of those responsible could be seen by anyone who cared to look” [p. 11].

It is no surprise that the Home Owners’ Loan Corporation (HOLC) redlining map of Baltimore, drawn in 1937, correlates highly with the existing patterns of segregation and poverty seen in the City today. Baltimore’s history of legal and extralegal segregation is an important piece in the story of persistent racial inequality in the City’s history because it facilitated the systematic denial of opportunity to the region’s black population. At the same time that black residents were denied access to white neighborhoods, black neighborhoods were systematically drained of their resources. Schools in black neighborhoods were permitted to languish, homes in black neighborhoods were undervalued on the market, inhibiting wealth accumulation for their owners, and an underclass developed as manufacturing jobs left the city, and the middle-class left with them (Pietila 2010; Wilson 1987). In the 1990s, this legacy came to a head in a landmark lawsuit designed to disrupt the spatial regime of separation and inequality.

3.2.3 THE BALTIMORE HOUSING MOBILITY PROGRAM

In 1994, a group of Baltimore's public housing residents filed a class-action lawsuit against the U.S. Department of Housing and Urban Development (HUD) and the Housing Authority of Baltimore City (HABC). The suit alleged that HUD and the Housing Authority of Baltimore City (HABC) failed to meet the Affirmatively Furthering Fair Housing statute set forth in the Fair Housing Act. Much of Baltimore's public housing had been scheduled for demolition and redevelopment, and the *Thompson* case, like several other public housing desegregation cases, was triggered by plans to relocate public housing residents into neighborhoods with similarly high levels of segregation. The plaintiffs claimed, and the judge agreed, that the city and housing authority had created a deeply segregated system of public housing and had done so with HUD's approval. These decisions, the judge ruled, were largely driven by opposition in suburban white neighborhoods and thus beyond the reach of the city housing authority. The Court therefore found HUD liable; it had failed its duty to affirmatively further fair housing (PRRAC 2005; Gina 2007).

Much like *Gautreaux*, the *Thompson* case resulted in a regional housing voucher program designed to connect low-income african american families with communities that facilitate socioeconomic mobility. The *Thompson* program, called the Baltimore Housing Mobility Program (BHMP) was focused not only on racial integration, but also reducing exposure to concentrated poverty. BHMP, thus, incorporated the location restrictions from both *Gautreaux* and MTO on its participants in an attempt to obtain the positive results revealed by each program; upon receiving their vouchers,

BHMP participants were required to move to neighborhoods (census tracts) with poverty rates less than or equal to 10%, African-American populations less than or equal to 30%, and subsidized housing populations less than or equal to 5% (Engdahl 2009). Beyond these location restrictions, the program included a variety of additional features designed to help families locate and remain in high-quality housing units in stable neighborhoods. These features included “move readiness counseling, suburban community tours, security deposit assistance, and housing counselors who have been trained to educate the families about the school opportunities in the suburbs and to support them if they have to relocate a second time” (DeLuca et al. 2013, p.290). As an additional benefit, the BHMP partnered with a “nonprofit car ownership program serving Maryland and Virginia communities called ‘Vehicles for Change,’ which offers low-cost financing to purchase used cars, with monthly payments ranging from \$70-\$98 for a 15-month loan,” and leveraged support from the Abell Foundation to help cover the costs of driving school tuition for program participants (Engdahl 2009, p.21).

Together, these features resulted in a program that was poised uniquely to alter substantially the types of neighborhoods occupied by housing voucher holders. A regionally-based program removed administrative burdens to allow access to more neighborhood choices; anti-poverty and segregation restrictions helped ensure that families avoided neighborhoods that work to reinforce inequality; a focus on counseling helped make sure that families were well-equipped to find high quality neighborhoods; and vehicle assistance helped ensure that families would not face undue transportation burdens in their new communities. After more than a decade in operation, much of the research on BHMP has been positive, suggesting that participating house-

holds not only moved to high-opportunity neighborhoods, but that most families stayed in these neighborhoods longer than the requirement stipulated by their vouchers. Despite these important results, there have been few studies that compare the locational outcomes for Thompson households relative to their counterparts in the general HCV program in the Baltimore region. This study, thus, seeks to address the following questions: Which voucher-assisted households move into high-opportunity neighborhoods? And how do BHMP vouchers affect the dynamics of residential sorting for assisted households?

3.3 Modeling Residential Mobility

For at least three decades, social scientists have been developing regression models that use household attributes to predict the neighborhood status of various household types (Alba & Logan 1993). These so called “locational attainment” models use household characteristics such as race and income to estimate characteristics of the neighborhoods in which they reside, such as poverty (Dawkins et al. 2015), socioeconomic status (Logan & Alba 1993), racial composition (Logan et al. 1996), and median income (Sampson & Sharkey 2008). Such studies have found consistently that minorities in general and blacks in particular are significantly less able to translate their human capital into locational advantages—a result that helps perpetuate both spatial and social inequality.

More recently, locational attainment models have been expanded to incorporate longitudinal neighborhood trajectories (Sampson & Sharkey 2008), and

they have also been used to study the spatial outcomes of housing mobility programs (Pendall et al. 2015). The analysis presented in this chapter combines these two approaches and expands upon the outcome variables examined. Following (Sampson & Sharkey 2008), I develop longitudinal models using a multilevel specification, and similar to Dawkins et al. (2015), I use data from housing mobility programs to study how this important type of government assistance could be made more effective. Unlike previous research, I use a multivariate definition of neighborhood “opportunity,” as described by Knaap (forthcoming).

3.4 Data

3.4.1 HOUSING VOUCHER HOLDERS

To understand the neighborhood sorting patterns of housing voucher holders, I use HUD administrative data from the housing choice voucher (HCV) program in the Baltimore metropolitan region. The dataset contains household-level microdata, including the street address of the housing unit occupied by the voucher holder, the composition of the household, and the attributes of its members. Importantly, the dataset also contains an indicator that identifies whether the household participates in the Baltimore Housing Mobility Program (BHMP). This indicator facilitates comparisons between general HCV participants and BHMP participants, and allows testing the hypothesis that BHMP voucher holders reside in better neighborhoods.

Table 3.1: HCV Descriptive Statistics

Year	N	Income	Black	Disabled	Householder Age	Members	Dependents
2002	15,868	\$11,367	67%	34%	45	2.5	1.3
2003	18,341	\$11,703	71%	34%	45	2.5	1.3
2004	20,620	\$11,798	74%	36%	46	2.4	1.3
2005	21,801	\$12,202	74%	37%	46	2.4	1.2
2006	20,649	\$12,849	71%	39%	48	2.3	1.1
2007	22,920	\$12,972	73%	40%	49	2.3	1.2
2008	20,109	\$13,468	71%	42%	50	2.2	1.0
2009	23,102	\$13,787	74%	46%	50	2.3	1.0
2010	23,579	\$13,776	75%	48%	50	2.3	1.0
2011	24,367	\$14,027	75%	49%	50	2.3	1.0
2012	23,399	\$14,444	75%	49%	51	2.2	0.9
2013	22,902	\$14,940	75%	50%	51	2.2	0.9

Table 3.2: BHMP Descriptive Statistics

Year	N	Income	Black	Disabled	Householder Age	Members	Dependents
2002	316	\$9,388	99%	8%	32	3.1	2.0
2003	329	\$10,651	99%	10%	33	3.1	1.9
2004	675	\$10,331	99%	10%	31	3.0	1.9
2005	768	\$11,070	99%	11%	31	3.0	1.9
2006	831	\$12,112	99%	11%	32	3.1	1.9
2007	1,069	\$11,731	98%	12%	33	3.0	2.0
2008	1,115	\$12,784	98%	13%	34	2.9	2.0
2009	1,537	\$13,452	98%	13%	35	3.3	2.4

Year	N	Income	Black	Disabled	Householder Age	Members	Dependents
2010	1,707	\$14,863	99%	14%	36	3.3	2.0
2011	1,854	\$15,142	99%	15%	36	2.3	1.7
2012	2,030	\$16,530	72%	11%	36	2.2	1.3
2013	2,269	\$16,590	99%	15%	37	2.1	1.7

In many respects, BHMP households are similar to the general population, but there are some important differences. Income levels are comparable between the two programs, but BHMP households tend to be headed by younger householders, contain more dependents on average, and are less likely to contain disabled members. HCV participants are approximately 75% African-American, while the BHMP program is virtually all African-American.

3.4.2 OPPORTUNITY MEASURES

Spatial opportunity is measured via confirmatory factor analysis (CFA) estimated in a structural equation modeling (SEM) framework (for details on this approach, see Knaap, forthcoming). The model estimates four essential dimensions of opportunity as outlined by Galster (2012), namely social-interactive, environmental, geographic, and institutional. The social-interactive measure captures the social capital and collective efficacy embedded in neighborhoods and includes measures like poverty, unemployment, and educational attainment. The geographic measure captures access to important resources, goods, and services. It includes measures like access

to jobs, healthcare providers, and social organizations. The environmental measure captures exposure to spatial externalities like environmental pollutants, crime, and vacant and abandoned housing. The institutional measure captures the quality of local school systems. Using data on local school catchment boundaries, it includes measures like standardized test scores, highly qualified teachers, and SAT scores. When these four dimensions are averaged together they yield an overall composite measure of spatial opportunity. The composite opportunity measure is then z-transformed to have a mean of 0 and a standard deviation of 1. The average opportunity score in the Baltimore region, is thus centered at 0, with positive scores indicating high-opportunity neighborhoods and negative scores indicating low-opportunity neighborhoods.

3.5 Methods

3.5.1 MEASURING LOCATIONAL ATTAINMENT FOR VOUCHER HOLDERS

I proceed by tracking each household in the HCV program from 2002 through 2013; Each household is assigned the opportunity scores of the neighborhood it occupied during each year it held a voucher. This process yields a longitudinal dataset that permits the analysis of “opportunity trajectories” over time. The analysis is limited to voucher holders that originated and remained in the Baltimore region for the duration of the study period. Average trajectories for HCV and BHMP participants are presented below in a series of line graphs, which show striking trends. In the general HCV program,

there's some modulation in average opportunity score, but the trend is generally flat. On average, HCV households tend to live in neighborhoods with lower than average opportunity scores, and there appears to be little spatial change over time.

For members of the Thompson class who participated in the BHMP, residential trajectories are starkly different. In 2002 and 2003, prior to the launch of the Baltimore Housing Mobility Program, the Thompson households lived in public housing in neighborhoods with very low opportunity scores. In 2004, after the launch of BHMP, there's a large spike in the average spatial opportunity scores, as families moved into better neighborhoods as stipulated by their vouchers. Over the next few years, progress was stunted, as families acclimated to their new environments. In 2007, however, there's a sharp inflection point, after which progress for BHMP households follows a continuously positive trajectory. This inflection point may be explained by the initiation of second-move counseling, that helped BHMP participants during their housing search after their initial location restrictions expired (Engdahl 2009).

For comparison's sake, it is useful to contextualize these findings by contrasting them to outcomes from the Moving to Opportunity program that took place in Baltimore between 1994 and 2010. In MTO, the treatment group is analogous to the BHMP program in that households received a restricted voucher which could only be used in low poverty neighborhoods for one year, whereas the section-8 group is analogous to general HCV program in that households receive unrestricted vouchers that may be used anywhere in the region.

Comparing BHMP trajectories to MTO trajectories, a notably different pattern emerges. In the latter case, there is an initial spike in the composite opportunity score for Treatment group households during early stages of the program as families moved to their first ‘placement’. As they left those initial placements in following years, however, they found themselves in neighborhoods far more similar to their Section 8 and Control group counterparts. The difference between MTO and BHMP trajectories shown in the graphs is an important one. Unlike MTO households in the treatment group, BHMP households do not gravitate toward low-opportunity neighborhoods once their voucher restrictions expire. These findings underscore the important differences in programmatic design between MTO and BHMP. Whereas MTO offered little beyond vouchers designed to be used in low-poverty neighborhoods, BHMP participants received a great deal of additional assistance that appears to have made a vast difference in participants’ ability to find and remain in high opportunity neighborhoods. As discussed in later sections, however, it is impossible to attribute all of the success of BHMP to program design. Unlike MTO, BHMP lacked a true experimental design and it is impossible to rule out the possibility that outcomes reflect differences in composition of the households who participated in each program.

The graphs make it clear that over time, the BHMP program has been more successful than the HCV program at helping move assisted families into better neighborhoods. What the graphs mask, however, is whether this distinction arises from improvements in program administration or from the trajectories of individual households. This distinction is clarified by fig. 3.4, which shows the average opportunity score for different program participants according to the number of years they have received vouchers, irrespective of

the year in which the first voucher was used.¹ The trends for all programs are remarkably stable.

Although BHMP participants, on average, find themselves in better neighborhoods than general HCV participants (and this trend is increasing over time) it appears that voucher holders in both programs experience relatively little neighborhood change over time (on average). In other words, the vast distinction between HCV and BHMP outcomes is due to the fact that BHMP voucher holders use their vouchers in much better neighborhoods *in the first place* and are more likely to stay there. The growing opportunity gap appears to stem from the increased capacity of BHMP to help families into better neighborhoods on their first voucher receipt.

3.5.2 A MULTILEVEL MODEL OF LOCATIONAL ATTAINMENT

To help quantify the trends outlined above and understand the sorting patterns of voucher holders and the effectiveness of voucher programs, I construct a multilevel locational attainment model in which the explanatory variables are characteristics of the households, and the dependent variable is the voucher holder's neighborhood opportunity score. Data are recorded each year a household participates in the voucher program, and since voucher holders typically occupied several neighborhoods the data structure is longitudinal, with repeated measurements nested in households. Taking advan-

¹The graph plots the first 6 years of voucher use, which captures about 80% of the households. Although some families used vouchers during the entire 11 year study period, the vast majority of households used vouchers for 6 years or less. The graph is truncated for simplicity. A graph of the entire study period shows the same trends albeit with widening confidence intervals as the time period extends

tage of this data structure, the model is specified in a multilevel framework that includes random intercepts, allowing each household to have its own starting location, and a random coefficient for time, allowing each household to follow its own residential trajectory. In the psychometrics literature, this is commonly called a growth curve model. To capture the effect of the Baltimore Housing Mobility Program, I select and retain only those vouchers used between 2004 and 2013. After removing records with incomplete data, this yields a dataset with 40,842 unique vouchers and 203,341 voucher-year observations.

The resulting model is a two-level regression, described by three equations. Level 1 is given by Equation 3, which describes the residential trajectory for each household over time as a function of two random variables: the initial neighborhood occupied by household i , and the residential trajectory taken by household i over time t . Level two is given by equation 4, which explains variation in the random intercept from equation 3, referring to the opportunity score of the first neighborhood occupied by household i , and equation 5, which explains variation in the random slope of household i over time (i.e. the residential trajectory of household i). Adopting the notation of Raudenbush & Bryk (2002), the level-1 model is specified as

(3)

$$Y_{ti} = \beta_{0i} + \beta_{1i}(time)_{ti} + r_{ti}$$

where Y_{ti} is the composite opportunity score for the neighborhood occupied by household i at time t ; β_{0i} is an intercept referring to the average neighborhood opportunity score for all households; $\beta_{1i}(time)_{ti}$ is the average linear change in the composite neighborhood opportunity score over the course of

the study period and r_{ti} is a normally distributed error term reflecting the deviation of household i at year t from the overall mean (Sampson & Sharkey 2008).

The level-2 model is described by two equations:

(4)

$$\begin{aligned} \beta_{0i} = & \gamma_{00} + \gamma_{01}(time)_i + \gamma_{02}(time * BHMP)_i + \gamma_{03}(black)_i + \\ & \gamma_{04}(age)_i + \gamma_{05}(income)_i + \gamma_{06}(disability)_i + \gamma_{07}(members)_i + \\ & \gamma_{08}(hispanic)_i + \gamma_{09}(BHMP)_i \gamma_{010}(MTW)_i + u_{0i} \end{aligned}$$

(5)

$$\begin{aligned} \beta_{1i} = & \gamma_{10} + \gamma_{11}(time)_i + \gamma_{12}(time * BHMP)_i + \gamma_{13}(black)_i + \\ & \gamma_{14}(age)_i + \gamma_{15}(income)_i + \gamma_{16}(disability)_i + \gamma_{17}(members)_i + \\ & \gamma_{18}(hispanic)_i + \gamma_{19}(BHMP)_i \gamma_{110}(MTW)_i + u_{1i} \end{aligned}$$

BHMP, *MTW*, *Black*, *Hispanic*, and *Disability* are binary variables. *BHMP* indicates whether a household participates in the Baltimore Housing Mobility Program and receives a specialized voucher and additional counseling. *MTW* indicates whether the housing voucher is funded through the Moving to Work demonstration program. *Black* indicates whether the head of household is African American. *Hispanic* indicates whether the household head is hispanic or latino. *Disability* indicates whether any member of the household is disabled.

Income is the natural logarithm of the household's total annual income.

Age is the age of the householder at the time of voucher receipt, centered about the grand mean. *Members* is the total number of individuals in the household, centered about the grand mean. *Time* is an integer corresponding to the number of years a household has participated in a voucher program (i.e. time = 0 during the first year a household receives its voucher and increases by 1 each year thereafter). *BHMP * time* is an interaction that captures the rate of change in neighborhood opportunity score for households who received different types of vouchers; in other words, this interaction captures the difference in residential trajectories between BHMP and regular voucher holders.

With this specification, it is possible to test (a) whether certain household characteristics influence movement into neighborhoods that facilitate socioeconomic mobility; (b) whether voucher holders move into better or worse neighborhoods over time; (c) whether BHMP voucher holders are likely to find housing in better neighborhoods than regular HCV holders, and (d) whether BHMP and HCV voucher holders have differing residential trajectories over time.

3.6 Results

The data show striking if not unexpected results. Results are presented using “Gelman standardized” coefficients, by dividing each input by two standard deviations. This technique makes coefficients comparable directly by transforming continuous and binary predictors into the same scale² (Gelman

²Numeric variables that take on more than two values are each rescaled to have a mean of 0 and a sd of 0.5; Binary variables are rescaled to have a mean of 0 and a difference

2008). All coefficients in the model are significant except for householder ethnicity and household size. The intercept term is large and negative, indicating that in general, voucher holders live in neighborhoods with opportunity scores significantly below the regional average[^][since the variables are centered, the intercept technically refers to the “average voucher household”, i.e. a household with average values for each of the input variables. The coefficient for race is also large and negative, indicating that Black households in the HCV program face an even greater disadvantage, and are even less likely to live in high opportunity neighborhoods. Although significant, the effect of income is negligent, meaning that the income level has little practical influence on whether voucher holders move into high-opportunity neighborhoods. Similarly, the coefficient for disability is quite small, suggesting that households with disabled members do not face serious disadvantages with respect to neighborhood quality.

Table 3.3: Model Results

term	estimate	std error	statistic
(Intercept)	-0.749	0.004	-198.288
age	0.092	0.008	11.530
hispanic	-0.001	0.022	-0.067
disability	-0.015	0.004	-3.772
black	-0.579	0.009	-67.721
log income	0.005	0.001	3.580
household members	0.007	0.003	1.918

of 1 between their two categories; Non-numeric variables that take on more than two values are unchanged; Variables that take on only one value are unchanged. For more information see the `rescale` function in the `arm` package for the R statistical language (Gelman & Su 2016; R Development Core Team 2011).

term	estimate	std error	statistic
MTW	-0.145	0.003	-57.018
time	0.105	0.003	30.120
BHMP	0.823	0.016	49.975
time * BHMP	0.188	0.013	14.093

According to the model, the effect of receiving a BHMP voucher is staggering. The positive BHMP coefficient is slightly larger than the negative intercept term, indicating that BHMP participants overcome the disadvantage faced by general HCV voucher holders, and are likely to live in neighborhoods with opportunity scores near the regional average. It is important to note that since BHMP participants are virtually all black, this gain is enormous, since similar voucher holders in the general HCV program are affected by both the negative intercept term *and* the negative racial coefficient. Furthermore, the interaction between BHMP vouchers and time is larger than the main effect of time, indicating that Thompson households make more progress (in spatial terms) over time than the average HCV household.

Households with Moving to Work vouchers seem to be at a disadvantage, but this is a difficult coefficient to interpret in terms of the net effect of the MTW program. MTW is a national demonstration program which gives housing authorities the flexibility to waive certain statutes and HUD regulations pertaining to the Public Housing and Housing Choice Voucher (HCV) programs. The MTW statutory objectives include the following:

- 1) Reduce cost and achieve greater cost effectiveness in Federal expendi-

tures;

- 2) Give incentives to families with children whose heads of household are either working, seeking work, or are participating in job training, educational or other programs that assist in obtaining employment and becoming economically self-sufficient; and,
- 3) Increase housing choices for low-income families (Housing Authority of Baltimore City 2012).

Thus, the finding that vouchers funded through the MTW program are less likely to be used in high opportunity neighborhoods should not, necessarily, be viewed as an indictment of the MTW program. Because MTW lets PHAs use their money more flexibly, it allows them give out more vouchers than would be possible otherwise. Also, most of the Thompson households are funded by MTW vouchers.

3.7 Discussion

The results show clear evidence that specialized voucher programs like the Baltimore Housing Mobility Program can have a major influence on the ability for households to find and remain in better neighborhoods. This finding is especially important through the lens of racial equity, as the model also makes clear that black voucher holders face disadvantages above and beyond those faced by white voucher holders.

Given the promising results of this study, it is important to contextualize the findings in light of the program design. BHMP vouchers were available to African American families with children in Baltimore City who either

lived in public housing or were on the waiting list for the Housing Choice Voucher Program. The participating families were selected quasi-randomly from an applicant list totaling over 13,000 (Engdahl 2009). The most liberal interpretation of these circumstances would be to view BHMP as a natural experiment, in which the treatment was the offer of specialized vouchers and all their accompanying benefits. In this case, the BHMP coefficient in the model would be viewed as a treatment-on-treated (TOT) effect—the locational outcome experienced by those applicants who were offered a BHMP voucher, remained in the program during its compulsory credit counseling, and leased up³. Using this interpretation, the inclusion of control variables for race and household size in the model should give unbiased estimates of the BHMP effect.

It is certainly possible, however, that there are unobserved characteristics omitted from the model which differ systematically between HCV and BHMP households. In this case, the BHMP effect would be biased. It is impossible to rule out possible omitted variable bias, particularly with a parsimonious model such as the one presented here. In addition to omitted unknown variables, two known variables warrant a brief discussion. The model would likely be improved if it included householder gender and educational attainment. It is certainly possible that female householders face gender discrimination in the housing market, leading to a disadvantage in the ability to move into high opportunity neighborhoods. More educated households may also have significantly different outcomes. Greater

³since there was a small amount of attrition during the credit counseling phase, it is necessary to distinguish the TOT effect from the intent-to-treat (ITT) effect, which would be the value of the BHMP coefficient if the BHMP sample included those families who began the BHMP process but did not ultimately lease up using BHMP vouchers

education levels may coincide with more knowledge of the housing market, better abilities to conduct housing searches, and more knowledge of the importance of neighborhood influences on human development. Apart from these household characteristics, transportation is likely an important factor that facilitates (or impedes) a low-income family's ability to move into better neighborhoods. Indeed, previous research has shown that voucher holders are significantly more likely to move into higher opportunity neighborhoods when they have access to a car (Pendall et al. 2015; Dawkins et al. 2015; Pendall et al. 2014; Blumenberg & Pierce 2014). Since many voucher assisted households may be transit dependent it is reasonable to assume that accessibility in the form of transit service may be a major driver of household location choice (Glaeser et al. 2008).

Unfortunately, HUD administrative data used in this study is somewhat limited with respect to household characteristics and contains no data on education, gender, or vehicle access. Nevertheless, while the inclusion of these variables may have led to a better model, their omission does not, in all likelihood, render the model invalid. Using the data available, both the primary coefficients of interest (namely race and voucher type) appear robust to specification.

3.8 Conclusion

The Housing Choice Voucher Program is designed to facilitate the movement of low-income families into higher quality neighborhoods than might otherwise be possible. Recognizing that public housing tends to be developed

in high poverty neighborhoods where markets are weak and development is inexpensive, the HCV program leverages the private market to provide poor families with greater mobility and residential choice. The ambition of such a program is to promote social mobility by providing greater access to the multitude of resources and neighborhood effects (what might be called spatial capital) which are proven to influence a wide variety of socioeconomic outcomes [Galster & Killen (1995); Galster (2010); Galster & Sharkey, forthcoming].

With this goal of voucher programs in mind, this study presents two important findings. First, there is a wide racial disparity in the types of neighborhoods occupied by white and black voucher holders. Using a multivariate measure of “opportunity” that takes into account social, environmental, geographic, and environmental features, this paper shows that voucher holders, on average, are likely to live in neighborhoods with opportunity scores lower than the regional average. By itself, this is not a surprising finding, and confirms the findings from several studies (Pendall 2000). What is clear from this study, however, is that the ability to translate housing assistance into spatial capital is not shared evenly among voucher-assisted households. After controlling for a variety of characteristics that could influence residential trajectories, this study provides clear evidence that black households are significantly less likely to reside in higher opportunity neighborhoods than their white counterparts.

To counteract the racial disparity in housing assistance outcomes, specialized voucher programs have been designed to provide additional assistance to African American families. Although evidence from Gautreaux has shown

that these programs can be effective tools for combatting racial inequality, convergent evidence from similar programs has been lacking since until recently such programs have been in their infancy. The second major finding from this study helps fill that gap. After more than a decade in operation it is clear that the Baltimore Housing Mobility program provides a major boost to black families in the Baltimore metropolitan region. Participating households are far more likely to live in high opportunity neighborhoods, overcoming even the spatial disadvantages faced by white voucher holders.

On a final note, it is important to consider Baltimore's contextual setting as an important backdrop for these findings. Both recent events and a well-documented history prove the vast, undeniable, and pervasive power of institutional and community racism to distinguish separate paths of development for black and white households. Although housing choice vouchers can help low income families escape the traditional inner city neighborhoods in which public housing is clustered, reliance on the free market to affirmatively further fair housing is, apparently, ineffective. If the federal government is serious about its commitment to racial and economic justice, specialized voucher programs and other innovative solutions may be absolutely necessary. From this study it is impossible to determine which aspect of the BHMP program leads to the greater success of its participants. Since BHMP is provided as a bundle that includes regional portability, transportation assistance, credit counseling, and housing search assistance, it is impossible to parse the effects of each of these individual effects apart—but that may be just the point. Absent such concerted efforts, similar efforts may prove less effective.

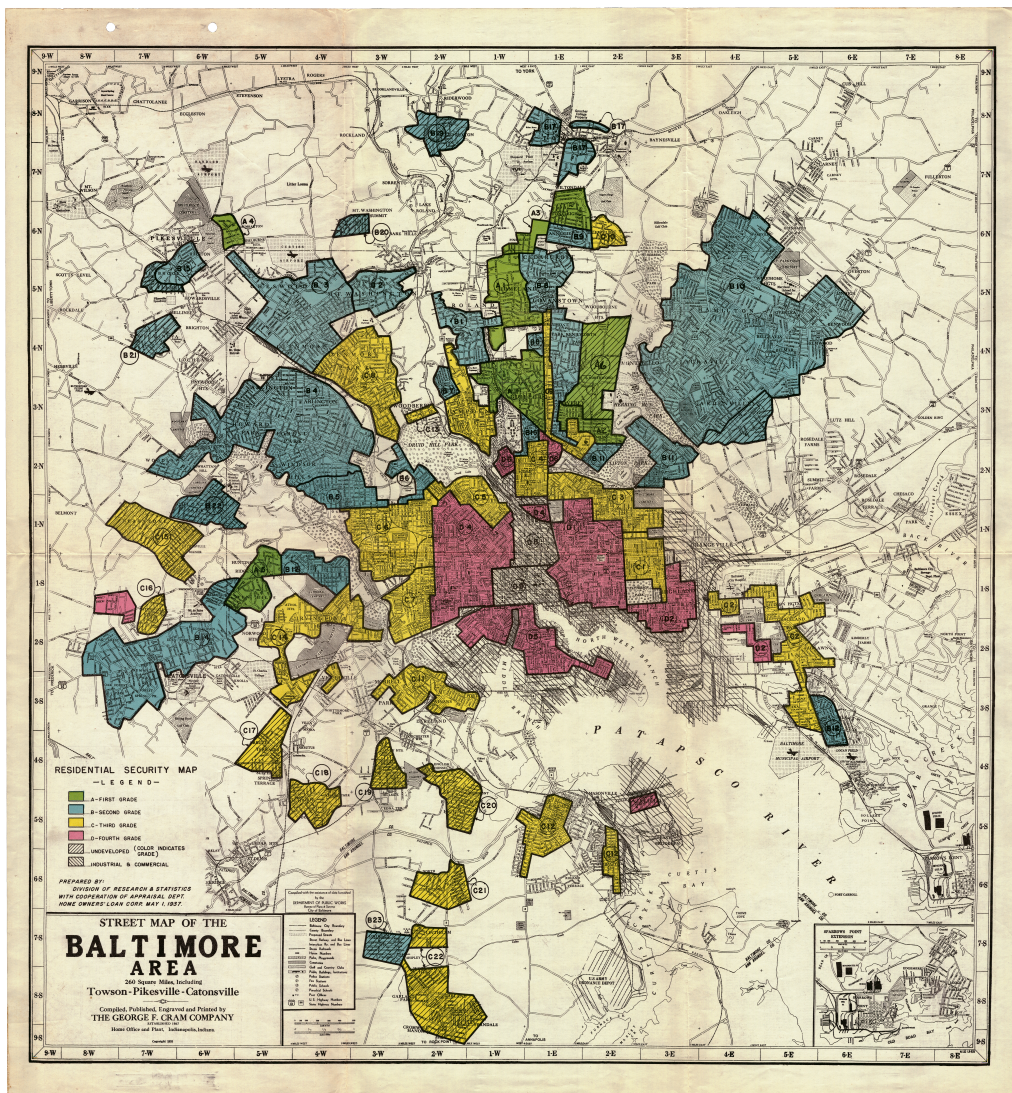


Figure 3.1: HOLC Residential Security Map of Baltimore

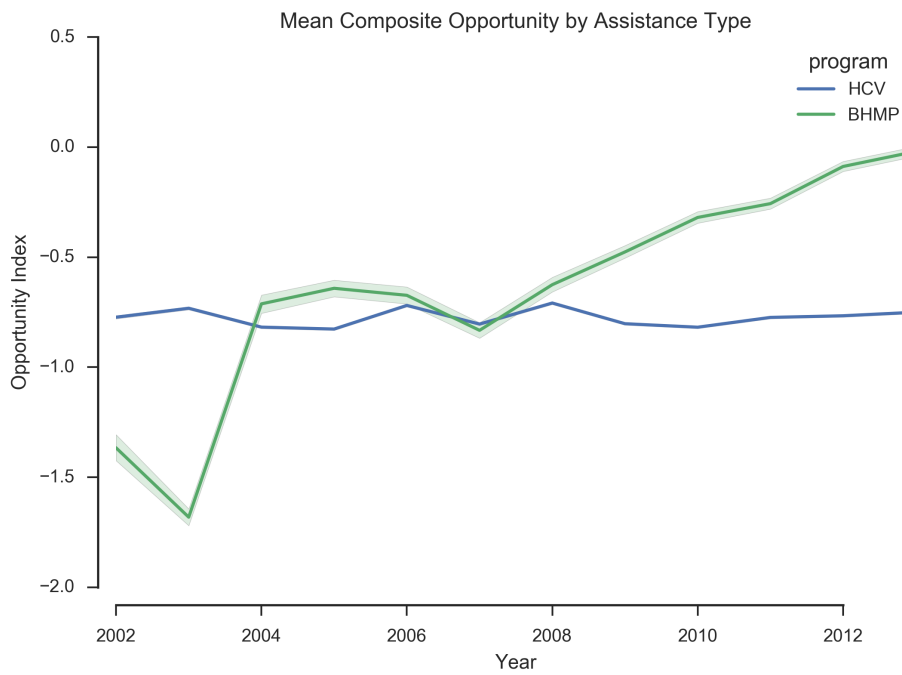


Figure 3.2: Composite Opportunity

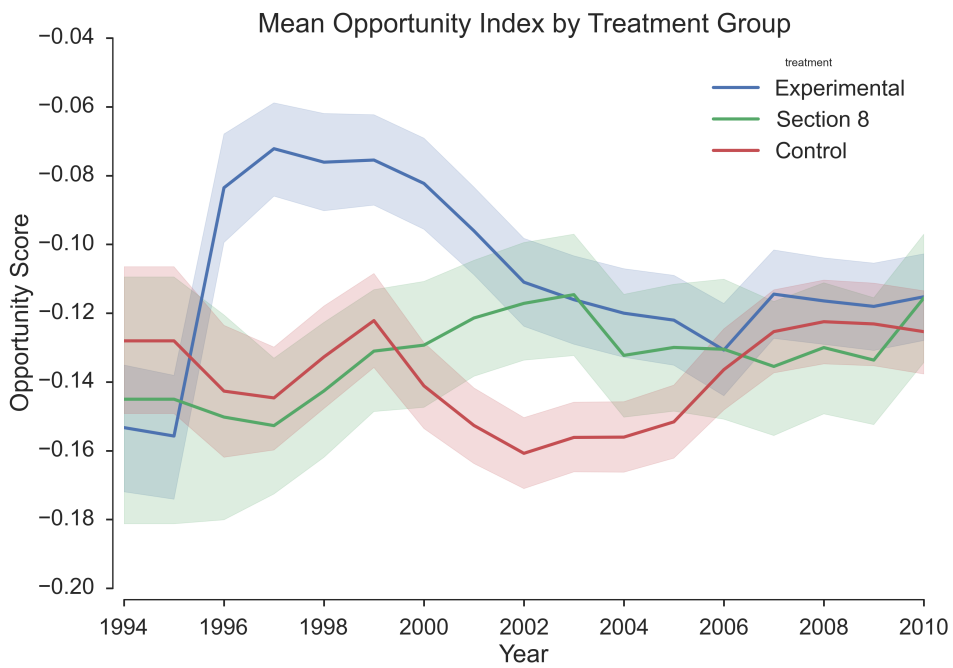


Figure 3.3: MTO Composite Opportunity by Treatment Group

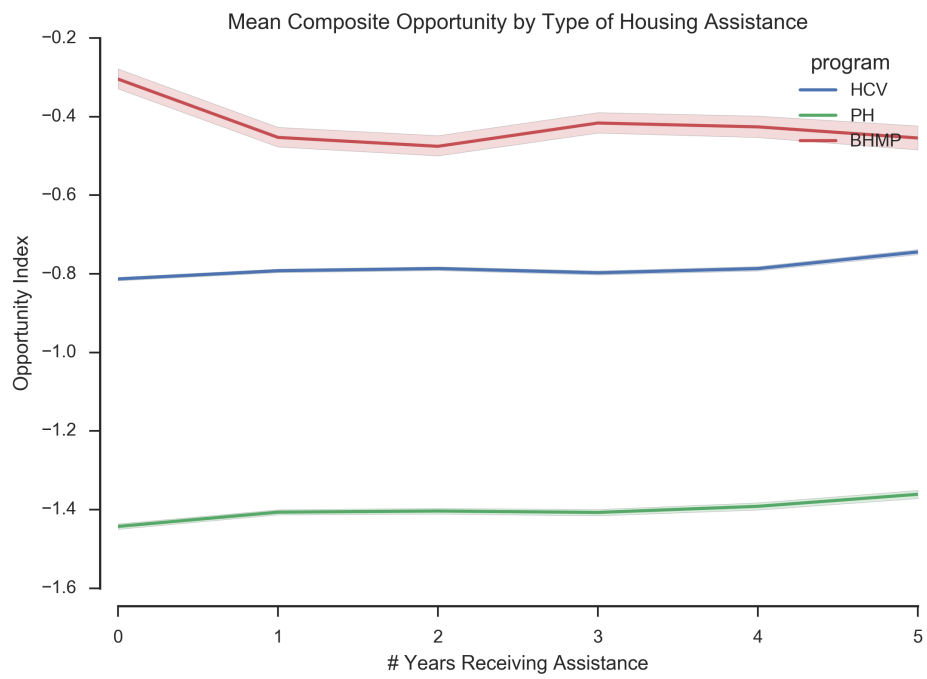


Figure 3.4: Composite Opportunity

Chapter 4

Housing Assistance in Black and White: A Discrete Choice Model of Residential Sorting in Housing Voucher Programs

4.1 Introduction

This study uses a discrete choice model to study residential sorting patterns of housing choice voucher holders in the Baltimore Metropolitan Region. Previous qualitative research has suggested that housing voucher holders are typically more sensitive to the characteristics of individual housing units than to the attributes of the neighborhoods in which they are located (Peter Rosenblatt & Deluca 2012a). Furthermore, qualitative studies have stressed the positive impact of housing counseling services in helping families move

to relatively better neighborhoods (Darrah & DeLuca 2014). Despite these important findings, quantitative models of residential sorting among voucher recipients are scant (Galiani et al. 2012; Davis et al. 2015). Thus, while a great deal of research has examined how neighborhood characteristics affect the socioeconomic outcomes of voucher holders, comparatively little quantitative research has examined how low-income families sort into their neighborhoods.

In the following paper I exploit precise location information across several datasets from the state of Maryland to develop a rich set of information about voucher recipients and the neighborhoods and housing units they occupied over a 10 year period. Using a series of discrete choice models, I describe how housing and neighborhood characteristics affect the location outcomes of program participants. I describe how neighborhood and housing choices differ by race as well as how location outcomes differ for regular voucher recipients versus recipients of vouchers distributed by Baltimore's regional housing mobility program. The models reveal important differences in location outcomes between black and white voucher holders. Results show that racial segregation is the dominant mode by which voucher holders sort into neighborhoods, but that a variety of other housing and neighborhood characteristics are important as well. Black voucher holders are overwhelmingly likely to move into predominantly black neighborhoods while the opposite is true for white voucher holders. Black voucher holders are also particularly sensitive to transit accessibility while white voucher holders tend to move away from neighborhoods characterized by high levels of job accessibility.

4.2 Background

In urban studies, there is a long tradition of “large scale” or “integrated” modeling, in which scholars build empirical models of real estate markets and transportation systems to study the potential ways in which different policy scenarios or future conditions may effect various economic or environmental systems (Klosterman 1994; Borning & Waddell 2006). While early attempts at these models were criticized for lacking appropriate theory, methods, and data, large scale models have seen a renaissance in urban planning thanks to the continuing increase of computational power, Big Data, and analytical methods (Lee 1973; Wegener 1994). Among the developments most critical to this renaissance was the introduction of random utility theory and discrete choice modeling. In his seminal (and Nobel Prize winning) work, McFadden (1978) introduced the conditional logit¹ model for studying the choice of residential location. Using this technique, McFadden demonstrated that a household’s location choice can be understood in terms of the trade-offs between the characteristics of different housing units, and that these preferences would be revealed in the model. Since then, numerous studies have been published using discrete choice analysis to study consumer preferences for housing, transportation and other goods—many of them in regional

¹Note that there is some confusion regarding the appropriate nomenclature for this type of model. Formally, a conditional logit model is distinct from a multinomial logit model, however this convention is not universal. As Croissant (2013) describes, “A model with only individual specific variables is sometimes called a multinomial logit model, one with only alternative specific variables a conditional logit model and one with both kind of variables a mixed logit model. This is seriously misleading : conditional logit model is also a logit model for longitudinal data in the statistical literature and mixed logit is one of the names of a logit model with random parameters. Therefore, in what follow, we’ll use the name multinomial logit model for the model we’ve just described whatever the nature of the explanatory variables included in the model” (Croissant 2013, p.8). Following this convention, I refer to discrete choice models as multinomial logit, regardless of whether the explanatory variables represent attributes of the chooser or her choices.

science, urban economics or civil engineering.

More recently, sociologists and demographers such as Hoffman & Duncan (1988), have argued that McFadden-style models are the most appropriate for reflecting behavioral realism in demography, and have begun to develop models of complex social phenomena like segregation and residential filtering using techniques that include discrete choice, Cellular Automata (CA), and Agent Based Models (ABMs)² (Quillian 2014; Bruch & Atwell 2013; Bruch & Mare 2011; Bruch & Mare 2008; Tuljapurkar et al. 2008; Bruch & Mare 2006; Benenson 2004; Portugali & Benenson 1994). While they are becoming more common in sociology, these models are typically viewed as “pure” rather than “applied” research, and are not intended to develop any particular policy prescriptions. This chapter is designed to bridge the gap between the demography literature and the planning literature; In the following work, I develop a discrete choice model designed to uncover the residential filtering processes faced by housing voucher holders in the Baltimore region. The results will be useful not only for understanding they types of decisions made by voucher holders, but also for designing different policy scenarios that could be implemented by HUD, local governments, or other administrative bodies.

²often these techniques are used in conjunction with one another; for instance, a discrete choice model may be use to estimate parameters from empirical data which are then used to simulate the decisions of households in an ABM

4.3 Housing Vouchers and the Dynamics of Location Choice

Much has been written about the individual choices (or lack thereof) by which residents sort into neighborhoods. It remains unclear, however, how much residential sorting is the result of individual agency or structural determinants. Certainly, agency and autonomy are major components that help explain why certain households live in distinct areas, and why macro-level patterns of segregation have remained remarkably consistent over time. The seminal work by Schelling (1971), for example shows how meso and macro level segregation patterns emerge from relatively small preferences for similar neighbors. In the empirical literature, others argue that individual agency and self segregation explain a small but nontrivial amount of the residential sorting patterns observed in metro areas. Ihlanfeldt & Scafidi (2002), for example, find that black self-segregation plays a statistically significant, albeit minor role in explaining housing segregation and Dawkins (2004) shows that that household-level socioeconomic and demographic characteristics explain only a small proportion of the racial differences in location choices, while racial processes such as prejudice and housing market discrimination continue to drive black-white segregation patterns.

In the context of housing vouchers, there is ample qualitative evidence that structural factors play a large role in the residential sorting process. Rosen (2014), for example, argues that location choices are shaped largely by interactions with landlords, and Galvez (2010) shows that voucher holders “reported encountering landlords they felt were initially cooperative during

phone conversations but then turned them away after discovering they had children, wanted to use a voucher, or were black. Others stated that they avoided searching in neighborhoods where they thought black people would be unwelcome. Because these studies rely on voucher holders' perceptions of possible incidents of racial and source-of-income discrimination, it is difficult to understand the extent to which discrimination occurred" [p.14]. Apart from structural sorting patterns, other qualitative researchers have found other important nuances in voucher recipient location choices, such as Peter Rosenblatt & Deluca (2012a), who argue that voucher holders choose *housing units* rather than *neighborhoods* and are, thus, more sensitive to the characteristics of the former rather than the latter.

More recently, authors have taken an alternative approach based on discrete-choice modeling of revealed preference, rather than relying upon surveys that capture stated preferences. Much of the work in this arena has been conducted using the Panel Study of Income Dynamics, and has examined the differences in residential sorting among different racial and/or income groups. As such, comparatively little of this research has been focused on housing voucher holders—a particularly important subpopulation for whom residential mobility may be the key to ending long-term, systemic, and intergenerational poverty.

In this study, I use a discrete choice framework to examine the sorting patterns of housing voucher holders in the Baltimore metropolitan region. I argue that racial composition is a major component of location utility, but far from the only consideration facing voucher holders. Other components of location utility—such as access to jobs, school quality, and walkability—can

be equally strong predictors of location outcomes for voucher holders, the factors by which voucher recipients sort into neighborhoods are malleable and subject to change given household circumstances and knowledge of the housing market. Since mobility programs are designed to help end the cycle of intergenerational poverty, it is crucial to understand these dynamics to help design voucher programs in a way that maximizes the location utility for each recipient.

Toward this end, there are two ways to manipulate location outcomes. The first is to alter the choice set by imposing restrictions on the neighborhoods and housing units that voucher holders are permitted to occupy. This strategy is likely to be effective because it is simple to enforce and implement. On the downside, however, this strategy can be overly restrictive and paternalistic. The other strategy is to manipulate the parameters of a particular household's utility function by providing additional or alternative information (e.g. increasing knowledge about unevaluated alternatives, or providing greater counseling about how different aspects of housing can affect socioeconomic mobility). In some housing mobility programs both of these strategies are employed in tandem. The Baltimore Housing Mobility Program (BHMP) is designed to connect families with opportunity by first specifying a set of "high opportunity" neighborhoods into which a household can move, then providing assistance during the housing search process, aiding in landlord outreach, and providing additional interventions like transportation assistance. In this study, I examine how these bundled interventions change the landscape of opportunity for households who received this type of assistance, and how it distinguishes their locational outcomes relative to black and white voucher recipients who did not receive it.

4.4 Data

A particular innovation in this work is the use of disaggregate microdata to represent both individual agents (choosers) and their choice set (housing alternatives). In some regional models used for urban planning and policy simulations, individual housing units are used to represent the choice set for microsimulations of the housing market (Palma et al. 2005; Waddell et al. 2010). In the demography, segregation, and residential sorting literature, however, I am aware of no study that employs disaggregate housing data to estimate the influence of individual housing unit characteristics. Of the few discrete choice studies that have used housing voucher data, they have only analyzed choices at the neighborhood level (Galiani et al. 2012; Davis et al. 2015). The present study fills that gap. Data on housing voucher holders and their characteristics is drawn from HUD's administrative database. The data cover all housing vouchers that were issued between 2002 and 2013 in the six-county Baltimore metropolitan region, including Baltimore City, Baltimore County, Anne Arundel County, Howard County, Harford County, and Carroll County. From these data, I include only the first location occupied by each voucher household, and only those vouchers used after the year 2005. Using this dataset, the model effectively estimates the sorting factors associated with the location occupied by a voucher holder upon first receipt of the voucher.

Data on housing units is drawn from the Maryland tax assessors database in the form of MDPropertyView, a geocoded version of the tax records using for policy and planning by the Maryland Department of Planning (MDP). The tax assessors data contain information on every parcel in the state of

Maryland, including data on the size and assessed value of the parcel (as well as the land and build structure), the number of housing units, age of the building, and grade of construction. For this study, I use the residential parcels in the tax assessors database, excluding those whose improvement value is less than \$10,000. I also exclude parcels with the highest construction grade and those whose value exceeds \$600,000 since these units are likely to be too expensive for a voucher recipient. This yields a dataset consisting of approximately 800,000 parcels.

4.5 Methods

Using the precise location information contained in both the tax assessor’s records and the HUD administrative data, I combine both sources (along with census information on neighborhood characteristics) to yield a dataset that contains information about the neighborhoods and housing units occupied by each voucher recipient between the years 2003 and 2015. I then partition the dataset into three sub-populations: white households with HCV vouchers, black households with HCV vouchers, and BHMP participants with specialized vouchers. For each sub-population I estimate a conditional logit model that reflects the likelihood that each housing unit in the study area will be occupied by a voucher holder. The model is estimated under a “random utility” framework using the UrbanSim2 software platform, in which a latent utility function is estimated based on the housing and neighborhood characteristics that define each unit (Foti & Waddell n.d.). Household characteristics, such as income and household size enter into the model through interaction variables. This gives the discrete choice model with a conditional

logit specification, as proposed by McFadden (1978), where the probability P of household n choosing unit i , is given by

$$(6) \quad P_{ni} = \frac{e^{V_{ni}}}{\sum_{i'} e^{V_{ni}}}$$

where V_{ni} is the utility provided by unit n for household i , which is expressed in linear-in-parameters form:

$$(7) \quad V_{ni} = \alpha' Z_i + \beta' X_{ni}$$

where,

Z_i is a vector of dwelling attractiveness measures drawn from the two sources. Housing characteristics like dwelling size (square feet) cost (estimated rent)³, dwelling type, and year built are collected from tax assessor's data. Neighborhood characteristics are among the primary variables of interest, and include the opportunity metrics developed in Chapter 2;

X_{ni} is a vector of interaction terms of socio-demographic characteristics of household n with the attractiveness measures of dwelling i . Demographic measures are collected from HUD administrative data and include variable such as household income, household head race, household head age, and household size.

³MD PropertyView does not contain data on household rents. Rents are thus estimated using a hedonic price model via Public Use Micro Sample (PUMS) data from the Baltimore metro region. This model is then used to simulate rents for each dwelling in the study area

α and β are parameter vectors to be estimated (Guo & Bhat 2002). Separate models are estimated for three distinct populations: black HCV recipients, white HCV recipients, and BHMP participants.

In civil engineering and regional science, where these types of large-scale location choice models are typically constructed, the primary goal is to construct a predictive model which can be used to study growth management policies or the environmental impacts of travel behavior. In these cases, the estimated coefficients are most valuable as instruments for simulation, and thus there tends to be little discussion of the estimation or the interpretation thereof. In the present case, however, the model coefficients are important as they yield information about voucher holders' relative preferences. The analytic strategy also permits me to address the question of whether unit characteristics appear to matter more than neighborhood characteristics—a kind of hypothesis test for previous qualitative results. This approach, however, does not diminish the utility of such a model for performing policy simulations under different conditions. Indeed, that that is a major goal for future projects.

4.6 Results

As expected, the results suggest that voucher holders are highly sensitive to housing unit characteristics, but also neighborhood characteristics—especially racial composition. Both black and white households are likely to choose apartment dwellings, though white households are more likely to reside in higher quality units. Households with more members are likely to move into

higher-priced housing units, reflecting the fact that larger households receive larger housing subsidies. Holding other variables constant, all voucher households are likely to choose larger housing units, in keeping with previous research by Peter Rosenblatt & Deluca (2012a) suggesting that voucher holders may be willing to trade neighborhood qualities for housing unit qualities. Interestingly, the coefficient for the interaction between household size and housing unit size is negative. This suggests that larger households (whose voucher translates to a bigger rent subsidy) do not use their increased spending power to secure larger housing units but instead allocate their resources toward other housing unit characteristics, like school quality and/or reduced crime (whose coefficients are in the expected direction, but now significant). These findings contrast those of Peter Rosenblatt & Deluca (2012b) who studied the location decisions of MTO movers in Baltimore and found that voucher holders were more sensitive to housing unit characteristics than neighborhood characteristics.

Apart from housing unit characteristics, the model suggests that the dominant sorting pattern for voucher holders is neighborhood racial composition. Black voucher holders overwhelmingly gravitate toward predominantly black neighborhoods. Once *within* predominantly black neighborhoods, black households are likely to move into neighborhoods with better transit service, lower crime rates, and somewhat higher median incomes—but not better schools. White households, by contrast, avoid black neighborhoods; once this criterion is satisfied, however, white households are likely to move into neighborhoods with higher crime rates, lower median incomes but somewhat better than average schools.

Table 4.1: LCM Results for Black Households

Component	Coefficient	Std. Error	T-Score
Apartment	0.660	0.502	1.315
Single Family	-0.288	0.507	-0.568
Town House	-0.181	0.506	-0.358
Year Built	-0.004	0.000	-15.460
Construction Grade	-0.109	0.016	-6.776
value	-0.760	0.020	-37.741
log(unit sqft)	0.199	0.013	14.778
density population	0.212	0.013	16.208
median income	-0.331	0.018	-17.928
m.s. performance	-0.133	0.013	-10.230
pctblack	1.702	0.036	47.838
jobs auto	-0.096	0.014	-6.769
jobs transit	0.243	0.010	23.816
crime	0.315	0.011	29.619
household members * value	0.037	0.008	4.885
household members * log(unit sqft)	-0.051	0.013	-4.071
household members * density population	0.079	0.010	7.832
household members * m.s. performance	0.118	0.009	12.765

Black voucher recipients are more likely live in lower quality apartment buildings, higher density neighborhoods, and communities with lower median incomes. They are also more likely to live in higher crime neighborhoods and those better served by transit. As noted above, black voucher holders

are overwhelmingly likely to live in predominantly black neighborhoods, and also likely to live in neighborhoods with lower quality schools. An important caveat, however, is that unlike other recipients, the coefficient for household size and school quality is positive and significant for black voucher holders, which implies that school quality becomes a more salient factor in location choice as the number of children in the home increases.

Table 4.2: LCM Results for White Households

Component	Coefficient	Std. Error	T-Score
Apartment	0.670	0.441	1.518
Single Family	-0.337	0.464	-0.727
Town House	-0.696	0.456	-1.526
Year Built	-0.006	0.000	-38.809
Construction Grade	0.124	0.025	4.936
value	-1.330	0.037	-35.947
log(unit sqft)	0.408	0.032	12.772
density population	0.067	0.023	2.987
median income	-1.131	0.026	-43.775
m.s. performance	0.103	0.022	4.642
pctblack	-1.652	0.058	-28.318
jobs auto	-0.112	0.019	-5.796
jobs transit	-0.160	0.026	-6.220
crime	0.644	0.017	38.970
household members * value	0.001	0.018	0.059
household members * log(unit sqft)	-0.146	0.029	-5.020
household members * density population	0.009	0.016	0.564

Component	Coefficient	Std. Error	T-Score
household members * m.s. performance	0.028	0.020	1.391

One unique feature of the results for white voucher recipients, is that they appear to reside in more suburban and exurban locations with less access to jobs by either automobile or transit. This may imply a structural difference between the black and white voucher populations in that black households may be more transit dependent. Another interesting feature is that the crime coefficient for white households is larger than for black households, suggesting that white voucher recipients are more likely to live in higher crime neighborhoods. Unlike black households, however, white households are more likely to live in better school districts whereas the opposite is true for black households.

I interpret this to mean that after controlling for racial sorting (i.e. paying the racial premium), white households must account for that cost by sacrificing other coveted neighborhood resources elsewhere; in other words, once white voucher holders locate housing in white neighborhoods (which are more highly valued on the market), they are resigned to higher crime neighborhoods with lower median incomes. In black neighborhoods (which have less market value), however, black voucher holders receive a kind of surplus that can be allocated to other resources. Thus, they live in neighborhoods with slightly less crime and slightly higher median incomes—but these advantages do not spill over into school quality. In the Baltimore region, there is an extremely strong correlation between race and school quality and it is almost impossible to find a good school in a black neighborhood. For that

reason, school quality is coveted and black voucher holders cant make it into better school districts once they sort into black neighborhoods. These results are consistent with Horn et al. (2014) who find that white voucher holders are significantly more likely than black voucher holders to live near good schools.

Table 4.3: LCM Results for BHMP Households

Component	Coefficient	Std. Error	T-Score
Apartment	1.859	2.797	0.665
Single Family	-1.180	2.787	-0.423
Town House	-0.488	2.798	-0.174
Year Built	0.003	0.001	2.047
Construction Grade	0.049	0.061	0.799
value	-0.526	0.100	-5.265
log(unit sqft)	-0.024	0.072	-0.327
density population	0.417	0.057	7.342
median income	0.135	0.064	2.125
m.s. performance	0.423	0.057	7.484
pctblack	0.137	0.137	1.000
jobs auto	0.469	0.050	9.400
jobs transit	-0.230	0.047	-4.932
crime	0.626	0.040	15.711
household members * value	0.085	0.038	2.241
household members * log(unit sqft)	0.055	0.064	0.856
household members * density population	-0.013	0.041	-0.306
household members * m.s. performance	-0.200	0.036	-5.530

Finally, model results from BHMP participants show unique patterns. Like white HCV recipients, BHMP households are more likely to live in higher quality school districts, as well as neighborhoods with higher crime rates. Unlike white HCV recipients, they are more likely to live in higher income neighborhoods with higher densities. For BHMP participants, the neighborhood racial composition is an insignificant factor explaining residential sorting—an important distinction between BHMP participants and HCV recipients of both races.

4.7 Discussion

Although the class of models used in this analysis is labeled discrete *choice*, it is critically important to note that this analysis cannot discern whether the observed residential sorting occurs purely through the choices made by individual agents or through structural factors beyond the control of any individual household. It is clear from this study that black voucher holders are overwhelmingly likely to reside in black neighborhoods. This pattern may be due to black preferences for same race neighbors, white hostility toward black neighbors (real or perceived), limited information about rental opportunities, or discrimination by landlords.

It is also likely that unobserved but vital differences among both households and neighborhoods play an important role in the residential sorting process. Ellen et al. (2016), for example, find that location decisions are influenced by the age of children in the household. Specifically, they find that voucher holders are more sensitive to school quality once their oldest child nears

schooling age. I find that households are more sensitive to school quality when households are larger (e.g. have more children) though the effect is small. Hedman (2013), meanwhile finds that households are sensitive to the location of family members, preferences for maintaining proximity to social support is an important driver of location choice among low-income households.

Finally, it is worth noting that the models included in this research rely on a number of simplifying assumptions that could be relaxed in future work to improve the specificity of the results. The most important assumption is that of the independence from irrelevant alternatives (IIA) property, a well-publicized feature of choice models (Walker 2001; Quillian 2015). The IIA property helps release the analyst from misspecification of the choice set and holds, essentially, that model estimates remain unchanged when model a different set of alternatives is considered. In other words, the IIA property holds that coefficients are robust to misspecification of the choice set. In the context of residential choice models, the IIA property is particularly important since full regional models could contain thousands or hundreds of thousands of choices and estimating choices among such a large set of alternatives is computationally infeasible. To overcome this issue, researchers have shown that consistent parameter estimates may be obtained by combining the chosen alternative with a small random sample of non-chosen alternatives. This technique relies on the IIA property, but facilitates the estimation models employing large samples. The UrbanSim software used to develop the models presented in this analysis employs this technique

4.8 Conclusion

This study makes several important contributions to the literature on residential sorting among low-income households. First, it incorporates disaggregate data on individual housing units, which facilitates examination of the tradeoffs made between housing and neighborhood characteristics. Second, it examines how differences in location outcomes are borne out among black and white voucher recipients. Specifically, the models presented here explain differences in locational attainment among a wide variety of housing and neighborhood characteristics between different races. Third, it incorporates data from Baltimore's regional housing mobility program to demonstrate how specialized vouchers can alter the dynamics of residential sorting, beyond what might be expected in more laissez-faire approaches like the general HCV program. Taken together, the findings suggest that there are strong racial divides in the type of neighborhood assets available to voucher holders, but that mobility programs can make a big difference.

An important issue that this study is unable to address is how much the results are driven by the autonomous decisions of individual voucher recipients, and how much of the sorting is explained by structural factors like discrimination by landlords. If the qualitative research record is any guide, then it is clear that structural issues play an important role in the sorting process. With respect to fair housing policy, this suggests an interesting path for both future research and policy prescription.

On one hand, this study makes clear that changing the demand side of the equation can lead to better, more racially equitable outcomes. The evidence for this finding comes from the fact that BHMP participants have vastly

different housing consumption patterns than similar black renters receiving HCV vouchers. There are some location restrictions in the BHMP program, but the majority of the program's intervention is on the demand side; housing counselors provide recipients with better tools and advice on how to locate affordable units, regional portability and transportation assistance help families consider a much larger share of potential units, and additional search time help families make deliberate housing choices under less pressure. The vast difference in model coefficients between BHMP participants and other voucher holders is clear evidence that these interventions reshape the demand function for housing.

On the other hand, the supply side of the equation is equally relevant but unaddressed in the present study. Voucher recipient location outcomes could look vastly different if there were a greater supply of affordable housing in neighborhoods with a wider variety of characteristics. One aspect of supply is simply the siting of housing affordable to voucher recipients; place-based subsidies like the Low Income Housing Tax Credit LIHTC in high opportunity neighborhoods could help reshape location outcomes dramatically. Further studies based on location choice simulations could help reveal how effective a major initiative aimed at increasing housing supply in high-opportunity neighborhoods might be. Such simulations might include policy scenarios based on statewide inclusionary zoning programs, targeted LIHTC investments, or redevelopment programs. Built from the discrete choice models described in this study, these simulation studies could be not only a valuable avenue for future research, but also a powerful vehicle for advocating for changes to regional fair housing policies.

Another aspect of housing supply does not concern place-based subsidies but is even more germane to the Baltimore context: discrimination. Among the supply of naturally-occurring affordable housing, the supply can be shrunk artificially by landlords that refuse to rent to voucher holders. In Baltimore County, legislation known as the HOME Act has been introduced, which would outlaw discrimination against renters based source of income. For voucher recipients, this would mean that landlords are unable to refuse a rental agreement simply because a tenant planned to use an HCV voucher as part of the rent payment. A similar bill has been introduced in the Maryland state legislature and failed each time. Given the results of the present study, a supply-side policy intervention, as a complement to the existing demand-side interventions in the Baltimore region, could have a profound effect on the patterns of racial and economic inequality. Given the qualitative research record outline earlier, it is possible (even likely) that landlords may use income discrimination as a veiled form of racial discrimination. In other words, landlords may choose selectively to allow housing voucher payments from white families but deny them from black families—a violation under the fair housing act, but defensible under the guise of denial by income source. Absent research focused specifically on this issue, it is impossible to estimate how prevalent such a practice may be. Nevertheless, it is clear that when combined with demand-side interventions like the BHMP, a supply side intervention like the HOME Act could significantly shift racial progress in the Baltimore region in the right direction. Absent such concerted efforts, the results provided by this study suggest that the HCV program may fail to meet the standard set by HUD’s new Affirmatively Furthering Fair Housing rule, as black voucher recipients under the general HCV program are consis-

tently unlikely to live near important spatial resources like good schools, low poverty rates, and low crime rates.

Chapter 5

Conclusion

5.1 Summary and Discussion

This dissertation seeks to increase scholarly and practical understanding of the impacts of residential context on individual socioeconomic status, and the policy interventions that can help increase access to spatial opportunity for those who need it most.

Chapter two discussed the state of practice in measuring and visualizing spatial opportunity, a practice designed to improve fair housing policy by understanding how to help low-income renters access spatial capital. This work provides several important advances that allow greater flexibility in the way that spatial capital is measured and visualized, and provides a much stronger connection to the empirical literature on neighborhood effects and the statistical literature on econometrics. In third chapter, I examined the locational outcomes of Baltimore's housing voucher recipients and compared the divergent outcomes for regular voucher holders versus those households who

participated in the regional housing mobility program designed to connect families with opportunity. The results showed voucher holders in the Baltimore region were likely to move into neighborhoods with low opportunity scores and that black voucher holders face an even greater disadvantage. The positive results from this study, however, showed that Baltimore's specialized regional voucher program provides a package of assistance that allows voucher recipients to overcome the traditional hurdles and find housing in high opportunity neighborhoods. In Chapter four, I constructed an econometric model of the factors that influence location choice for housing voucher recipients, contrasting the sorting factors between black and white voucher recipients. I also discussed how sorting in Baltimore's regional voucher program diverged significantly relative to the patterns observed in the general Housing Choice Voucher program. The results showed how white and black voucher holders sort into vastly different neighborhood—a pattern driven, in large part, by racial neighborhood composition. Again, however, results also showed that Baltimore's mobility program had different results and provided a path forward.

The results from these studies help demonstrate how cities and regions can analyze the resources embedded in local neighborhoods and how to provide access to the different types of spatial capital for low-income households. The findings help suggest improvements for both methodological practices and housing policies. In particular, they suggest better ways to measure opportunity, better methods for helping assisted households find neighborhoods, and better regulations for housing voucher programs that guide families into communities of opportunity.

5.2 Policy Implications

Taken together, these studies suggest an important direction for fair housing policy in the United States. As HUD solidifies its commitment to Affirmatively Furthering Fair Housing, it is important to know how the many aspects of spatial capital contribute to socioeconomic mobility and how housing policy can provide more equal access to those various sources of capital. In Chapter 2, I show how both the theory and quantitative analysis around measuring spatial capital can be made more flexible to incorporate better policy design. Using limited methods to design housing policy is paternalistic at best and counterproductive at worst. By incorporating the suggestions in Chapter 2, HUD can provide guidance to local jurisdictions that not only facilitate a better understanding of the local barriers to opportunity, but also important entry points for policies that are designed to equal the playing field of opportunity. From a policy perspective, this work represents an important contribution for two reasons. First, by focusing a spatial measurement strategy on the mechanisms that drive neighborhood effects, public housing authorities and housing mobility counselors have a better, more relevant set of data to make recommendations to families looking for affordable housing, and by developing neighborhood typologies, rather than collapsing all important metrics into a univariate scale, the data are more readily useable in a practical context. This is especially true beyond the realm of housing mobility and in fields such as community development, in which the goal is to create more opportunity in neighborhoods lacking. A typology-drive approach gives city planners and policymakers the tools to understand what resources a particular neighborhood may be lacking and what should be done

to improve it.

The models presented in chapters 3 and 4 together tell a vivid story of racial inequality in the Baltimore metropolitan region, but they also show how effective a well-funded specialized voucher program can be at combatting these persistent patterns. Together, these studies show that HUD has a long way to go before achieving its mandate to Affirmatively Further Fair Housing. Both white and black housing recipients face severe disadvantages when trying to translate housing assistance into spatial capital. These disadvantages, however, are far more severe for black voucher recipients who are more likely to sort into segregated communities with underperforming schools and high crime rates. These findings underscore the need for sustained attention to race in the design of housing programs, and make it clear that although voucher programs help deconcentrate poverty more than traditional public housing, they are no panacea, and still require improvements to meet the new standard. Interpreting the Baltimore Housing Mobility Program, liberally, as a natural experiment, the models presented in this dissertation represent the first rigorous, quantitative test of the effectiveness of such programs. A great deal has been written about early mobility programs like Gautreaux, but the work presented here is among the first to examine how multifaceted programs that include mobility counseling, transportation assistance, landlord outreach, and location restrictions change the landscape of opportunity for low income renters. The results make it clear that comprehensive mobility programs like BHMP help Affirmatively Further Fair Housing, whereas the national HCV program often falls short.

On a more substantive note, the longitudinal model shows that residential

trajectories for most voucher holders are remarkably stable over time, and that among the most important benefits provided by BHMP is the ability to help voucher recipients locate housing in high-opportunity neighborhoods upon their first receipt of the voucher. These results suggest that one relatively cost-effective way for the HCV program to achieve better locational outcomes would be to expand the time and services allocated to new voucher recipients. If Public Housing Authorities (PHAs) extended the lease-up time allotted to new voucher recipients and employed mobility counselors to help families find housing in high quality neighborhoods, the model presented here suggests that those initial location advantages would persist throughout the family's tenure in the voucher program. To facilitate such counseling services, PHAs could rely on neighborhood typologies similar to those presented in Chapter 2. If such maps were available to counselors, they could quickly narrow down the applicable set of neighborhood types in which a family might best use its voucher, then use those types to expedite housing searches in suitable neighborhoods. Unlike alternative opportunity mapping approaches, counseling based on neighborhood typologies recognizes that location utility is heterogenous across household types, and is better positioned to help voucher holders find housing suitable to their particular needs.

Unfortunately, both the longitudinal and the discrete choice models presented in this dissertation make it clear that there are wide racial disparities in the provision of housing assistance. Black voucher holders are consistently less able to translate their housing assistance into spatial capital. From a policy perspective, these findings suggest that racial equity may not be achievable until desegregation is an explicit goal of the housing choice voucher program. With HUD's increasing commitment to Affirmatively Furthering

Fair Housing, these findings come as a major indictment of current efforts and suggest that, absent programmatic changes, HUD's new statutory environment opens it up to additional litigation on the grounds of fair housing. Unfortunately, HUD's reliance on the private rental market for voucher programs like HCV, means that it has relatively little control over the resulting patterns of segregation. Mobility counseling can help provide information about available units in integrated neighborhoods, but there are few regulatory devices for combatting covert racial discrimination in the housing market. One way that HUD could, however, make a difference in this arena is to advocate for national or regional legislation that outlaws discrimination based on source of income. As discussed in chapter 4, there is some evidence that landlords use income discrimination as a cover for racial discrimination, a phenomenon which would explain why white voucher holders end up in better neighborhoods than black voucher holders despite having the same income limitations. HUD should, therefore, take seriously the notion that income discrimination is a barrier to fair housing, and that policy changes outlawing such discrimination would contribute to its mandate.

5.3 Future Research

The work presented in this dissertation presents three clear paths for future research: first, more neighborhood effects research should be conducted to understand the validity of the instruments used to measure opportunity; second, matched pair studies should help explore the question of racial bias in the housing choice voucher program; and third, agent-based simulation studies should be conducted to understand how changes to the design and ad-

ministration of the Housing Choice Voucher Program could lead to different location outcomes for its participants.

In chapter two, I proposed a method for developing spatial measures of opportunity that are well-supported by the empirical literature and are shown to have defensible construct validity. Future research should test these metrics explicitly. Specifically, research should test whether the neighborhood typologies (treated as indicators variables) have causal effects on the socioeconomic achievement of residents living in each type. Such a study should be longitudinal in nature, capture a wealth of information about individuals, families and neighborhoods. It should also test for non-linear effects of different neighborhood attributes, and test separately for neighborhood effects heterogeneous across racial groups, gender identities, and age groups. Parallel research should examine more about the perceptions of different neighborhoods by both residents and outsiders. Continuing in the vein of econometrics, a great deal of additional research is needed to understand how social interpretations of neighborhoods (e.g. spatial stigmas) contribute to the overall geography of opportunity, and how perceptions are related to the objectively measured attributes of place.

In Chapter three I examined the long term effects of a specialized mobility program operating in the Baltimore metropolitan region. Although the results suggest that comprehensive mobility programs like BHMP are useful for combatting systemic inequality, more research is necessary to qualify this finding. A great deal of additional research should examine (a) which aspects of BHMP contribute to its success, and (b) how replicable, and scalable are such programs? With respect to the first question, relatively small-scale stud-

ies employing experimental design could, for instance, help parse the effects of transportation assistance, versus mobility counseling, versus a combined approach. This work would help tighten the programmatic design of future mobility programs and optimize limited funding. With respect to the second question, studies similar to those presented here should be conducted on other mobility programs operating in other cities and regions, like Dallas, San Diego, Minnesota, Buffalo, and Philadelphia to understand how different regions, political contexts, demographic makeups, and program designs may lead to different results.

In Chapter four, I built a series of discrete choice models to examine the residential sorting patterns of black and white voucher holders and how they differed from mobility program participants. Although this study employs a *choice* modeling framework, it is unclear how much of the results are driven by individual choices or structural steering patterns like racial discrimination. Future research should address this question explicitly. One way to uncover the incidence of racial discrimination on the part of landlords is the use of a matched pair design, in which white and black renters with otherwise identical tenant and credit histories apply for the same housing. Significant differences between racial groups in successful lease-up rates would indicate discrimination. This study designed has been used extensively to uncover racial discrimination in labor markets and hiring practices, but there are comparably few studies that examine such discrimination in housing markets and leasing practices. Finally, although the models in chapter four provide a useful baseline for understanding residential sorting patterns, the next logical step is to study how the observed sorting patterns would change under alternative policy scenarios. One example might be to simulate the location

choice process under different conditions of affordable housing supply (e.g. a region-wide inclusionary zoning provision). Under this scenario, families have a much broader range of choices, as affordable housing can be found a wider variety of neighborhoods, and researchers could examine how such a policy would provide different access to resources like schools and jobs.

References

- Alba, R.D. & Logan, J.R., 1993. Minority Proximity to Whites in Suburbs: An Individual-Level Analysis of Segregation. *American Journal of Sociology*, 98(6), p.1388.
- Anderson, M.L., 2015. As the Wind Blows: the Effects of Long-Term Exposure To Air Pollution on Mortality. *NBER Working Paper Series*, 21578.
- Anselin, L., 2013. *Spatial econometrics: methods and models*, Springer Science & Business Media.
- Bader, M.D.M. et al., 2015. Development and deployment of the Computer Assisted Neighborhood Visual Assessment System (CANVAS) to measure health-related neighborhood conditions. *Health & place*, 31, pp.163–72. Available at: <http://www.sciencedirect.com/science/article/pii/S1353829214001580>.
- Bagley, M.N. & Mokhtarian, P.L., 2001. The impact of residential neighborhood type on travel behavior: A structural equations modeling approach. *The Annals of Regional Science*.
- Benenson, I., 2004. Agent-Based Modeling : From Individual Residential Choice to Urban Residential Dynamics. *Geography*, 42(6-7), pp.67–95. Available at: <http://www.tau.ac.il/~benny/publications/SISS2004Benenson.pdf>.
- Blumenberg, E. & Pierce, G., 2014. A Driving Factor in Mobility? Transportation's Role in Connecting Subsidized Housing and Employment Outcomes in the Moving to Opportunity (MTO) Program. *Journal of the American Planning Association*, 80(1), pp.52–66. Available at: <http://www.tandfonline.com/doi/abs/10.1080/01944363.2014.935267>

//escholarship.org/uc/item/6sh23596.

Burdick-Will, J. et al., 2011. Converging evidence for neighborhood effects on children's test scores: An experimental, quasi-experimental, and observational comparison. *Whither opportunity*, pp.255–276.

Chapple, K., 2014. *Planning sustainable cities and regions: towards more equitable development*, Routledge.

Chetty, R. & Hendren, N., 2015. *The Impacts of Neighborhoods on Intergenerational Mobility: Childhood Exposure Effects and County-Level Estimates and numerous seminar participants for helpful comments and discussions*,

Chetty, R., Hendren, N. & Katz, L., 2015. *The Effects of Exposure to Better Neighborhoods on Children: New Evidence from the Moving to Opportunity Experiment*, National Bureau of Economic Research.

Clampet-Lundquist, S. & Massey, D.S., 2008. Neighborhood Effects on Economic Self-Sufficiency: A Reconsideration of the Moving to Opportunity Experiment1. *American Journal of Sociology*, 114(1), pp.107–143.

Collins, M.G., Steiner, F.R. & Rushman, M.J., 2001. Land-use suitability analysis in the United States: Historical development and promising technological achievements. *Environmental Management*, 28(5), pp.611–621.

Croissant, Y., 2013. Estimation of multinomial logit models in R: The mlogit Packages. *Data Management*, p.73. Available at: <https://cran.r-project.org/web/packages/mlogit/vignettes/mlogit.pdf>
<http://scholar.google.com/scholar?hl=en&btnG=Search&q=intitle:Estimation+of+multinomial+logit+n>

Darrah, J. & DeLuca, S., 2014. “Living Here has Changed My Whole Perspective”: How Escaping Inner-City Poverty Shapes Neighborhood and Housing Choice. *Journal of Policy Analysis and Management*, 33(2), pp.350–384. Available at: <http://onlinelibrary.wiley.com/doi/10.1002/pam.21758/abstract>
<http://onlinelibrary.wiley.com/store/10.1002/pam.21758/abstract>

Davis, M. et al., 2015. Neighborhood Choices and Neighborhood Effects., p.37. Available

at: <http://www.econ-pol.unisi.it/quaderni/533.pdf>.

Dawkins, C., Jeon, J.S. & Pendall, R., 2015. Vehicle Access and Exposure to Neighborhood Poverty: Evidence from the Moving to Opportunity Program. *Journal of Regional Science*, 55(5), pp.687–707.

Dawkins, C.J., 2004. Recent evidence on the continuing causes of black-white residential segregation. *Journal of Urban Affairs*, 26(3), pp.379–400.

DeLuca, S. & Rosenblatt, P., 2010. Does moving to better neighborhoods lead to better schooling opportunities? Parental school choice in an experimental housing voucher program. *The Teachers College Record*, 112(5), pp.7–8. Available at: <http://www.tcrecord.org/Content.asp?ContentId=15683>.

DeLuca, S., Garboden, P.M.E. & Rosenblatt, P., 2013. Segregating Shelter: How Housing Policies Shape the Residential Locations of Low-Income Minority Families. *The ANNALS of the American Academy of Political and Social Science*, 647(1), pp.268–299. Available at: <http://ann.sagepub.com/cgi/doi/10.1177/0002716213479310>.

Dietz, R.D., 2002. The estimation of neighborhood effects in the social sciences: An interdisciplinary approach. *Social Science Research*, 31(4), pp.539–575.

Diez Roux AV, W.S.M.K. et al., 2006. Supermarkets, other food stores, and obesity: The Atherosclerosis Risk in Communities Study. *American Journal of Preventive Medicine*, 30(4), pp.333–339. Available at: <http://linkinghub.elsevier.com/retrieve/pii/S0749379705004836>.

DiPasquale, D. & Glaeser, E.L., 1999. Incentives and social capital: are homeowners better citizens? *Journal of urban Economics*, 45(2), pp.354–384. Available at: <http://www.sciencedirect.com/science/article/pii/S0094119098920988>.

Ellen, I.G. & Turner, M.A., 1997. Does neighborhood matter? Assessing recent evidence. *Housing Policy Debate*, 8(4), pp.833–866.

Ellen, I.G., Horn, K.M. & Schwartz, A.E., 2016. Why don't housing choice voucher recipients live near better schools? Insights from big data. *Journal of Policy Analysis and*

Management, (June).

Engdahl, L., 2009. New Homes, New Neighborhoods, New Schools: A Progress Report on the Baltimore Housing Mobility Program. *Poverty & Race Research Action Council (NJ1)*.

Ewing, R. et al., 2003. Relationship Between Urban Sprawl and Physical Activity, Obesity, and Morbidity. *American Journal of Health Promotion, Inc.*, 18(01), p.11.

Fauth, R.C., Leventhal, T. & Brooks-Gunn, J., 2005. Early impacts of moving from poor to middle-class neighborhoods on low-income youth. *Journal of Applied Developmental Psychology*, 26(4), pp.415–439. Available at: <http://linkinghub.elsevier.com/retrieve/pii/S0193397305000195>.

Foti, F. & Waddell, P., UrbanSim2 : Building a Bridge from Urban Modeling to the Open Source GeoSpatial Community., pp.1–14.

Fraley, C. & Raftery, A.E., 2002. Model-Based Clustering, Discriminant Analysis, and Density Estimation. *Journal of the American Statistical Association*, 97(458), pp.611–631.

Fraley, C. et al., 2012. *mclust Version 4 for R: Normal Mixture Modeling for Model-Based Clustering, Classification, and Density Estimation*,

Galiani, S., Murphy, A. & Pantano, J., 2012. Estimating neighborhood choice models: Lessons from a housing assistance experiment. *Available at SSRN 2015474*, pp.1–35.

Galster, G., 2008a. Quantifying the Effect of Neighbourhood on Individuals: Challenges, Alternative Approaches, and Promising Directions. *Schmollers Jahrbuch*, 128(1), pp.7–48.

Galster, G., 2008b. Quantifying the effect of neighbourhood on individuals: Challenges, alternative approaches, and promising directions. *Schmollers Jahrbuch*, 128(1), pp.7–48.

Galster, G., 2010. The Mechanism (s) of Neighborhood Effects Theory, Evidence, and Policy Implications. *ESRC Seminar*, pp.1–32.

Galster, G. & Hedman, L., 2013. Measuring Neighbourhood Effects Non-experimentally: How Much Do Alternative Methods Matter? *Housing Studies*, 28(3), pp.473–498. Avail-

able at: <http://www.tandfonline.com/doi/abs/10.1080/02673037.2013.759544>.

Galster, G. & Killen, S., 1995. The geography of metropolitan opportunity: A reconnaissance and conceptual framework. *Housing Policy Debate*, 6(1), pp.7–43.

Galster, G. & Santiago, A., 2015. Neighbourhood ethnic composition and outcomes for low-income Latino and African American children. *Urban Studies*, p.0042098015598067.

Galster, G., Metzger, K. & Waite, R., 1999. Neighborhood opportunity structures and immigrants' socioeconomic advancement. *Journal of Housing Research*, 10(1), pp.95–127.

Galster, G., Quercia, R. & Cortes, A., 2000. Identifying neighborhood thresholds: An empirical exploration. *Housing Policy Debate*, 11(3), pp.701–732. Available at: <http://www.tandfonline.com/doi/abs/10.1080/10511482.2000.9521383>.

Galster, G. et al., 2015. Adolescent neighborhood context and young adult economic outcomes for low-income African Americans and Latinos. *Journal of Economic Geography*, p.lbv004.

Galster, G.C., 2012. The mechanism (s) of neighbourhood effects: Theory, evidence, and policy implications. In *Neighbourhood effects research: New perspectives*. Springer, pp. 23–56.

Galvez, M., 2010. *What Do We Know About Housing Choice Voucher Program Location Outcomes?*, Available at: <http://www.urban.org/research/publication/what-do-we-know-about-housing-choice-voucher-program-location-outcomes> <http://www.urban.org/uploadedpdf/412218-housing-choice-voucher.pdf>.

Gelman, A., 2008. Scaling regression inputs by dividing by two standard deviations. *Statistics in Medicine*, 27(15), pp.2865–2873.

Gelman, A. & Su, Y.-S., 2016. *arm: Data Analysis Using Regression and Multi-level/Hierarchical Models*, Available at: <https://cran.r-project.org/package=arm>.

Gina, K., 2007. Thompson v. HUD: Groundbreaking Housing Desegregation Litigation, and the Significant Task Ahead of Achieving an Effective Desegregation Remedy Without

Engendering New Social Harms. *U. Md. LJ Race, Religion, Gender & Class*, 7, p.172.

Giovannini, E. et al., 2005. *Handbook on constructing composite indicators: methodology and user guide*, OECD Statistics Working Paper, STD/DOC OECD publishing.

Glaeser, E.L., Kahn, M.E. & Rappaport, J., 2008. Why do the poor live in cities? The role of public transportation. *Journal of Urban Economics*, 63(1), pp.1–24.

Guo, J. & Bhat, C., 2002. Residential Location Choice Modeling : Accommodating Sociodemographic , School Quality and Accessibility Effects.

Hansen, W.G., 1959. Accessibility and Residential Growth. *Massachusetts Institute of Technology*.

Hedman, L., 2013. Moving Near Family? The Influence of Extended Family on Neighbourhood Choice in an Intra-urban Context. *Population, Space and Place*, 19(1), pp.32–45.

Hedman, L. et al., 2013. Cumulative exposure to disadvantage and the intergenerational transmission of neighbourhood effects. *Journal of Economic Geography*, p.lbt042. Available at: <http://joeg.oxfordjournals.org/cgi/doi/10.1093/jeg/lbt042>.

Hirsch, A.R., 2003. *Public Policy and Residential Segregation in Baltimore, 1900-1968*, Baltimore, MD: University of Baltimore, Special Collections. Available at: <http://archives.ubalt.edu/aclu/pdf/Plex3.pdf>.

Hoffman, S.D. & Duncan, G.J., 1988. Multinomial and conditional logit discrete-choice models in demography. *Demography*, 25(3), pp.415–427.

Horn, K.M., Ellen, I.G. & Schwartz, A.E., 2014. Do Housing Choice Voucher Holders Live Near Good Schools? *Journal of Housing Economics*, 23, pp.28–40. Available at: <http://www.sciencedirect.com/science/article/pii/S1051137713000594>
<http://www.sciencedirect.com/science/article/pii/S1051137713000594/pdfft?md5=8a8158d841cf3250811a8477df>
<http://www.sciencedirect.com/science/art>.

Housing Authority of Baltimore City, 2012. *Moving To Work Program Annual Report for Fiscal Year 2012*, Baltimore, MD: U.S. Department of Housing; Urban Development. Available at: <http://portal.hud.gov/hudportal/documents/huddoc?id=>

bmore-fy12annlmtwrpt.pdf.

Ihlanfeldt, K.R. & Scafidi, B., 2002. Black Self-Segregation as a Cause of Housing Segregation: Evidence from the Multi-City Study of Urban Inequality. *Journal of Urban Economics*, 51, pp.366–390. Available at: <http://www.sciencedirect.com/science/article/pii/S0094119001922491>.

Ingraham, C., 2016. The Dirty Little Secret that Data Journalists Aren't Telling You. Available at: <https://www.washingtonpost.com/news/wonk/wp/2016/04/11/the-dirty-little-secret-that-data-journalists-arent-telling-you/>.

Jacob, B.A., Ludwig, J. & Smith, J., 2009. Estimating Neighborhood Effects on Low-Income Youth. *National Vital Statistics Reports*, 52(9), p.13.

Kaczynski, A.T. & Henderson, K.a., 2007. Environmental Correlates of Physical Activity: A Review of Evidence about Parks and Recreation. *Leisure Sciences*, 29(4), pp.315–354.

Kain, J.F., 1968. Housing Segregation, Negro Employment, and Metropolitan Decentralization. *The Quarterly Journal of Economics*, 82(2), pp.175–197.

Kain, J.F., 1992. The spatial mismatch hypothesis: three decades later. *Housing policy debate*, 3(2), pp.371–460.

Keels, M. et al., 2005. Fifteen years later: can residential mobility programs provide a long-term escape from neighborhood segregation, crime, and poverty? *Demography*, 42(1), pp.51–73.

Kingsley, G.T. & Pettit, K.K.L.S., 2008. Have MTO families lost access to opportunity neighborhoods over time? *Three-City Study of Moving to Opportunity Brief*, 2(2), pp.1–12. Available at: http://www.urban.org/UploadedPDF/411637{_}opportunity{_}neighborhoods.pdf?RSS.

Kirwan Institute for the Study of Race and Ethnicity, 2013. *Opportunity Metrics Resource of Data and Research*, Columbus, OH: Kirwan Institute for the Study of Race; Ethnicity. Available at: http://kirwaninstitute.osu.edu/docs/FINAL{_}2013 Opp Metrics.pdf.

Kling, J.R., Liebman, J.B. & Katz, L.F., 2007. Experimental analysis of neighborhood

effects. *Econometrica*, 75(1), pp.83–119.

Kling, J.R., Ludwig, J. & Katz, L.F., 2005. Neighborhood Effects on Crime for Female and Male Youth: Evidence from a Randomized Housing Voucher Experiment. *The Quarterly Journal of Economics*, 120(1), pp.87–130. Available at:

<http://www.jstor.org/stable/25098732> <http://www.jstor.org.turing.library.northwestern.edu/stable/pdf>

Klosterman, R.E., 1994. An Introduction to the Literature on Large-Scale Urban Models. *Journal of the American Planning Association*, 60(1), pp.41–44. Available at:

<http://www.tandfonline.com/doi/abs/10.1080/01944369408975550> <http://www.tandfonline.com/doi/abs>

Lee, D.B., 1973. Requiem for Large-Scale Models. *Journal of the American Institute of Planners*, (December 2014), pp.37–41.

Leventhal, T. & Brooks-Gunn, J., 2000. The neighborhoods they live in: the effects of neighborhood residence on child and adolescent outcomes. *Psychological bulletin*, 126(2), p.309. Available at: <http://doi.apa.org/getdoi.cfm?doi=10.1037/0033-2909.126.2.309>.

Leventhal, T., Fauth, R.C. & Brooks-Gunn, J., 2005. Neighborhood poverty and public policy: a 5-year follow-up of children's educational outcomes in the New York City moving to opportunity demonstration. *Dev Psychol*, 41(6), pp.933–952. Available at: <http://www.ncbi.nlm.nih.gov/pubmed/16351338>.

Logan, J.R. & Alba, R.D., 1993. Locational returns to human capital: Minority access to suburban community resources. *Demography*, 30(2), pp.243–268.

Logan, J.R. et al., 1996. Making a place in the metropolis: locational attainment in cities and suburbs. *Demography*, 33(4), pp.443–453.

Ludwig, J. et al., 2012a. Neighborhood effects on the long-term well-being of low-income adults. *Science*, 337(6101), pp.1505–1510. Available at: <http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=3491569>

Ludwig, J. et al., 2012b. Neighborhood effects on the long-term well-being of low-income adults. *Science (New York, N.Y.)*, 337(6101), pp.1505–10. Available at: <http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=3491569&tool=pmcentrez&rendertype=abstract>

Ludwig, J. et al., 2013. *Long-term neighborhood effects on low-income families: Evidence*

from Moving to Opportunity, National Bureau of Economic Research.

Ludwig, J. et al., 2008. What can we learn about neighborhood effects from the Moving to Opportunity experiment. *American Journal of Sociology*, 114(1), pp.144–188.

Marsh, H., Hau, K.-T. & Wen, Z., 2004. In Search of Golden Rules: Comment on Hypothesis-Testing Approaches to Setting Cutoff Values for Fit Indexes and Dangers in Overgeneralizing Hu and Bentler's (1999) Findings. *Structural Equation Modeling: A Multidisciplinary Journal*, 11(3), pp.320–341. Available at: <http://search.ebscohost.com/login.aspx?direct=true&db=eoh&AN=6045777&lang=fr&site=ehost-live>.

Massey, D.S., 2015. The Social Science of Affordable Housing. *Housing Policy Debate*, 25(3), pp.634–638.

Massey, D.S. & Denton, N.A., 1993. *American apartheid: Segregation and the making of the underclass*, Harvard University Press.

Mayer, S.E. & Jencks, C., 1989. Growing up in poor neighborhoods: how much does it matter? *Science*, 243(4897), pp.1441–1445.

McFadden, D., 1978. *Modelling the choice of residential location*, Institute of Transportation Studies, University of California. Available at: <http://cowles.econ.yale.edu/P/cd/d04b/d0477.pdf>.

Mendenhall, R., DeLuca, S. & Duncan, G., 2006. Neighborhood resources, racial segregation, and economic mobility: Results from the Gautreaux program. *Social Science Research*, 35(4), pp.892–923. Available at: <http://linkinghub.elsevier.com/retrieve/pii/S0049089X05000293>.

Mujahid, M.S. et al., 2007. Assessing the measurement properties of neighborhood scales: from psychometrics to econometrics. *Am J Epidemiol*, 165(8), pp.858–867.

Nosoohi, I. & Zeinal-Hamadani, A., 2011. Urban Planning With the Aid of Factor Analysis Approach: The Case of Isfahan Municipality. *Theoretical and Empirical Researches*

in Urban Management, 6(1).

Orr, L. et al., 2003. Moving to opportunity: Interim impacts evaluation.

O'Brien, D., Sampson, R. & Winship, C., 2013. Ecometrics in the Age of Big Data: Measuring and Assessing “Broken Windows” Using Administrative Records.

Palma, A. de et al., 2005. A model of residential location choice with endogenous housing prices and traffic for the Paris region. *European Transport / Trasporti Europei*, 31, pp.67–82. Available at: http://www.openstarts.units.it/dspace/bitstream/10077/5884/1/dePalma{_}et{_}al{_}24

Park, R.E., Burgess, E.W. & McKenzie, R.D., 1925. *The City*, Chicago, IL: University of Chicago Press.

Pendall, R., 2000. Why voucher and certificate users live in distressed neighborhoods. *Housing Policy Debate*, 11(4), pp.881–910.

Pendall, R. et al., 2015. Driving to Opportunities: Voucher Users, Cars, and Movement to Sustainable Neighborhoods. *Cityscape*, 17(2), pp.57–87. Available at: <https://www.huduser.gov/portal/periodicals/cityscpe/vol17num2/article2.html>.

Pendall, R. et al., 2014. Driving to Opportunity : (March).

Pietila, A., 2010. *Not in my neighborhood: How bigotry shaped a great American city*, Ivan R. Dee.

Portugali, J. & Benenson, I., 1994. Instability within a Self-organizing City. *Geographical*, 26(4).

Powell, J., 2005. *Remedial Phase Expert Report In Thompson v. HUD*, Kirwan Institute.

Powell, john a., 2003. Opportunity-Based Housing. *Journal of Affordable Housing & Community Development Law*, 12(2), pp.188–228.

PRRAC, 2005. *An Analysis of the Thompson v. HUD Decision*, Washington, DC: Poverty & Race Research Action Council. Available at: <http://www.prrac.org/pdf/ThompsonAnalysis.pdf>.

Quillian, L., 2015. A Comparison of Traditional and Discrete-Choice Approaches to

the Analysis of Residential Mobility and Locational Attainment. *The ANNALS of the American Academy of Political and Social Science*, 660(1), pp.240–260. Available at: <http://ann.sagepub.com/cgi/doi/10.1177/0002716215577770>.

Quillian, L., 2014. Race, class, and location in neighborhood migration: A multidimensional analysis of locational attainment. *Unpublished manuscript, Northwestern University, Department of Sociology.*, pp.559–579.

R Development Core Team, R., 2011. *R: A Language and Environment for Statistical Computing*, Available at: <http://www.r-project.org>.

Raudenbush, S. & Sampson, R., 1999. Ecometrics: toward a science of assessing ecological settings, with application to the systematic social observation of neighborhoods. *Sociological methodology*, 29(1), pp.1–41. Available at: <http://onlinelibrary.wiley.com/doi/10.1111/0081-1750.00059/abstract>{\%}5Cn<http://doi.wiley.com/10.1111/0081-1750.00059>.

Raudenbush, S.W. & Bryk, A.S., 2002. *Hierarchical linear models: Applications and data analysis methods*, Sage.

Reece, J. & Gambhir, S., 2008. *The Geography of Opportunity Review of Opportunity Mapping Research Initiatives*, Kirwan Intsitute for the Study of Race; Ethnicity.

Rosen, E., 2014. Rigging the Rules of the Game: How Landlords Geographically Sort Low-Income Renters. *City and Community*, 13(4), pp.310–340.

Rosenbaum, J.E., 1995. Changing the geography of opportunity by expanding residential choice: Lessons from the Gautreaux program. *Housing Policy Debate*, 6(1), pp.231–269.

Rosenbaum, J.E. & Deluca, S., 2008. What Kinds of Neighborhoods Change Lives? The Chicago Gautreaux Housing Program and Recent Mobility Programs. *Indiana Law Review*, 41(2004), pp.653–662.

Rosenbaum, J.E. & Zuberi, A., 2010. Comparing residential mobility programs: design elements, neighborhood placements, and outcomes in MTO and Gautreaux. *Housing policy debate*, 20(1), pp.27–41. Available at: <http://www.tandfonline.com/doi/abs/10.1080/10439862.2010.504444>.

1080/10511481003599845.

Rosenblatt, P. & Deluca, S., 2012a. We Don't Live Outside, We Live in Here: Neighborhood and Residential Mobility Decisions Among Low-Income Families. *City & Community*, 11(3), pp.254–284. Available at: <http://doi.wiley.com/10.1111/j.1540-6040.2012.01413.x>.

Rosenblatt, P. & Deluca, S., 2012b. “We Don't Live Outside, We Live in Here”: Neighborhood and Residential Mobility Decisions Among Low-Income Families???. *City and Community*, 11(3), pp.254–284. Available at: <http://doi.wiley.com/10.1111/j.1540-6040.2012.01413.x>.

Rosseel, Y., 2012. lavaan: An R Package for Structural Equation Modeling. *Journal of Statistical Software*, 48(2), pp.1–36.

Sampson, R., 2012. *Great American city: Chicago and the enduring neighborhood effect*, University of Chicago Press.

Sampson, R., 2008. Moving to Inequality: Neighborhood Effects and Experiments Meet Social Structure1. *American Journal of Sociology*, 114(1), pp.189–231.

Sampson, R. & Sharkey, P., 2008. Neighborhood selection and the social reproduction of concentrated racial inequality. *Demography*, 45(1), pp.1–29.

Sampson, R., Morenoff, J. & Earls, F., 1999. Beyond social capital: Spatial dynamics of collective efficacy for children. *American sociological review*, pp.633–660.

Sampson, R., Morenoff, J. & Gannon-Rowley, T., 2002a. Assessing “Neighborhood Effects”: Social Processes and New Directions in Research. *Annual Review of Sociology*, 28(1), pp.443–478.

Sampson, R., Morenoff, J. & Gannon-Rowley, T., 2002b. Assessing “Neighborhood Effects”: Social Processes and New Directions in Research. *Annual Review of Sociology*, 28(1), pp.443–478. Available at: <http://www.annualreviews.org/doi/abs/10.1146/annurev.soc.28.110601.141114>.

Sampson, R., Morenoff, J. & Raudenbush, S., 2005. Social anatomy of racial and

ethnic disparities in violence. *Am J Public Health*, 95(2), pp.224–232. Available at: <http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=1449156&tool=pmcentrez&rendertype=abstract>

Sampson, R., Sharkey, P. & Raudenbush, S., 2008. Durable effects of concentrated disadvantage on verbal ability among African-American children. *Proceedings of the National Academy of Sciences of the United States of America*, 105(3), pp.845–852.

Sanbonmatsu, L. et al., 2011. *Moving to Opportunity for Fair Housing Demonstration Moving to Opportunity for Fair Housing Demonstration Program Final Impacts Evaluation*, Washington DC.

Sanbonmatsu, L. et al., 2004. Moving to Opportunity for Fair Housing Demonstration Program: Final Impacts Evaluation., 32(11).

Schelling, T.C., 1971. Dynamic Models of Segregation. *Journal of Mathematical Sociology*, 1, pp.143–186.

Sharkey, P., 2013. *Stuck in place: Urban neighborhoods and the end of progress toward racial equality*, University of Chicago Press.

Sharkey, P., 2011. The Legacy of Disadvantage : Multigenerational Neighborhood Effects on Cognitive Ability. *American Journal of Sociology*.

Sharkey, P. & Faber, J., 2014. Where, When, Why, and For Whom Do Residential Contexts Matter? Moving Away from the Dichotomous Understanding of Neighborhood Effects. *Annual Review of Sociology*, 40(1), pp.559–579. Available at: <http://www.annualreviews.org/doi/abs/10.1146/annurev-soc-071913-043350>.

Sharkey, P. & Faber, J.W., 2014. Where, When, Why, and for Whom Do Residential Contexts Matter? Moving Away from the Dichotomous Understanding of Neighborhood Effects. *Annual Review of Sociology*, 40(1), pp.559–579. Available at: <http://www.annualreviews.org/doi/abs/10.1146/annurev-soc-071913-043350>.

Spielman, S.E. & Singleton, A., 2015. Studying Neighborhoods Using Uncertain Data from the American Community Survey: A Contextual Approach. *Annals of the Associa-*

- tion of American Geographers*, 5608(August), pp.1–23.
- Talen, E., 1998. Visualizing Fairness: Equity Maps for Planners. *Journal of the American Planning Association*, 64(1), pp.22–38. Available at: <http://www.tandfonline.com/doi/abs/10.1080/01944369808975954>.
- Talen, E. & Anselin, L., 1998. Assessing spatial equity: An evaluation of measures of accessibility to public playgrounds. *Environment and Planning A*, 30(4), pp.595–613.
- Toulmin, L.M., 1988. Equity as a decision rule in determining the distribution of urban public services. *Urban Affairs Review*, 23(3), pp.389–413.
- Truelove, M., 1993. Measurement of spatial equity. *Environment and Planning C: Government and Policy*, 11(1), pp.19–34.
- Tufte, E.R., 1983. *The visual display of quantitative information*, Graphics press Cheshire, CT.
- Tuljapurkar, S., Bruch, E. & Mare, R.D., 2008. Neighborhoods and Individual Preferences: A Markovian Model., pp.1–24.
- Waddell, P. et al., 2010. Microsimulating parcel-level land use and activity-based travel: Development of a prototype application in San Francisco. *Journal of Transport and Land Use*, 3(2), pp.65–84.
- Walker, J.L., 2001. Extended Discrete Choice Models : Integrated Framework , Flexible Error Structures , and Latent Variables. *Environmental Engineering*.
- Walter, R.J. & Wang, R., 2016. Searching for Affordability and Opportunity: A Framework for the Housing Choice Voucher Program. *Housing Policy Debate*, (May), pp.1–22. Available at: <http://www.tandfonline.com/doi/abs/10.1080/10511482.2016.1163276>.
- Wegener, M., 1994. Operational urban models: state of the art. *Journal - American Planning Association*, 60(1), pp.17–29.
- Wilson, W.J., 1987. *The truly disadvantaged: The inner city, the underclass, and public*

policy, University of Chicago Press.

Wodtke, G.T., Harding, D.J. & Elwert, F., 2011. Neighborhood Effects in Temporal Perspective. *Am Sociol Rev*, 76(5), pp.713–736. Available at: <http://www.pubmedcentral.nih.gov/articlerender.fcgi?>

Xie, Z. & Yan, J., 2008. Kernel Density Estimation of traffic accidents in a network space. *Computers, Environment and Urban Systems*, 32(5), pp.396–406.

Yang, M. & Chou, S.-Y., 2015. *Impacts of Being Downwind of a Coal-Fired Power Plant on Infant Health at Birth: Evidence from the Precedent-Setting Portland Rule*, National Bureau of Economic Research.