Allocation of the Limited Subsidies for Affordable Housing

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Abstract

Low-income housing assistance is rationed in the United States. While jurisdictions employ a wide range of waiting list policies, there is little empirical evidence on how these systems affect who receives assistance or which housing they gain access to. Using publicly available data on eligible and tenant households from one public housing authority (in Cambridge, MA), we develop and estimate a model of public housing waiting lists that accounts for the available supply of public housing units and the decisions of applicants while on the waitlist. Using the estimated model, we run policy simulations to predict how alternative priority systems will affect the characteristics and neighborhood exposure of tenants. We find that prioritizing certain groups can, in some cases, dramatically increase the rates at which those groups are housed. However, these effects are limited both by the preferences of applicants and by the availability of appropriately sized apartments. The results illustrate how capacity constraints resulting from past policy decisions can limit the effectiveness of current policy efforts intended to target resources to particular groups.

1 Introduction

The demand for affordable housing in the U.S. far outstrips the supply. In response, jurisdictions and housing agencies across the country have adopted myriad rationing systems to allocate the scarce resource of affordable housing assistance. The nation's dwindling supply of publicly owned affordable housing, for example, is often allocated by waitlist, and a 2012 survey (the most recent) showed that 2.8 million families were on public housing waitlists, many of which have been closed for years.[1] The New York City Housing Authority, the nation's largest, allocates its 175,636 units through a waitlist, and in 2018, there were 209,180 households on the list.[2]

In some cities, housing units made affordable through the Low Income Housing Tax Credits or other federal, state, or local subsidies are allocated among competing claimants by lottery. In the latest lotteries of such privately owned affordable units in New York City, the odds of winning the lottery were one in 592.[3] Recent lotteries attracted 391 households for each affordable unit in Alameda, California; 84 for every affordable home in Boston; and 53 for each new affordable unit in Los Angeles.[4]

Rather than accessing subsidized units, many assisted households instead receive rental assistance subsidies through the federal "Section 8" Housing Choice Voucher program, or similar state and locally-financed programs.[5] Vouchers are often allocated on a first come, first served basis, using a waitlist that is periodically opened to new entrants.[6] In New York City, 148,084 families were on the waitlist for Section 8 housing vouchers in May, 2018.[7] Experts estimate that across the country, only one out of every

[1] Andrew Flowers, "Why So Many Poor Americans Don't Get Help Paying for Housing," FiveThirtyEight, Sept. 16, 2016, `https://fivethirtyeight.com/features/why-so-many-poor-americans-dont-get-help-paying-for-housing/`

[2] NYCHA 2018 Fact Sheet, `https://webcache.googleusercontent.com/search?q=cache:d9n9v8QXLrsJ:https://www1.nyc.gov/assets/nycha/downloads/pdf/NYCHA-Fact-Sheet_2018_Final.pdf+&cd=1&hl=en&ct=clnk&gl=us&client=firefox-b-1-d`

[3] Devin Gannon, Odds of Winning an Affordable Housing Lottery in NYC are Better than You Think, 6 SqFt, Jan. 11, 2019, `https://www.6sqft.com/odds-of-winning-an-affordable-housing-lottery-in-nyc-are-better-than-you-think/`

[4] Emily Badger, "These 95 Apartments Promised Affordable Rent in San Francisco. Then 6,580 People Applied," New York Times, May 12, 2018.

[5] For a catalog of state and local housing programs, see `http://nlihc.org/rental-programs/search/rental-assistance`

[6] M. Kathleen Moore, Lists and Lotteries: Rationing in the Housing Choice Voucher Program, 26 Housing Policy Debate, 474 (2016). Moore points out that some jurisdictions allocate places on the waitlist by lottery, rather than first come, first served. Id., at 474 (citing Chicago as an example). For insight into how long people can wait for assistance distributed through waitlists for vouchers, see, e.g., "Section 8 Waiting List Opens for the First Time in 13 Years," Los Angeles CBS Channel 2, Oct. 16, 2017, `https://losangeles.cbslocal.com/2017/10/16/section-8-waiting-list-lottery-opens-in-13-years/` (noting that 600,000 people were expected to apply, and a lottery would then be used to place 20,000 households on the waitlist).

[7] NYCHA 2018 Fact Sheet, supra n. [].

four or five households eligible for federal rental assistance through the federal Section 8 voucher program actually receive any federal rental subsidy,[8] and in 2017, those who received a voucher had waited an average of 27 months before obtaining one.[9]

Despite this enormous imbalance between the supply of and need for affordable housing resources, little attention has been paid to how the limited supply is allocated among the many households who are eligible for assistance. As noted above, some jurisdictions use waitlists; others use lotteries; some modify the waitlist or lottery processes by imposing preferences or additional screening criteria; and some leave the selection process to the developer of the housing, with varying degrees of oversight by the governmental agency financing the housing. There is considerable variation in the screening criteria and preferences used across the country. Further, both the methods used to allocate the housing and the preferences or screening criteria guiding the allocation interact with varying rules about the choices available to a household offered assistance under the allocation method.

Recently, the media, litigants, and housing policy experts have begun to question whether housing assistance is being allocated most effectively. Some question whether systems in which the allocation is described as "winning the lottery" or "being first in the line" obscures the fact that equally eligible and deserving households are denied assistance because funding choices are making the resource so scarce.[10] Others argue that allocation systems are failing to target the housing assistance to the most needy families. As Emily Badger wrote in the New York Times, for example:

> Subsidized housing is often rationed this way, by lottery. Many apply, few win, most are disappointed. The process is meant to be more fair than first-come, first-served. . . .
>
> Lotteries that allocate scarce resources are not set up to distinguish the neediest from the merely needy. Rather, they reward random chance, which is a distinctly different notion of what's "fair."[11]

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[8]Jeff Andrews, "Trump's budget guts affordable housing during and affordable housing shortage," Curbed, Feb. 13, 2018, `https://www.curbed.com/2018/2/13/17009062/trump-budget-affordable-housing-crisis` (quoting Sue Popkin from the Urban Institute). Other estimates include Park, Fertig, & Metraux, Factors contributing to the receipt of housing assistance by low-income families with children in twenty American cities. 88 Social Service Review 166 (2014) (analysis of Fragile Families database shows that 3 in 10 low-income families with children eligible for housing assistance ultimately received it within a 9-year period of observation) [confirm and correct cite]; and the Joint Center for Housing Studies, STATE OF THE NATION'S HOUSING 2018 p. 5 and fig. 7 (only 25% of very low-income renter households that are likely eligible for housing assistance receive assistance). A recent survey of public housing authorities found that only 50% of HCV wait lists were open, with 6% of open wait lists planning to close soon. Dunton, Henry, Kean, & Khadduri. (2014) [check and correct cite].

[9]HUD, PICTURE OF SUBSIDIZED HOUSEHOLDS, `https://www.huduser.gov/portal/datasets/assthsg.html`

[10]Katherine Young, Queues and Rights, [cite to SSRN version and check whether it is published yet].

[11]Badger, supra n. []. See also Moore, supra n. [], at 478.

Still others argue that allocation processes are discriminatory.[12] Some research shows, for example, that seniors are best served by the housing programs, with four out of every nine eligible receiving housing benefits, while working families are worst served, with only one in every six eligible households receiving benefit.[13] Yet another criticism is that the allocation systems are inefficient and lead to suboptimal matches between the "winning" household's desires and the characteristics and location of the housing.[14]

This article examines these concerns by analyzing how variations in allocating systems affect who gains access to subsidized housing. Section 2 motivates the discussion by briefly examining the gap between the need for affordable housing and the available supply, which generates the need for rationing. It further motivates the work by reviewing what we know about who receives housing assistance and the extent to which they differ from other needy families who do not receive the assistance. Section 3 explains the various factors that determine which members of an eligible pool actually receive housing assistance and describes what we know about how housing resources are allocated across the United States. Section 4 lays out our approach to modeling the allocation process for the housing authority of one jurisdiction, the Cambridge Housing Authority in Cambridge, MA. Section 5 provides empirical results of the model and simulates how four alternative sets of priorities would alter who actually receives housing assistance, the composition of specific public housing developments, and the sorting of tenants across neighborhoods. Section 6 concludes with recommendations about the research needed to refine allocation processes.

2 Motivation for Research

2.1 Gap Between Need for and Supply of Affordable Housing

In 2017, approximately 39.7 million people, or 12.3% of the population, had incomes that fell below the federal poverty "line" – the official definition of poverty in the United

[12] See, e.g., Winfield [correct cite to litigation in SDNY]; National Low Income Housing Coalition, "HUD Finds Dubuque Voucher Policies Violate Civil Rights Act"(June 28, 2013), `http://nlihc.org/article/hud-finds-dubuque-voucher-policies-violate-civil-rights-act`

[13] Public and Affordable Housing Research Corporation, 2018 Housing Impact Report [give url and put in blue book form]

[14] For an empirical analysis, see Daniel Waldinger, *Targeting In-Kind Transfers through Market Design: A Revealed Preference Analysis of Public Housing Allocation.* Working Paper, April 2019. For a theoretical discussion, see Nick Arnosti and Peng Shi, *How (Not) to Allocate Affordable Housing* (February 13, 2017). Columbia Business School Research Paper No. 17-52. Available at SSRN: `https://ssrn.com/abstract=2963178` or; Conall Boyle, *Fairness in Allocation of Social Rented Housing*, Paper for Glasgow Conference: Performance Culture and the Management of Social Housing (1994), `http://conallboyle.com/lottery/Glasgow_final.pdf` (lotteries are inefficient because refusals of offers "are poor substitutes for the sort of revealed preference which emerges from normal market operations").

States.[15] (The poverty line was $19,749 for a household with one adult and two related children in 2017).[16] Another 56 million people were defined as "near poor" and lived on incomes that were more than 100% but less than 200% of the poverty line. [17] Of the households living below the poverty line that were renters, 81% were rent-burdened, or paying more than 30% of their income for housing expenses.[18] Fifty-two percent were severely rent burdened, or paying more than half their income on housing costs.[19] Yet in 2013, only 15 percent of renters with incomes below the poverty line lived in public housing; and only 17 percent received government rental assistance, such as a voucher to reduce the amount of the rent the tenant must pay. The remaining 67 percent received nothing.[20] As a result, in 2015, 8.3 million households had "worst case" housing needs, meaning they were renters with very low incomes – no more than 50 percent of the Area Median Income (AMI) – who do not receive government housing assistance and who pay more than one-half of their income for rent, live in severely inadequate conditions, or both."[21]

Further, although the lowest income households face the greatest housing burdens, the housing affordability crisis extends up the economic ladder. In 2015, 47 percent of *all* renter households were rent burdened.[22] While those numbers have dropped slightly in

[15]Kayla R. Fontenot, Jessica L. Semega, and Melissa A. Kollar, Income and Poverty in the United States: 2017 at 11, Figure 4 & Table 3 (U.S. Census Bureau, Current Population Reports, P60-263, 2018).

[16]Income and Poverty in the United States, supra n. 15, at 47 (Appendix B).

[17]Income and Poverty in the United States, supra n. 15, at 18 & Table 5.

[18]Matthew Desmond, *Unaffordable America: Poverty, Housing, and Eviction.* University of Wisconsin-Madison Institute for Research on Poverty. Pp 2. No. 22-2015. March 2015. Courtney Lauren Anderson, *You Cannot Afford to Live Here,* 44 FORDHAM URB. L.J. 247, [pin cites] (2017) provides a history, and critique of the 30% threshold that defines rent-burden. See also David J. Hulchanski, *The Concept of Housing Affordability: Six Contemporary Uses of the Housing Expenditure-to-Income Ratio,* 10 HOUSING STUD. 471 (1995), `http://www.urbancentre.utoronto.ca/pdfresearchassociates/Hulchanski_Concept-H-Affd_H.pdf` [`https://perma.cc/CM3D-HDVC`]; Michael Stone et al., *The Residual Income Approach to Housing Affordability: The Theory and the Practice* 22-27 (Austl. Hous. & Urb. Res. Inst. ed., 2011), [bluebook ? list all authors?] `https://www.ahuri.edu.au/__data/assets/pdf_file/0011/2810/AHURI_Positioning_Paper_No139_The-residualincome-approach-to-housing-affordability-the-theory-and-the-practice.pdf` [`https://perma.cc/B9NP-97Y9`]; Melanie D. Jewkes and Lucy M. Delgadillo, *Weaknesses of Housing Affordability Indices Used by Practitioners,* 21 J. FIN. COUNSELING & PLAN. 43, 46 (2010), `https://afcpe.org/assets/pdf/volume_21_issue_1/jewkes_delgadillo.pdf` [`https://perma.cc/2P5U-XNVT`]; William O'Dell et al., Weaknesses in Current Measures of Housing Needs, 31 HOUSING & SOC'Y 29, 34 (2004). Bluebook — list all authors?

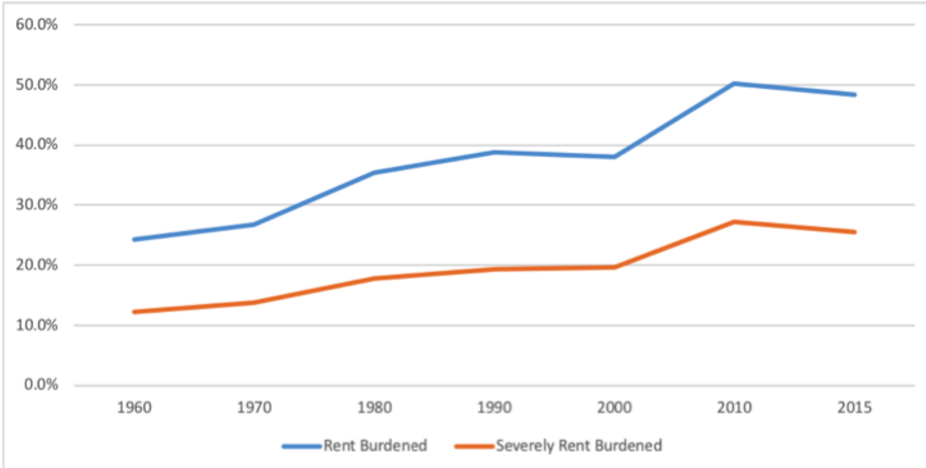
[19]Desmond, supra n. 18, at 1.

[20]Desmond, supra n. 18, at 2.

[21]HUD, Worst Case Housing Needs: 2017 Report to Congress, ix (2017), `https://www.huduser.gov/portal/sites/default/files/pdf/Worst-Case-Housing-Needs.pdf`

[22]Sean Veal and Jonathan Spader, Nearly a Third of American Households Were Cost-Burdened Last Year (Harvard Joint Center for Housing Studies, Dec. 7, 2018), `https://www.jchs.harvard.edu/blog/more-than-a-third-of-american-households-were-cost-burdened-last-year/`; see also Susan K. Urahn, Travis Plunkett, American Families Face a Growing Rent Burden, The PEW Charitable Trusts. 2017. `http://www.pewtrusts.org/-/media/assets/2018/04/rent-burden_report_v2.pdf`

Figure 1: Share of All U.S. Renter Households That Were Rent Burdened and Severely Rent Burdened, 1960-2015



Notes: This figure shows the percent of all U.S. renter households that spent 30% or more (rent burdened) and 50% or more (severely rent burdened) of their household income on rent. Rent for 1960 is coded to the midpoint of the range (e.g. rent is coded as $54.5 if the range is $50-$59). American Community Survey, IPUMS-USA, University of Minnesota, NYU Furman Center calculations.

the last few years, rent burdens across the nation are far higher than in past decades.[23]

Figure 1 shows that the problem is especially acute in the large metropolitan areas: In New York City, 53.4 percent of all renters were paying more than 30 percent, and 28.4 percent were paying more than 50 percent, of their income for rent in 2018.[24] Across the nation's 53 largest metropolitan areas, the median share of renters who were rent burdened in 2015 was 47.7 percent.[25]

Another way of assessing the unmet need for affordable housing is the availability of homes renting for prices that households making various incomes can afford. For households with low and moderate incomes, the number of homes that are affordable (costing 30% of the household's income or less) and available (not rented by higher income households)[26] falls far short of needs. The National Low Income Housing Coalition estimates that there are only 35 affordable and available homes for every 100 renter households with extremely low incomes ("ELI"), those making 30% or less of the "area

[23]Those declines have to be read cautiously because of the changes resulting from the fact that more higher-income households are continuing to rent rather than buy than in the past. See SEWIN CHAN & GITA KUHN JUSH, 2017 NATIONAL RENTAL HOUSING LANDSCAPE: RENTING IN THE NATION'S LARGEST METROS, NYU FURMAN CENTER 17, 28 (2017).

[24]Furman Center, State of New York City's Housing and Neighborhoods: 2018.

[25]CHAN & JUSH, supra n. [], at [pin cite].

[26]Indeed, many of the households that are now renters, but would likely have been homeowners in the past, are higher income households that can outbid lower income households for lower cost housing. Id.

median income" (AMI) for their metropolitan area.[27] Among the largest metropolitan areas, the number of affordable and available homes ranges from 12 for every 100 ELI renter households in Las Vegas, NV to 46 for every 100 in Boston, MA.[28] The gap is still quite large for renters making somewhat more income: for every 100 families making 50% of the area median income or less (about 41% of all renter households), there are only 55 homes available and affordable across the nation.[29]

In sum, there are a huge number of people who need some form of housing assistance – either rental subsidies or public housing or subsidized affordable housing – in order to bring their housing costs down to an amount that leaves sufficient funds for food, health care, and other necessities. That number far outstrips the housing assistance available, and as a result, only a fraction of those eligible for housing assistance actually receive the assistance.[30] Due to this scarcity, how these scarce resources are allocated is immensely important.

2.2 Differences between Those Who Do and Do Not Receive Housing Assistance

We know very little about how those who receive housing assistance compare to those who are eligible but do not receive the assistance, and what drives any differences. Actual allocations are made by state and local entities, and there is no centralized data on who has applied for assistance. We do have data on those receiving federal housing assistance, however. HUD's Picture of Subsidized Housing (PIC) provides data about the characteristics of those who live in public housing, receive rental assistance through Section 8 Housing Choice Vouchers, or live in privately owned housing subsidized through HUD's project-based Moderate Rehabilitation, Section 236, and other multifamily subsidies.[31] Table 1 compares the characteristics of those households to other likely eligible households – those whose household incomes fall below 200% of the federal poverty line.[32]

[27] NAT'L LOW INCOME HOUS. COAL., THE GAP: A SHORTAGE OF AFFORDABLE HOMES 2, 4?5 (2017), http://nlihc.org/sites/default/files/Gap-Report_2017.pdf.
[28] Id. at 8-9.
[29] Id. at 4-5.
[30] Supra, n. 8.
[31] HUD, Picture of Subsidized Housing, https://www.huduser.gov/portal/datasets/assthsg.html
[32] Add fn to discuss how 200% of poverty compares to 80% of AMI.

Table 1: Characteristics of Households Receiving HUD Assistance and Those Likely Eligible

	Households Receiving HUD Housing Assistance	Households with Income Below 200% of Federal Poverty Line
Number of Households	4,628,247	49,486,788
Number of Household Members	2.1	2.2
Annual Household Income ($)	14,347	16,377
Monthly Housing Expenditure ($)	346	859
Any Child under 18 (%)	36	31
One Adult with Children (%)	32	10
Female Household Head (%)	75	56
Disability among Head, Co-Head, or Spouse (%)		
Age 61 or Younger	35	15
Age 62 or Older	44	14
Household Head Age 62 or Older (%)	36	26
Household Head White, non-Hispanic (%)	35	58
Household Head African American, Non-Hispanic	42	18
Household Head Hispanic (%)	17	18
0-1 Bedrooms (%)	44	62
2 Bedrooms (%)	30	18
3+ Bedrooms (%)	26	20

As Table 1 shows, there are far more households likely to be eligible for HUD assistance (nearly 50 million) than there are beneficiaries (4.6 million). Households receiving HUD assistance have lower incomes and spend much less on their housing than those eligible for, but likely not receiving assistance. There are also large demographic differences between the two groups. HUD-assisted households are more likely to have children (36% vs 31%), and much more likely to be headed by a single, female adult – strikingly, 31% of HUD-assisted households are headed by a single adult with children, compared to 10% among the likely eligible. HUD-assisted households are more likely to have an elderly or disabled household head or spouse, are less likely to be white (35% vs 58%), and are much more likely to be African American (42% vs 18%). What the data do not reveal is the extent to which these difference are driven by who actually applies for assistance, rather than how agencies allocate among applicants.

The limited existing evidence about the needs and characteristics of households who are eligible for assistance but have not yet received or did not apply for assistance comes from studies of those households on waiting lists for housing assistance. Most recently, Dan Waldinger studied households who applied for public housing in Cambridge, Massachusetts and were wait-listed for the housing. He found that those on the waitlist had much lower incomes, were less likely to be white, and were more likely to already live in Cambridge, than households who were eligible but did not apply.[33] Strikingly, the average income of those who likely were eligible for public housing but did not apply was more than twice the income of those who were on the wait list, suggesting that much of the observed differences in Table 1 may be driven by differences in who applies (and perhaps not necessarily by targeting among applicants).

A 2009 survey of nearly 1,000 non-elderly, non-disabled applicants for rental assistance, selected from a nationwide sample of 25 public housing authorities, however, found that those on the wait list for vouchers or public housing were less likely to be severely rent-burdened than very low income renters in the same metropolitan area surveyed by the American Housing Survey.[34] That likely is because many of those on the wait list, while quite poor (75 percent had extremely low incomes –less than 30 percent of the Area Median Income – and 92 percent had very low incomes –less than 50 percent of AMI),[35] were living with family or friends and paying little or no rent.[36] This population may face particularly high instability in their housing.

In summary, we don't know whether the various systems for allocating housing assistance are actually targeting the assistance to those with the greatest needs,[37] or to those who should be prioritized on some other basis, or are distributing the assistance randomly in order to give every eligible household an equal chance of receiving assistance.

[33] Waldinger, at 14 (April 2019 version).

[34] Josh Leopold, "The Housing Needs of Rental Assistance Applicants," 14 *Cityscape* 275, 286 (2012).

[35] Leopold, supra n. 37, at 283.

[36] Leopold, supra n. 37, at 283.

[37] There is no evidence to support an assumption that those who apply for housing assistance are those with the worst quality housing, or highest rent burdens. As Leopold notes: "Applicants may seek rental assistance because they are living in housing that is overcrowded, of poor quality (although not severely substandard), or in a poor-quality neighborhood (Koebel and Renneckar, 2003). They may also apply for assistance so they can afford to live closer to where they work or go to school (Belsky, Goodman, and Drew, 2005). Finally, applicants may use rental assistance as a means to establish their own household rather than live with family or friends (Shroder, 2002)." Leopold, supra n. 37, at 278.

3 Determinants of Who Receives Housing Assistance

3.1 Selection Process

Who among the eligible pool actually receives housing assistance depends upon five key dimensions:

1. The propensity of the eligible households to apply for and successfully complete the application for housing assistance;
2. How the housing available matches the needs (and preferences) of the eligible households;
3. How the order in which applicants for the resource will receive allocations is determined;
4. The criteria used to screen or prioritize either all applicants for the resource, or just those who are high enough in the queue to receive the resource if eligible;
5. Whether those who are offered an allocation are given any choice regarding what type or location of housing they will receive.

Not all eligible households will apply for assistance. Some will prefer to remain in their current housing and neighborhood, even if it leaves them rent-burdened. Others will not know about the availability of the housing assistance. Some will lack the executive functioning abilities, language skills, or other capacities needed to apply, or to successfully complete the application process.[38] The various features of the allocating system that affect the likelihood of receiving housing assistance may in turn influence whether a household chooses to apply in the first place.

Even if a household does apply, the likelihood that it will receive assistance will depend upon how its needs match the housing that is available. If a jurisdiction's housing assistance is targeted towards the construction or preservation of housing for senior citizens for example, households who are younger will be less likely to receive assistance even if they make up a larger share of those eligible. Conversely, if a jurisdiction's housing largely consists of three bedroom units, then the share of eligible single person households that receive housing assistance may fall below the share of the eligible pool that they constitute.

[38] As Kathleen Moore points out, supra n. [] at 480: The more complex a mechanism is, the less likely individuals are to complete it. The more visible the mechanism is, the more likely eligible individuals will be aware of it. The more competently mechanisms are administered, the more likely they are to properly identify eligible individuals." See also L. Dunton, M. Henry, E. Kean, and Jill Khadduri, Study of PHAs' Efforts to Serve People Experiencing Homelessness (Abt Associates: 2014) (documenting difficulties administrative processes pose for homeless individuals applying for housing assistance) [need pin cites]. Similarly, institutional barriers such as discrimination by landlords and landlords' refusal to accept vouchers, also play a role in the allocation of housing. Moore, supra n. [] at 481.

The order in which a resource is to be allocated among eligible applicants can be determined randomly (by lottery, for example),[39] by queues that are not random (such as waiting lists that are first-come, first-served),[40] or through the application of some criterion (such as a determination of need). Housing also could be allocated through a combination of chance and substantive criteria.[41] Weighted lotteries, for example, in which claimants meeting specified criteria get more chances of winning, are an example.[42] Similarly, queues can have multiple lines, with some shorter than others for people meeting particular criteria, or can allow people meeting certain criteria to "jump" to the front of the line.[43] Queues can also open the wait list only to people meeting certain

[39]Where the ordering of the queue is allocated by lottery, all applicants for the housing are drawn from the pool under a system of "equiprobability" in which every applicant has an objectively equal chance of being selected. Lewis A. Kornhauser & Lawrence G. Sager, Just Lotteries, 27 SOC. SCI. INFO. 483, 485?88 (1988). See also Perry & Zarsky, supra n., at 1039; Gary E. Bolton et al., Fair Procedures: Evidence from Games Involving Lotteries, 115 ECON. J. 1054, 1055 (2005) [check and give a parenthetical]; Hank Greely, Comment, The Equality of Allocation by Lot, 12 HARV. C.R.-C.L. L. REV. 113, 126-30 (1977) [check each; add parenthetical for those worth keeping]. Lotteries "are distinguished most prominently by the fact that they eschew rather than embrace identifiable elements of personal desert or social value; lotteries are driven by chance, not reason." Kornhauser and Sager, supra n. [], at 483. Nevertheless, it is rarely (if ever) the case that there are purely random allocations of housing, because generally either the pool is restricted through a preliminary screening for income and other eligibility criteria, or those screening criteria are used after the drawing and may result in an applicant "winning" the lottery only to be deemed ineligible.

[40]Some housing assistance queues are based on first in, first out (FIFO) ordering. E.g., 42 U.S.C.A. 12755(d) (2018) (for housing funded through HUD's HOME program, mandating the "selection of tenants from a written waiting list in the chronological order of their application, insofar as is practicable?"). A 2004 study reported that 22% of public housing authorities use a first come, first served ordering for their wait lists. (NLIHC, 2004, p. 6) [correct cite] While even a FIFO system may be essentially random if who applies first is happenstance, many critics argue that who gets to the front of FIFO housing waitlists is driven by factors such as differences in applicants' need or desire for the assistance, flexibility to show up early when the waitlist opens, or organizational and executive functioning, and therefore FIFO tends to favor more advantaged households. FIFO "favors people who are well-off, who become informed, and travel more quickly, and can queue for interventions without competing for employment or child-care concerns" (Persad et al., 2009, p. 424) [correct cite]. Some housing assistance queues are ordered randomly, with applicants assigned a place in the line according to a randomized lottery or other process. See, e.g., LA lottery/wait list [cite to their website].

[41]The administrative processes involved in applying for, qualifying for, using, and recertifying eligibility for, housing assistance also play a role in allocating the assistance. As Kathleen Moore points out, supra n. [] at 480: The more complex a mechanism is, the less likely individuals are to complete it. The more visible the mechanism is, the more likely eligible individuals will be aware of it. The more competently mechanisms are administered, the more likely they are to properly identify eligible individuals." See also L. Dunton, M. Henry, E. Kean, and Jill Khadduri, Study of PHAs' Efforts to Serve People Experiencing Homelessness (Abt Associates: 2014) (documenting difficulties administrative processes pose for homeless individuals applying for housing assistance) [need pin cites]. Similarly, institutional barriers such as discrimination by landlords and landlords' refusal to accept vouchers, also play a role in the allocation of housing. Moore, supra n. [] at 481.

[42]Ronen Perry and Tal Z. Zarsky, "May the Odds Be Ever in Your Favor"; Lotteries in Law, 66 Ala. L. Rev. 1035, 1038 (2015) (The Georgia Land Lottery of 1832, which gave each citizen "one chance," while members of certain groups (orphans, Revolutionary War veterans, etc.) had "two chances" according to Jon Elster, Solomonic Judgements: Studies in the Limitations Of Rationality 47 (1989)).

[43]Young, at 37.

criteria.[44]

In addition, even those arrayed on the list by the allocation process may be moved to a different place on the list (or a different list altogether) because of priorities or preferences that the allocating authority applies.[45]

If the ordering of eligible applicants is based upon criteria such as need,[46] the criteria applied obviously will affect which of the eligible applicants is chosen for the housing. In addition to the direct channel, there are some implications of priorities that are less obvious. For example, if prioritization is based upon the household's rent burden in its existing housing, then the household's own neighborhood and housing decisions, which may relate to characteristics of the household, may affect which household's are likely to receive assistance. In addition, households may make different choices to improve their chances of receiving housing assistance.

Finally, in some allocation schemes, applicants are applying only for a particular housing development in a particular location and must take or leave any offer of assistance; in others, applicants may be placed in separate queues depending upon choices they've made about location or type of housing; and in still others, applicants may be given the choice of rejecting a particular unit or development, but allowed to stay in the

[44] Moore, supra n. [], at 477.

[45] Even if the housing resource is generally allocated according to FIFO or another ordering system, people may move to the front of the queue because of exemptions from the usual rules that are granted for emergencies, particularly critical needs, or other criteria. The waiting lists that public housing authorities maintain are sometimes circumvented in order to house the homeless, or victims of domestic violence or other crimes, before others in the line, for example. See, e.g., 42 U.S.C.A. 1437n (2018) ("the skipping of a family on a waiting list" for housing assistance in order to de-concentrate poverty and achieve mixed income housing shall not be considered an "adverse action"). According to Leopold, "in 1979, Congress established federal priorities for admission for households with severe rent burdens, households in severely substandard housing, and households that were displaced by government actions. The Quality Housing and Work Responsibility Act (QHWRA), enacted in 1998, removed these federal preferences." Leopold, supra n. 37, at 276. [Confirm that was the law in 1979, and provide cites to the law and the repeal in QHWRA, so we don't need to cite to Leopold] M. Kathleen Moore provides an example:

> . . . [T]he Metropolitan Development and Housing Agency in Nashville, Tennessee, uses preferences to prioritize its HCV queue mainly through a point system. Overall list order is first determined through randomization, then households are further ranked based on preferences. Applicant households are given a score based on the number and types of preferences they can claim. Displaced households are given 4 points; households residing in Davidson County, Tennessee, are given 3 points; elderly and disabled heads of households are given 2 points; homeless households are given 1 point; homeless individuals referred from a particular agency are given additional points based on a vulnerability assessment score. All applicable preference points are summed for a household. Available vouchers are issued to the households with the highest scores.

Kathleen Moore, Lists and Lotteries: Rationing in the Housing Choice Voucher Program, 26 Housing Pol'y Debate 474, 479 (2016); see also Metropolitan Development and Housing Agency, Rental Assistance Administrative Plan, 32-34, `http://www.nashville-mdha.org/wp-content/uploads/2017/06/Administrative-Plan5-10-17.pdf`.

[46] Housing could be allocated according to a system like that used for the allocation of organs, for example, which uses an elaborate point system and iterative offer process designed to ensure that the organs are efficiently and fairly used.

queue for other units that become available.

The possible combinations of these dimensions are summarized in Figure 2. Note that these combinations apply only to those households who have successfully completed the application for housing.

3.2 Methods in Use Across Jurisdictions

We know very little about the methods jurisdictions use to allocate assistance.

In his 2009 survey of 25 PHAs, Leopold found that only four PHAs reported that they selected households from their waiting lists purely on a lottery or first-come, first-served basis.[47] The other 21 PHAs used some form of admissions preferences to prioritize assistance for certain households. (As noted in Figure 2, preferences can be used in combination with any form of ordering of wait lists or lotteries.) The two most common preferences, each cited by 48 percent of PHAs, were for applicants who were displaced by either natural disasters or government action and for applicants who were employed or enrolled in some kind of training program. The next most common preferences were for applicants living within the PHA service area (40 percent) and homeless applicants (24 percent). Only 8 percent of PHAs reported a preference for applicants who were rent burdened or living in substandard housing.[48]

In his more recent survey of 25 PHAs' public housing waiting list policies, Waldinger (2019) finds that PHAs differ dramatically both in their priority systems and in the amount of choice afforded to applicants over where they live. Choice is an important dimension of waiting list policy specific to project-based assistance (including public housing), in which assistance is tied to a household living in a specific unit. Waldinger finds large differences in priority systems, particularly in terms of how applicants are prioritized based on economic characteristics. Some PHAs prioritize working, economically self-sufficient, or higher-income (above 30% AMI) households, while others prioritize households with indicators of economic distress (income below 30% AMI, severe rent burden, experienced no-fault eviction). Most of the surveyed PHAs allocate housing on a first-come first-served basis within priority group, though the order of the waiting list may be initially determined by lottery after an open application period.

Work based on interviews with 35 PHAs on their voucher waitlist practices highlights just how important preferences and allocation systems are for who receives assistance. For example, the executive director of one PHA stated that providing priority for some groups (the homeless, disabled, elderly, and veterans) means no other groups ever get

[47] J. Leopold, *The housing needs of rental assistance applicants,* 14 Cityscape 275?298 (2012).

[48] Pin cites to Leopold.

Figure 2: Dimensions of Allocation Systems

Ordering:		**Prioritization or preferences:**	**Applicant's choices regarding housing**
Initial ordering	Screening for eligibility		
Random	-Lottery among all applicants, who must show eligibility when offered housing -Lottery among only those applicants who have demonstrated eligibility (or apparent eligibility)	-Lottery with preferences -Lottery without any further prioritization	-Lottery in which "winner" is then given a choice among units/developments -Lottery in which "winner" is given no choice but to take or leave offer -Lottery in which "winner" may reject a unit or development but retain place on the list
Non-random Queue	Generally paired with eligibility screens at the time the person is reached in the queue	-Applicants with certain characteristics "skip" to front of the line -Applicants face no criteria other than eligibility	-Applicant placed on a separate list according to choice of location/type of unit -Applicant offered a choice among unit types or developments when reached in the queue -Applicant given no choice
Screened	All applicants screened for eligibility, then ordered according to screening criteria	Inherent in screening criteria	Applicants given a choice of unit or development at the time the assistance is offered -Applicant given no choice other than accept/reject. Applicant allowed to reject offered unit or development, but remain on the list

to the top of their waiting list to receive assistance.[49]

To try to learn more, and update the literature, we gathered information from the largest 19 U.S. cities, examining their rules for the allocation of housing assistance. In brief, we found that rental assistance (such as a Section 8 Housing Choice Voucher) is often allocated by a waitlist initially ordered by a lottery. In nearly half of the cities surveyed, applicants for Section 8 Housing Choice Vouchers (HCVs) are selected by lottery in order to get onto the waitlist at all. The other half operates more traditional, first-in-first-out waitlists in which applicants are ordered by their application date. The allocation of subsidized affordable units tends to be by lottery.

Relatively few systems for allocating housing seem to be purely random, even within a pool that has met specific eligibility criteria. The most recent surveys showed that about 62-72% of PHAs had some system of local preferences that affected the allocation.[50] Some of the most common preferences are for displaced households, households with residency in the PHA's jurisdiction, and victims of domestic violence.[51]

4 Modeling the Allocation Process

To better understand how the systems used to allocate housing affect which members of the eligible pool actually receive which housing, we focus on one Public Housing Agency, the Cambridge, MA Public Housing Agency (CHA) at a specific point in time (the 2012 calendar year).

4.1 Overview of Our Methodology

4.1.1 Conceptual Overview

Section 3 laid out five factors that affect who receives housing assistance (and which housing): who applies for the housing, how the stock matches need, and three key policy dimensions – the ordering of waitlists, priorities applied to those lists, and whether applicants have any degree of choice. To be concrete about how the three key policy dimensions affect allocations, we use data on the eligible and served populations for CHA, as well as its existing stock of public housing, to estimate a model of the decisions by both the CHA and the applicants that determine who receives the CHA's housing.

[49] B. McCabe and M. Moore, *Absorption Disruptions and Serial Billers: Administrative Burdens and Discretionary Authority in the Housing Choice Voucher Program.* 2018 working paper, page 21.

[50] HUD, *PHA homelessness preferences*, Web census survey data (2012). `Retrievedfromhttp://www.huduser.org/portal/datasets/pha_study.html`. Dataset; National Low Income Housing Coalition, "A look at waiting lists: What can we learn from the HUD approved plans?" NLIHC Research Note, 04 (2004).

[51] *PHA Homelessness Preferences*, supra n. [], at ; NLIHC, supra n. [], at XX.[check and add pin cites].

Once the model is estimated, we can change a policy feature of the model to simulate *who would get which housing if this policy were changed.* To do this requires four steps:

1. Determine who is eligible for CHA housing.
2. Make assumptions about who, among those eligible, applies.
3. Model the existing allocation system.
4. Simulate policy changes.

To simulate policy changes, we will focus in this paper on examining the effect of alternative priority systems. We will also take the existing CHA public housing stock – the number and sizes of units as well as age-restrictions (elderly housing) – as given, though it is itself the product of previous policy choices. Before turning to determining who is eligible, we describe the data used in the empirical work.

4.1.2 Policies and Outcomes of Interest

We are primarily interested in the three policy levers used to organize public housing waiting lists: ordering, priority, and choice. These levers can affect who is likely to gain access to which housing.

Of these three policy levers, this paper focuses on priority systems. We emphasize, however, that all three of these features ultimately affect the allocation of public housing units. The effects of alternative priority systems may therefore depend on the choice and ordering systems in place. For purposes of our model estimation and policy-scenario simulations, we assume applicants are able to choose specific developments and are ordered first-come, first-served (FCFS), similar to the CHA's actual policies in 2012. The CHA gave all households living, or with a member working, in Cambridge, and also military veterans, equal priority.

The alternative priority systems we consider are:

1. *Income-based Priorities:* We consider using household income to prioritize applicants. We specifically consider two different version of income-based priorities:
   (a) *Higher-Income Priority:* applicants earning above 30% AMI are offered apartments before applicants earning below 30% AMI.
   (b) *Lower-Income Priority:* applicants earning below 30% AMI are offered apartments before applicants earning above 30% AMI.
2. *Elderly Priority:* Households with an elderly (or disabled) head or spouse are offered available apartments before other applicants.

3. *Priority for Families with Children:* Households with a child under 18 years of age are offered available apartments before other applicants.

In terms of income priorities, there are two main arguments for prioritizing higher income households. The first is concern about the role public housing has played in concentrating poverty and a desire for a broader mix of income in developments.[52] Some PHAs, such as Houston and San Diego, directly incorporate de-concentration of lowest-income tenants within buildings into their allocation system. The second relates to the correlation between income and employment. Many PHAs prioritize working adults, perhaps to ensure the presence of employed adults as role models within developments. Eight of the 19 PHAs we studied have priorities for households with a working adult.

On the other hand, a desire to serve those with the greatest needs would support prioritizing lowest-income households (or prioritizing by other measures of need, such as rent burden). Federal law requires that at least 40 percent of new admissions into public housing be "extremely low income" (ELI), or making less than 30% of AMI.[53] In addition, three of the 19 PHAs we reviewed include lowest-income households in their priorities (Chicago, IL; Seattle, WA; and Charlotte, NC). While not an explicit priority for lowest-income households, San Francisco provides a priority point for families paying more than 70 percent of income in rent. And San Antonio will allow ELI households to "skip" up the waitlist as part of their effort to de-concentrate the lowest income households in the public housing developments.

In terms of family structure and age, priorities for the elderly may be driven by concerns about the particular housing challenges facing an aging population. Incomes drop considerably at the point of retirement, with no expectations or likely means of increased income in the future. Elderly applicants on public housing waitlists have been found to have higher health care needs and costs.[54] Furthermore, prioritizing the elderly in public housing may allow jurisdictions to avoid some of the costs of moving the elderly to nursing homes before such care is really needed. On the other hand, there is a large and increasing body of evidence on the role of stable, decent and affordable housing in child development.[55] Recent work providing some of the most rigorous causal evidence includes a HUD randomized trial that documented significant reductions in a

[52]For a review, W. Rohe and L. Freeman. "Assisted housing and residential segregation: The role of race and ethnicity in the siting of assisted housing developments." Journal of the American Planning Association 67 (3): 279?92. 2001.

[53]Cite.

[54]For a summary as this applies to assisted housing, see P. Carder, G. Luhr and J. Kohon. "Differential Health and Social Needs of Older Adults Waitlisted for Public Housing or Housing Choice Vouchers. Institute on Aging."

[55]For a summary, see V. Gaitn (2019), "How Housing Affects Children?s Outcomes" at `https://howhousingmatters.org/articles/housing-affects-childrens-outcomes/`

variety of adverse childhood experiences among young children in homeless families offered long term housing assistance.[56] There is also very compelling causal work on the long-term effects of receiving housing assistance and moving to neighborhoods accessible with housing assistance, particularly in terms of adults earnings and upward economic mobility.[57] San Diego is the only jurisdiction we reviewed that provides a priority to families with children, and it also provides priority to the elderly and disabled.

4.2 Data & Descriptive Evidence

4.2.1 Data Sources

To determine which households were eligible for CHA public housing,[58] we use the American Community Survey (ACS) microdata. Since 2005, the ACS has collected a nationally representative 1 percent sample of U.S. households each year. To have adequate sample size at low levels of geography, we pool across five years of data. Pooling data from 2010 to 2014 yields an approximate 5 percent sample of U.S. households during that period.

We use development-level data from HUD's Picture of Subsidized Households (PIC) to obtain a snapshot of public housing tenants living in Cambridge, MA in 2012. The data contain information on the characteristics of public housing tenants in each development, as well as vacancy rates and average waiting times for each development.

The ACS and PIC datasets are not perfectly aligned. The ACS data, which allow us to approximate the pool of households eligible for public housing, covers the period 2010 to 2014. We compare that eligible pool to the residents of Cambridge Public Housing in 2012 recorded in the PIC data. However, most public housing residents will have been in their apartments for many years, and will have had different characteristics at the time they were offered the apartment. In addition, the allocation rules and any preferences and priorities used to determine the allocation may have changed since the CHA residents were offered their apartments, so the characteristics of those residents may have been influenced by rules other than the rules we are studying. Further, some household characteristics used by PHAs for determining eligibility or prioritization of

[56] D. Gubits, Daniel, et al. (2016). "Family Options Study: Three-Year Impacts of Housing and Services Interventions for Homeless Families." Washington, DC: U.S. Department of Housing and Urban Development. 2016.

[57] F. Andersson, F. Haltiwanger, M. Kutzbach, G. Palloni, H. Pollakowski, and D. Weinberg. "Childhood Housing and Adult Earnings: A Between-Siblings Analysis of Housing Vouchers and Public Housing" US Census Bureau Center for Economic Studies Paper No. CES-WP-13-48. 2012; R. Chetty, N. Hendren, and L. Katz. "The effects of exposure to better neighborhoods on children: New evidence from the Moving to Opportunity experiment.? American Economic Review 106(4): 855-902. 2016.

[58] See Family and Elderly Housing Site Based Waitlist Requirements and Overview, `http://cambridge-housing.org/about/additional_information/waitlist.asp`

applicants are not available in the ACS.

Finally, we focus on 2012 to exploit a third dataset, the actual waitlist at CHA in 2012.[59] These confidential data permit us to set or test the reasonableness of some model assumptions and parameters.

4.2.2 Eligible Population

To estimate which of the households eligible for Cambridge public housing will become tenants, we first identify households in the ACS sampled between 2010 and 2014 who appear to be eligible based on characteristics reported in the data. For each surveyed household, the ACS records many of the characteristics used to determine eligibility for public housing, as well as other important demographic information. The variables we use include the household's annual gross income and assets; the age, race/ethnicity, and gender of each household member; and the geographic areas where each household member lives and works. We also include whether each household member has a disability that might affect whether the household would qualify for preferences or priorities that might be given to people with disabilities.

In constructing the pool of eligible households, we omit certain groups that are eligible for but very unlikely to apply for or receive public housing. In particular, almost any household whose income is below 80 percent of the Area Median Income (AMI) may apply for public housing in Cambridge, but due to excess demand, only applicants with a member living or working in Cambridge have a chance of being housed because they receive priority over other applicants.[60] Therefore, an ACS household is deemed eligible if: at least one member lives or works in Cambridge; the household income is below 80 percent of AMI (for the Boston-Cambridge-Quincy, MA-NH HUD Metro FMR Area in their survey year); and the household has at least one member who is elderly, disabled, or not a full-time student.

There are groups who may be prioritized among the eligible population that we are unable to identify. All military veterans receive priority, for example, but the PIC data do not contain information on veteran status, so we are unable to determine the implications of this priority. Similarly, the CHA gives emergency priority to victims of domestic violence and natural disasters, but we cannot identify these households in either the ACS or PIC. Based upon the confidential data we have about the wait list, however, we know that only small number of veterans apply for housing in Cambridge,

[59]See Waldinger (2019) for a description of this dataset.

[60]Because we have access to data about the households on the CHA, we verified that applicants not living or working in Cambridge were not offered apartments, except that a small number of elderly and disabled applicants who did not live or work in Cambridge were given CHA apartments in 2011.

and only a small number of CHA tenants receive priority because they were victims of domestic violence or natural disasters.

There are also a small number of characteristics that would disqualify a household from CHA housing, but which we do not observe in the ACS. For federally subsidized public housing, at least one household member must have valid documented immigration status in order to be eligible. In addition, individuals convicted of certain drug and other felony crimes are barred from public housing. For these reasons, we may overstate or understate the total number of households eligible for CHA public housing.

4.2.3 Comparison of CHA Eligible and Tenant Households

Table 2 compares characteristics of existing CHA tenant households with those of the eligible population. We calculate average tenant characteristics using the project-level HUD PIC data from 2012, the middle of our ACS sample period. Characteristics are averaged across developments weighting by the number of tenant households in each development. Statistics for the eligible population (from the ACS) are calculated by averaging the characteristics of each sampled eligible household, weighted by the ACS sampling weights.

As Table 2 shows, CHA tenants differ in significant ways from the broader eligible population. While both groups have low incomes, CHA households are poorer – the median household income of CHA tenants is about 86 percent of the median household income for the eligible pool. CHA tenants are more likely to live in apartments with two or more bedrooms, and much less likely to live in studio or one bedroom apartments, than the eligible population (and have larger household size). CHA tenant households are also more likely to contain children, and are more than twice as likely to have a household head or spouse of head who is elderly (age 62 or older). CHA tenant households also are more likely to have a household head or spouse of head who has a disability. Finally, CHA tenants are much more likely to be African American – 2.7 times as likely than households in the eligible population.

Table 2: CHA Eligible vs Tenant Populations

	ACS (Eligible)	PIC (Tenants)
Number of Households	43,206	2,168
Average Monthly Gross Rent	856	399
Household Income ($)	23,000	19,763
% Area Median Income	32	25
Mean Household Size	1.68	1.99
0-1 Bedroom Households	0.75	0.54
2 Bedroom Households	0.15	0.23
3+ Bedroom Households	0.10	0.23
Any Children	0.17	0.29
Age of Head Lower than 25	0.22	0.01
Age of Head 25-50	0.39	0.29
Age of Head 51-61	0.17	0.22
Elderly Head/Spouse	0.21	0.48
Disabled Head/Spouse	0.16	0.25
African-American Head/Spouse	0.18	0.48
Hispanic Head/Spouse	0.11	0.11

There also are considerable differences between tenants in elderly/disabled developments (which are restricted to households with a head or spouse who is at least 62 or has a disability) and those in general developments, which have no such restrictions (Table 3). Tenants in elderly/disabled developments have much lower incomes than tenants in general CHA developments, both in dollars ($13,436 vs $25,021) and as a percentage of AMI (20% vs 29%). Almost no tenants in elderly/disabled developments have children, while more than half of tenants in general developments do. Some of this difference is driven by the apartment stocks: elderly/disabled developments have almost no 2- and 3-bedroom units, while such units comprise 80% of the stock in general developments, and household size is twice as large for those in general public housing. Most tenants in elderly developments are white, while most tenants in general CHA developments are African American or Hispanic. Elderly developments are located in neighborhoods that have lower poverty rates and lower shares of minority residents than general developments.

Table 3: CHA tenants, by type of development

	PIC		
	All	Elderly Developments	General Developments
Number of Households	2,168	984	1,184
Average Monthly Gross Rent	399	287	491
Mean Household Income ($)	19,763	13,436	25,021
Mean % Area Median Income	25	20	29
Mean Household Size	1.99	1.09	2.74
Months on Waitlist at Move-In	29	21	35
Months from Move-In	112	80	139
0-1 Bedroom Households	0.54	0.98	0.18
2 Bedroom Households	0.23	0.02	0.40
3+ Bedroom Households	0.23	0.01	0.42
Any Children			
Age of Head Lower than 25	0.01	0.00	0.01
Age of Head 25-50	0.29	0.07	0.48
Age of Head 51-61	0.22	0.15	0.28
Elderly Head/Spouse	0.48	0.78	0.23
Disabled Head/Spouse	0.25	0.37	0.15
African-American Head/Spouse	0.48	0.30	0.63
Hispanic Head/Spouse	0.11	0.07	0.14
Tract Poverty Rate (%)	15	12	18
Tract Minority (%)	44	33	54

The characteristics of tenants also vary substantially across developments within the same category (particularly within general public housing developments), as shown in the top portion of Table 4. Across general developments, average tenant incomes range from $18,366 (24% AMI) in Wilson Court to $29,724 (34% AMI) in Washington Elms. The share of households containing minor children varies from a low of 32 percent (Lincoln) to a high of 66 (Roosevelt). There are also differences in racial composition; fewer than 50 percent of tenants in Jackson Gardens have an African American household head, compared to 69 percent in Woodrow Wilson Court. There are also differences across developments in tenant age and the fraction of households with children.

Table 4: Tenant, Development and Census Tract Characteristics for CHA General Public Housing

	Developments not Designated for Elderly/Disabled Households									All
	Corcoran	Jackson	Jefferson	Lincoln	Newtowne	Putnam	Roosevelt	Washington	Wilson	
Development Characteristics										
Number of Tenant Households	142	45	202	28	255	150	136	171	82	1211
Months on Waitlist at Move-In	37	45	26	45	28	36	62	35	24	35
Months from Move-In	158	54	142	140	145	161	119	175	47	139
Characteristics of Tenants										
Rent ($/month)	518	374	521	542	459	469	539	556	347	491
Household Income	25,375	20,393	26,610	29,559	22,982	22,583	27,487	29,724	18,366	25,020
% Area Median Income	30	25	30	35	27	26	32	34	24	29
Any Children (%)	61	42	54	32	49	57	66	50	39	53
Household Head Age 25-50 (%)	60	44	43	40	49	48	60	41	45	49
Household Head Age 51-61 (%)	22	29	29	31	30	25	26	33	22	28
Household Head Age 62+ (%)	15	27	28	26	20	25	13	25	33	23
Household Head Elderly (%)	15	27	28	26	20	25	13	25	33	23
Household Head Disabled (%)	9	2	16	17	23	15	10	19	9	15
Household Head Black (%)	66	49	65	63	64	62	65	57	69	63
Household Head Hispanic (%)	11	20	11	17	11	15	16	17	17	14
0-1 Bedrooms (%)	9	20	26	17	20	15	0	17	45	18
2 Bedrooms (%)	41	47	19	26	45	49	60	30	46	40
3+ Bedrooms (%)	50	33	54	57	35	36	40	54	9	42
Census Tract Characteristics										
Tract Poverty Rate (%)	7	14	11	12	26	15	23	26	11	18
Tract Minority (%)	26	34	61	46	76	45	38	76	28	54

In addition to differences in the characteristics of one's neighbors within a public housing development, developments offer tenants different surrounding neighborhoods, as shown in the bottom panel of the table. Census tract poverty rates range from 7 percent to 26 percent, and fractions of minority residents in the surrounding communities range from 26 percent to 76 percent, in Corcoran Park compared to Newtown Court and Washington Elms. There is qualitatively similar variation across elderly/disabled developments. Because census tracts contain several thousand residents, while developments contain at most several hundred, these differences are not mechanically driven by the contribution of the public housing developments to these statistics, especially for racial composition.

Within general developments, however, tenants are not necessarily sorting into developments in neighborhoods that have similar characteristics to their own. For example, among general public housing developments, some of the highest mean tenant incomes are observed in developments with the highest census tract poverty rates (Washington Elms and Roosevelt Towers). Similarly, some of the developments with the greatest proportions of African American heads of household are in census tracts with low minority shares (Woodrow Wilson, Corcoran Park).

Specific types of eligible households may have stronger or weaker preferences for the characteristics of a development or a neighborhood. The observed sorting of tenants is generated by the combination of all applicant and development characteristics, and their interaction with the capacity constraints of the public housing system and the structure of the CHA waiting list. The remaining sections will estimate a model that accounts for the interaction of all of these forces, and uses the model to predict how the composition of CHA public housing tenants would change under different allocation policies.

4.3 Model of the CHA Waiting List

This section presents a mathematical model of the public housing waiting list run by the Cambridge Housing Authority. It involves two components: (1) a model of how applicants make decisions about which developments to apply for given the waiting times they would face, and (2) a model of how frequently new applicants arrive on the waiting list, when public housing apartments become available, and when applicants depart the waiting list without an assignment. While the model is grounded in the CHA's actual policies, there are a number of areas where we will have to make assumptions about aspects of the waitlist we do not observe. In the next section, we use this model to estimate the preferences different types of households, and then to make policy-scenario predictions if the CHA implemented different waiting list policies.

4.3.1 Applicant Decisions on the Waiting List

To estimate how the composition of CHA tenants will change under different allocation rules, we need to predict how applicants would respond to the incentives they face under these systems. In systems like the CHA's, which allow applicants to state their preferred development, some applicants will face a trade-off between waiting for less time and being assigned to their preferred development. Different priority systems will lead to different waiting time trade-offs for a particular applicant. An applicant with high priority will be able to receive their preferred development more quickly, while an applicant with lower priority may see large waiting time differences across options. To accurately predict who will be housed and how tenants will be sorted across developments and neighborhoods under these systems, we must understand how applicants will modify their development choices when faced with these different incentives.

To model applicants' decisions while on the waitlist, we estimate a discrete choice model in which applicants care about which development they live in and how long they have to wait in order to get it. To describe the model, we denote each eligible household by i, and each development by j. Each household has observed characteristics Z_i (e.g. income, race/ethnicity, age), and each development has characteristics X_j (e.g. size, location). Households have preferences over developments captured by utilities u_{ij}. One can interpret each utility u_{ij} as i's net present value of being assigned to development j instead of never moving into CHA public housing. If an applicant had the opportunity to move into any development the applicant wanted immediately, the applicant would choose the development with the highest u_{ij}.

These utilities can depend on both observed applicant and development characteristics (Z_i, X_j), and also on unobserved characteristics that influence an applicant's preferences. For example, it could be the case that compared to lower-income applicants, higher-income applicants have a stronger preference for living in small developments. If this were true, then we might expect to observe in the data that smaller developments have larger shares of higher-income tenants. However, even if this were true on average, there might be some higher-income applicants who prefer to live in a large development, perhaps because it is near a specific school or workplace that the applicant would like to access or is currently located near. These characteristics are not observed by us as researchers, but we will allow for them in our model through an "error term" in each u_{ij}.

Households also care about how quickly they can be housed. To capture a preference for shorter waiting times, we assume that households exponentially discount future payoffs at a continuous rate $r > 0$. If household i is assigned to development j in

T years, their discounted payoff is $V_{ij}(T) = e^{-rT}u_{ij}$. Since waiting time decreases an applicant's value of their eventual assignment, an applicant might choose a development that would not be their first choice if they could receive an assignment sooner. In other words, this modeling device allows applicants to trade their preferred assignment for a shorter waiting time.

To estimate the model, we parameterize the utilities as

$$u_{ij} = \exp(\delta_j + \alpha Z_i + \beta f(Z_i, X_j) + \epsilon_{ij}) \ , \tag{1}$$

where δ_j is a development fixed effect; $f(.)$ is a known function of observed applicant and development characteristics; and ϵ_{ij} is applicant i's idiosyncratic taste for development j. The development fixed effects allow some developments to be systematically more desirable than others. The coefficient vector α allows household characteristics to predict a household's overall value of living in public housing, given their non-public housing options. For example, we saw in Table 2 that public housing tenants tend to have lower incomes than the eligible population. This would be reflected by a negative coefficient on household income in the vector α. The coefficient vector β allows for different types of households to differentially value certain development characteristics – for example, higher income households may have a stronger preference for living in smaller developments than other eligible households. Finally, the idiosyncratic tastes ϵ_{ij} allow for unobserved characteristics that affect a household's utility from living in development j.

We assume that when an applicant joins the waiting list, the applicant chooses the development j that maximizes their discounted utility:

$$\max_j \quad \exp(-rT_j) * \exp(\delta_j + \alpha Z_i + \beta f(Z_i, X_j) + \epsilon_{ij}) \ . \tag{2}$$

In solving this problem, the household always has an outside option of not living in public housing, the payoff from which is normalized to $u_{i0} = 1$. We assume that a household which prefers its outside option to any CHA development simply will not apply. Taking the natural logarithm of each discounted payoff V_{ij}, an applicant's choice problem can be written equivalently as

$$\max_j \quad \delta_j - rT_j + \alpha Z_i + \beta f(Z_i, X_j) + \epsilon_{ij} \ . \tag{3}$$

The parameters of the model are δ_j for $j = 1, ..., J$, r, α, and β. For convenience, we assume that ϵ_{ij} is distributed Type 1 Extreme Value, and that these errors are drawn independently across households and developments. Under this assumption, the probability that applicant i chooses development j is

$$P_{ij} = \frac{\exp(\delta_j - rT_j + \alpha Z_i + \beta f(Z_i, X_j))}{1 + \sum_{k=1,\ldots,J} \exp(\delta_k - rT_k + \alpha Z_i + \beta f(Z_i, X_k))} \ . \tag{4}$$

4.3.2 Mechanics of the CHA Waiting List

Our goal is to estimate the model parameters $(\{\delta_j\}, \alpha, \beta)$. We will do so by comparing the characteristics of public housing tenants to those of eligible households. The idea behind our strategy is that if eligible households with certain characteristics are more likely to apply for public housing and choose certain types of developments, those households should be more likely to appear as tenants in the PIC data. However, to quantify how this relationship reflects preferences, and in turn predict how the tenant composition would change under different waiting list policies, we need to model how the CHA waiting list process selects tenants from the set of eligible households. We therefore propose a specific model of the CHA public housing waiting list in this section.

The model specifies when new applicants arrive, when apartments become available, and when applicants are removed from the waiting list before they are offered an apartment. Applicants make decisions on the waitlist according to equation 3, knowing their own preferences and the waiting time T_j they face for each development. The other processes are specified as follows:

- *Applicant Arrivals:* Applicants for public housing arrive on the waitlist at a poisson rate a. This means that each year, the number of arrivals follows a Poisson distribution with a expected arrivals each year. Eligible households receive the opportunity to apply on a random rate uniformly distributed between 2010 and 2014, and will submit an application if any development is preferable to their outside option. In effect, this assumes that each year, new applicants have characteristics similar to the composition of all households in the eligible population who would be willing to move into at least one public housing development. This assumption of similar application rates can be modified in future work.
- *Applicant Departures:* Past work has found that many applicants leave the waiting list before they are offered an apartment (Waldinger, 2019). This may be a decision on the part of the applicant, perhaps in response to improvements in a their outside options or changes in their eligibility. It can also happen simply because a household moves and does not update their contact information with the public housing authority. We call leaving the waiting list before being offered an apartment a "departure." For ease of modeling, we assume that all applicants have the

same probability of departure from the waitlist. Specifically, each applicant departs the waiting list on a random date after initial application, which it cannot predict. The time to departure follows an exponential distribution with parameter d. If an applicant chooses a development with waiting time T, their probability of actually receiving an assignment is $\exp(-dT)$. Thus, if an applicant chooses a development with a longer waiting time, the applicant has a lower chance of eventually receiving an apartment.

- *Apartment Vacancies:* Apartments in development j become vacant at rate ν_j. Since the stock of public housing is fixed, new "supply" is generated by existing tenants vacating their units. The rate at which this occurs can and does vary across developments. We estimate the vacancy rate in each development using the PIC data, which records the average tenure of current tenants.

The equilibrium waiting time T_j for development j is determined by the rate at which applicants apply for development j ($a_j \equiv a * \sum_i P_{ij}$), the vacancy rate ν_j, and the departure rate from the waiting list d:

$$T_j = \frac{\log(a_j) - \log(\nu_j)}{d} \ . \tag{5}$$

This equation is intuitive. The more applicants choosing development j (a_j), the longer the waiting time; the higher the vacancy rate (ν_j), the shorter the waiting time; and the higher the rate at which applicants depart the waiting list without an assignment (d), the shorter the waiting time.

Through this formula, we can use the average waiting times for each development recorded in the PIC data to learn about the supply-demand ratio for each development j. This will be useful for pinning down the development fixed effects δ_j because we do not directly observe how many households applied for a particular development. However, to do so we will have to make assumptions about the departure rate and the rate at which eligible households receive the opportunity to apply. Previous work has shown that among applicants for CHA general public housing, the annual attrition rate is about 25%. We will also assume that each eligible household had one opportunity to apply for CHA public housing between 2010 and 2014.

5 Estimation and Policy-Scenario Predictions

5.1 Estimation Procedure

We estimate the parameter vector $\theta = (\{\delta_j\}, \alpha, \beta)$ by matching specific features of the PIC data (discussed below) to those predicted by the model outlined in the previous section, given the set of eligible households in the ACS. The estimator searches over different parameter values to minimize the difference between the characteristics of tenants and developments observed in the PIC data and what our model predicts they should be. This section first describes the data features we match and how we calculate the model's predictions for each feature. It then explains the estimator used to choose theta.

5.1.1 Matched Data Features

We match three sets of features from the PIC data: (1) the mean waiting time for each development; (2) characteristics of CHA tenants; and (3) covariances between applicant and development characteristics. The specific tenant characteristics we match are the fraction of household heads who are African American, Hispanic, elderly, under age 50, and disabled; the fraction of households with children; and also the mean income and % AMI of tenant households. The specific covariances we match are between tenant race, elderly head, any children, and % AMI; and development size, census tract poverty rate, and census tract fraction of minority residents. We also try to match the fraction of elderly households living in family public housing developments. The model should match this and other patterns in the PIC data. The model is therefore parameterized analogously to the characteristics we match; applicants can systematically differ in their overall values of public housing based on the observed characteristics in group (2), and in their tastes for specific development characteristics according to the interactions in group (3).

5.1.2 Model Predictions

To calculate predicted data features for each parameter vector θ, we combine our development choice model with our model of the CHA waiting list. For a particular value of θ, we can calculate for each eligible household in the ACS the probability that they would choose each development, given their characteristics and the waiting times for all developments. These choice probabilities give us the information we need to calculate the predicted equilibrium waiting time for each development, as well as the characteristics of tenants in each development.

To see exactly how this is done, recall from equation 5 that our model's predicted waiting time is

$$T_j = \frac{\log(a_j) - \log(\nu_j)}{d} \ .$$

We observe each development's vacancy rate ν_j in the PIC data, which records the average tenure of current tenants. We have also set the departure rate d to 25 percent, and estimated the applicant arrival rate a. With the predicted choice probability $P_{ij}(\theta)$ for each applicant, predicted waiting time is given by

$$T_j(\theta) = \frac{\log(a * \sum_i P_{ij}(\theta)) - \log(\nu_j)}{d} \tag{6}$$

Intuitively, if the model predicts that too many applicants choose development j, that will lead to a longer predicted waiting time $T_j(\theta)$ than the waiting time T_j we observe in the data. The estimator will then search for values of theta which predict fewer applicants choosing development j.

We can calculate the predicted characteristics of public housing tenants based on the fact that applicants who choose a development with a shorter waiting time have a greater chance of making it to the top of the waiting list and receiving an apartment. Recall that because applicants depart the waiting list at rate d, if an applicant chooses a development with waiting time T_j, the probability the applicant is eventually housed is $\exp(-dT_j)$. Therefore, the average characteristics of public housing tenants are given by

$$Z(\theta) = \frac{\sum_{i,j} P_{ij}(\theta) \exp(-dT_j)\, Z_i}{\sum_{i,j} P_{ij}(\theta) \exp(-dT_j)} \ . \tag{7}$$

For example, if the model predicts that tenant incomes are too high, the estimator will then search for parameter values that predict that fewer high-income households apply, or that they choose developments with longer waiting times, or both.

We can use a similar formula to calculate the covariances between tenant and development characteristics. For a specific applicant characteristic Z and development characteristic X, we predict

$$ZX(\theta) = \frac{\sum_{i,j} P_{ij}(\theta) \exp(-dT_j)\, Z_i X_j}{\sum_{i,j} P_{ij}(\theta) \exp(-dT_j)} \ . \tag{8}$$

Suppose, for example, that a particular parameter value θ predicts a stronger negative correlation between tenant income and development size than what we observe in the PIC data. The estimator will then lower the coefficient on the interaction term between household income and development size. This will lead predicted choice probabilities by development size to depend less on income, and as a result, the model will predict a more even distribution of tenant incomes across developments of different sizes. Of course, incomes are correlated with other household characteristics, and the estimator will be attempting to improve the match on income and development size while also matching along all the dimensions selected.

5.1.3 Quantities We Cannot Estimate

Limited to the data we currently have in hand, there are several parameters that cannot be estimated directly and for which we simply set rates that appear reasonable from the literature:

- The discount rate r: set to 10% per year
- The departure rate d: set to 25% per year
- The rate at which eligible households receive the "opportunity" to apply: once every 5 years

In future versions of the paper, we will explore to what extent our results depend on the values of these parameters.

5.1.4 Estimator

With these three sets of features in the data and predicted by the model – waiting times, tenant characteristics, and covariances between tenant and development characteristics – we can construct our estimator of the parameter vector θ. We choose θ by minimizing the sum of squared differences between each data feature and the model's prediction. If the model can perfectly match the data, this sum will be zero. Formally, our estimator is

$$\theta^* = \arg\min_{\theta} \sum_k (m_k(\theta) - m_k)^2 \ . \tag{9}$$

In this notation, k denotes a specific data feature; m_k is its value in the data; and $m_k(\theta)$ is the value predicted by the model for a particular parameter value θ.

5.1.5 Estimation Results

Appendix Table 1 presents the coefficient estimates from the structural model. Standard errors are a work in progress and will be incorporated into future versions of the paper. The coefficients on household characteristics broadly reflect the differences between eligible and tenant households summarized in Table 2. For example, African American headed households are estimated to have a higher value of living in public housing, while households with higher incomes have lower values. The coefficients governing interactions between eligible households and development characteristics also generally show patterns consistent with the data, controlling for other characteristics. Households with children and with higher incomes (as a percent of AMI) are more willing to live in large developments; elderly households are less willing to live in developments located in high-poverty tracts; and elderly headed, and higher-income households, as well as households with children, relatively prefer developments in tracts with lower minority rates.

Some of these these estimated interactions may seem surprising given the descriptive patterns in Table 4; however, it is important to remember that the estimates condition on the set of public housing units for which a household is eligible. For example, even though African American headed households live in relatively high-minority tracts compared to all public housing tenants, this is because African American headed households are more likely to only be eligible for general public housing developments. General developments are located in higher-minority tracts than elderly/disabled developments, driving the overall pattern, but within general developments, African Americans tend to live in lower-minority tracts. Hence, the estimated interaction between African American and tract minority rate is negative, controlling for all else.

Finally, we estimate a strong and very negative coefficient on the interaction between an elderly household head and general public housing developments. This last estimate reflects one case in which our model does not fit the data well; we predict that no elderly households will choose general public housing developments, whereas 23% of general public housing tenants have an elderly head or spouse. The estimator sacrificed matching this feature of the data to better fit other data features. However, as we will soon see, this will bias the predicted effects of certain alternative priority systems. (It is also worth noting that the model is estimating the decisions of applicants who are senior at the time of choosing developments; the average tenant of CHA general public housing has lived there for more than a decade, and may well not have been elderly when they moved in.)

To more comprehensively assess the fit of our estimates, Table 5 compares the distribution of tenant households from PIC to the distribution predicted by our model of the CHA waiting list and preference estimates. To calculate the latter, we use the same code used for policy-scenario simulations to predict the equilibrium under the CHA's current (equal) priority system. If our model perfectly fit the data, this calculation would reproduce the distribution of tenants and waiting times that we observe in PIC; if the fit is imperfect, we may see differences between the actual distribution of tenants and the predicted equilibrium.

Table 5: Comparison of Characteristics of CHA tenants to Those Predicted by Model

	PIC Data			Predicted Equilibrium		
	All	Elderly Developments	General Developments	All	Elderly Developments	General Developments
Months on Waitlist at Move-In	29	21	35	26	23	35
Rent ($/month)	399	287	491	488	465	560
Household Income	19,763	13,436	25,021	19,537	18,596	22,388
% Area Median Income	25	20	29	27	27	27
Any Children (%)	29	0	53	25	7	80
Household Head Age Under 25 (%)	1	0	1	10	10	8
Household Head Age 25-50 (%)	29	7	48	22	10	59
Household Head Age 51-61 (%)	22	15	28	18	13	33
Household Head Elderly (%)	48	78	23	50	67	0
Household Head Disabled (%)	25	37	15	25	34	0
Household Head Black (%)	48	30	63	50	46	60
Household Head Hispanic (%)	11	7	14	10	8	16

Notes: "Elderly" columns summarize tenants in elderly/disabled developments. "General" columns summarize tenants in developments not designated for elderly/disabled households.

Comparing the "All" columns, we see that overall, our estimates match the average characteristics of CHA tenants, as well as mean waiting times. However, breaking out the predicted characteristics of tenants in general and elderly/disabled developments, there are significant differences between predicted tenant characteristics and those in the data. We predict higher incomes in elderly/disabled developments and lower ones in general developments; a larger fraction of children in general public housing (80% vs 53%); and no elderly or disabled tenants in general public housing (compared to 23% and 15% in the data, respectively). Our fit is relatively better for elderly/disabled developments than for general public housing. As we will see in the next section, in part because our estimates do not match the fraction of elderly tenants in general public housing, priorities for elderly/disabled households and households with children will have very small predicted effects. We believe these are underestimated and have more confidence in our results for low- and high-income priorities.

5.2 Simulating the Effects of Changing the Priority System

The estimates from the previous section allow us to predict how the composition of CHA tenants would change if the CHA used a different policy to allocate available units. In this section, we consider the effects of changing the priority system. These simulation exercises hold fixed all other features of the market, including the CHA public housing stock, the characteristics and preferences of eligible households, and other features of the CHA allocation mechanism.

5.2.1 Calculating a New, Predicted Equilibrium

What would happen if the CHA implemented each of these priority systems? At a high level, one may think the answer is obvious: high-priority applicants will be housed at higher rates, at the expense of low-priority applicants. However, the magnitude of these effects, and their distributional consequences, will depend on several factors.

First, capacity constraints limit the rate at which any group can be housed because each public housing unit is of a specific bedroom size. Let's use the example of introducing priority for elderly households. Most households with an elderly member can only occupy studio or 1-bedroom units. Because most general public housing apartments are 2- or 3-bedrooms, few elderly households would move into these units even if elderly households were prioritized. In essence, elderly applicants are only competing with general applicants who would occupy apartments of the same bedroom size.

Second, the effects of prioritizing elderly households could be mitigated by their behavioral responses. Elderly applicants will be able to be housed more quickly in their preferred developments; because of this, they will more likely choose their first choice development, even if that development has a (relatively) longer waiting time than the development they would have chosen under equal priority. Conversely, general public housing applicants will become less selective, substituting toward developments with shorter waiting times in order to increase the chance they receive some kind of assistance. These behavioral responses will partially offset the mechanical effect of increasing priority for some applicants and decreasing it for others.

Priorities may also affect how tenants are sorted across developments. Elderly priority could lead to stronger sorting of general public housing applicants across developments, by race or income for example. This would occur because general public housing applicants will face a starker waiting time trade-off. Higher-income applicants may still be willing to wait for the more desirable developments, while lower-income applicants will take the first thing available, leading to increased segregation across developments by tenant income. More generally, applicants who are more "desperate" – i.e. who would prefer to get some type of public housing quickly rather than waiting for their preferred developments – will sort more strongly towards less desirable developments if they are granted lower priority.

With these factors in mind, in this section we predict the composition of CHA tenants under alternative priority systems (or policy scenarios). To do so, we must account for the fact that each applicant is only eligible to occupy a subset of public housing apartments (based on unit-size and, for elderly/disabled developments, age and disability status), and for the fact that the equilibrium waiting times an applicant faces will depend on their priority group. We will use our model of the CHA waiting list and our estimates of applicant preferences to find a new equilibrium of the system. Specifically, we will search for a new set of waiting times for each priority group that are consistent with the vacancy rate in each development and the development choices applicants would make when faced with those waiting times. These waiting times will generally be different than the waiting times we observe in the PIC data, because they are generated under a different priority system.

More formally, let there be two priority groups – a high-priority group (Group 1) and a low-priority group (Group 2). Let T_j^1 denote the waiting time for group 1 to be housed in development j, and let T_j^2 denote the waiting time for group 2. It is useful to consider the different possibilities for what waiting times could look like for each priority group. If group 1 applicants apply for development j at a higher rate than the vacancy rate, they will fill all of the apartments in j and T_j^1 will be positive. In this case, group 2 applicants will (almost) never be housed in development j; in effect, they face an infinite waiting time: $T_j^2 = \infty$. If instead, fewer group 1 applicants apply for j than the number of vacancies, some group 2 applicants will be housed. In this case, $T_j^1 = 0$ – every group 1 applicant can be housed almost immediately – while group 2 applicants have a positive but finite waiting time: $\infty > T_j^2 > 0$. It is also technically possible that a development is completely undersubscribed, in which case $T_j^1 = T_j^2 = 0$; all applicants of any priority group can be housed there immediately. This is unlikely to occur in the present context, but we allow for the possibility. Note that since every high-priority applicant is offered an appropriately sized available apartment before any low-priority applicants, at most one priority group will have a positive (but finite) waiting time in equilibrium.

Accounting for these cases, we modify equations 3 and 5 to allow different priority groups to have different waiting times, and for waiting times to be zero, positive, or infinite for each group. Then, to calculate the new equilibrium under each priority system, we search for vectors of waiting times (T_j^1, T_j^2) so that each eligible household makes optimal development choices according to equation 3, and such that those vectors are generated by the aggregation of all applicants' decisions through equation 5. We wrote computer code to search for the new equilibrium in MATLAB. The algorithm iterates between calculating each eligible household's optimal choice probabilities given a set of waiting times, and calculating the waiting times implied by those decisions. We iterate until a fixed point is reached, i.e. until optimal decisions produce the same waiting times that led to those decisions.

5.2.2 Results

Table 6 summarizes the predicted characteristics of CHA tenants under different priority systems. The first column reports the predicted equilibrium under current CHA priorities, and the remaining columns do the same for the four priority systems described in Section 4: Low-Income, High-Income, Elderly, and Children Priority. By comparing these systems to the predicted equilibrium under the CHA's current policy, we isolate the model's predicted effect. If we instead were to compare these alternative systems directly to the PIC data, any differences would combine the fact that our model does not perfectly fit the data with the policy effects of interest.

Table 6: Predicted Outcomes of Policy Scenarios, Tenant Characteristics

	Current CHA Priority	Low-Income Priority	High-Income Priority	Elderly Priority	Children Priority
Months on Waitlist at Move-In	26	11	13	26	25
Rent ($/month)	488	248	751	488	484
Household Income	19,537	9,911	30,021	19,535	19,375
% Area Median Income	27	14	41	27	27
Any Children (%)	25	26	24	25	28
Household Head Age Under 25 (%)	10	14	6	10	11
Household Head Age 25-50 (%)	22	23	21	22	22
Household Head Age 51-61 (%)	18	17	20	18	18
Household Head Elderly (%)	50	47	54	50	49
Household Head Disabled (%)	25	29	22	25	27
Household Head Black (%)	50	54	45	50	49
Household Head Hispanic (%)	10	9	12	10	10

Compared to the current CHA priority system, prioritizing Low-Income (below 30% AMI) applicants would dramatically change the characteristics of tenants. The starkest change would be a fall in the average tenant's income, from $19,537 to $9,911 (27% to 14% AMI). The average waiting time for a tenant also falls from 26 months to 11 months. This occurs because under Low-Income Priority, most tenants had high priority and hence were housed quickly. The effects on other tenant characteristics are smaller, largely driven by the correlation between those characteristics and household income. There is a slight increase in the fraction of African American headed and disabled households (50% to 54% and 25% to 29%, respectively), and a slight decrease in the fraction of elderly households (50% to 47%). High-Income Priority has symmetric effects in the other direction; the average tenant's income rises to $30,021, the fraction of elderly tenants rises, and the fraction of disabled and African American headed households falls. Disabled households are less likely to work than elderly households, and are therefore more likely to be housed under Low-Income Priority than under the current system, rising from 25% to 29%.

We next turn to the effects of giving additional priority to elderly/disabled applicants (Elderly Priority) and to applicants with children (Children Priority). One sees immediately in Table 6 that neither of these priority systems have much effect on the composition of the tenant population. This is driven partly by our preference estimates, but also, importantly, by the available bedroom sizes in the CHA public housing stock and by the decision to reserve certain developments for elderly and disabled households.

To understand why, consider the effects of prioritizing elderly/disabled households. These households are already the only applicants who can be admitted to elderly/disabled developments under the current priority system, so Elderly Priority should not substantially affect the composition of tenants in those buildings. Furthermore, our preference estimates imply that elderly/disabled households will never apply for general public housing; as a result, the characteristics of general public housing tenants will not change either, and since the effective opportunities for elderly/disabled applicants to be housed in general public housing do not change, they will apply for the same elderly/disabled developments as before. Also, recall that 98 percent of tenants in elderly/disabled developments reside in units with one bedroom or less; even when prioritized, they are ineligible for more than 80 percent of units in the general CHA developments. We therefore predict almost no change in the characteristics of elderly/disabled or general public housing residents.

We also predict very little change in tenant composition under Children Priority. This is perhaps more surprising because under Children Priority, we allow households with children to apply for elderly/disabled developments. However, the apartments in elderly/disabled developments are almost entirely studios and 1-bedrooms, while households with children qualify for units with at least 2 bedrooms. As a result, the fraction of households with children in elderly/disabled developments only increases from 7% to 10%. In general public housing, the fraction of households with children also barely increases because of a high predicted fraction (80%) under the current priority system. In other words, we predict that almost all 2- and 3-bedroom apartments were already occupied by households with children. Thus, the unit-composition of the CHA public housing stock itself is the limiting factor in admitting more households with children into public housing. This conclusion would be different if not all 2- and 3-bedroom units were already occupied by households with children. However, the effects of Children Priority would still be limited to the additional units households with children could occupy.

An important question is how these priority systems would affect the exposure of different types of public housing tenants to different types of neighborhoods. We saw in Table 4 that there is substantial variation in the poverty and minority rates of the census tracts in which general CHA developments are located (and similar patterns but slightly less variation exists for elderly developments). A priority system that concentrates certain types of tenant households (in terms of income or race/ethnicity, for example) in high-poverty or high-minority neighborhoods would raise concern.

Overall, the predicted effects of the different priority systems on neighborhood poverty and minority concentration are fairly small. Table 7 summarizes the tract poverty rate that the average public housing tenant is exposed to for different household characteristics. Compared to the current system, Low- and High-Income Priority would mainly affect the neighborhood poverty exposure of households based on their incomes. Under Low-Income Priority, while tenants with incomes below 30% of income are prioritized, this does not translate into living in lower poverty neighborhoods; their exposure to poverty actually increases slightly. But a much larger fraction of lowest-income tenants will now receive housing assistance. Tenants with incomes above 30% AMI who manage to get into public housing would tend to live in lower-poverty neighborhoods because they would mostly be admitted to elderly/disabled developments, which tend to be located in lower-poverty tracts. Symmetrically, under High-Income Priority, households with incomes below 30% AMI see lower tract poverty rates for the same reason. Notably, the effects on poverty exposure by household race/ethnicity, elderly/disabled status, or the presence of children are small. The effects of Elderly and Children Priority are almost zero for all types of households since the overall composition of tenants remains the same.

Table 7: Predicted Outcomes of Policy Scenarios, Tract Poverty Exposure

	Current Priority	Low-Income Priority	High-Income Priority	Elderly Priority	Children Priority
Any Children	17.8	17.7	17.8	17.8	17.7
Elderly Head/Spouse	11.8	11.8	11.9	11.8	11.8
Disabled Head/Spouse	13.0	12.9	13.1	13.0	13.0
African American Head	15.0	15.1	14.8	15.0	15.0
Hispanic Head	16.4	16.1	16.8	16.4	16.4
Income Below 30% AMI	15.1	15.4	11.7	15.1	15.1
Income 30-50% AMI	15.0	11.8	15.5	15.0	15.0
Income Above 50% AMI	15.3	12.1	15.8	15.3	15.3

Table 8: Predicted Outcomes of Policy Scenarios, Tract Minority Exposure

	Current Priority	Low-Income Priority	High-Income Priority	Elderly Priority	Children Priority
Any Children	52.8	52.6	53.0	52.8	52.5
Elderly Head/Spouse	32.8	32.7	32.8	32.8	32.7
Disabled Head/Spouse	35.0	34.8	35.3	35.2	35.0
African American Head	44.2	44.4	43.8	44.2	44.2
Hispanic Head	48.5	48.0	48.8	48.5	48.3
Income Below 30% AMI	44.1	45.1	34.8	44.1	44.1
Income 30-50% AMI	44.0	33.2	45.0	44.0	44.1
Income Above 50% AMI	45.6	33.7	46.6	45.6	45.6

We see similar patterns in terms of exposure to the share of minority residents in neighborhoods. Table 8 shows that Low- and High-Income Priorities affect the racial composition of the tracts tenants of different incomes are exposed to. Under Low-Income Priority, households with incomes above 30% AMI see lower tract minority rates (33% instead of about 45%), while households with incomes below 30% AMI see lower tract minority rates under High-Income Priority. Similar to poverty exposure, other tenant subgroups are unaffected along the minority exposure dimension, and Elderly and Children Priority have no effects at all.

Of course, these predicted outcomes are based on the modeling of one jurisdiction, with a given stock of public housing units of particular sizes and at one point in time. How changing allocation priorities or other features of the allocation system would affect who receives assistance will vary by context.

6 Conclusion

The results we present are preliminary and only apply to one jurisdiction. Nevertheless, they highlight the potential importance of priorities in allocating scarce housing assistance, one of several features of the allocation system over which local authorities have much discretion. The use of predicted outcomes under different policy scenarios also revealed the critical role of the units-size distribution of the public housing stock in driving who gets served, something within the policy control of local authorities but not necessarily as visible in terms of policy choices.

There are several features of the current modeling and empirical analysis that could be improved upon in future versions, thereby better predicting outcomes under alternative policy regimes. In particular:

- Exploiting household-level panel microdata on public housing tenants will allow us to model heterogeneity in the rates at which public housing tenants *exit* specific developments in the program. This is important because these exits generate vacant units that can be allocated to applicants on the waitlist. In other words, they determine supply.
- Many aspects of the preference model could be improved to better match the data. In particular, allowing preferences to depend more richly on household structure and demographics should enable our waitlist model to better match tenant characteristics.
- Incorporating the time lag between when a household submitted an application for public housing and when they are observed as tenants will also improve model fit and accuracy.
- Expanding the sample to a larger set of PHAs (approximately 30) to exploit the variation in settings and policies will provide richer insights that apply to a more diverse set of jurisdictions.

Finally, we hope to eventually obtain waitlist data directly from a set of PHAs in order to better understand how waiting lists actually work. This will allow us to estimate more realistic models of the waiting list process and ultimately provide better guidance for housing policymakers designing complex allocation systems.

A Additional Tables and Figures

Table A2: Parameter Estimates of Household Preferences

	Point Estimate
Fixed Parameter Values	
Annual Discount Factor	0.905
Attrition Rate	0.25
Application Window (Years)	5
Household Characteristics	
Household Head African American	2.51
Household Head Hispanic	0.13
Household Head Elderly	-4.07
Household Has Children	2.56
Household Head Disabled	-5.10
Household Income ($10,000)	-0.70
Household Fraction AMI	2.00
Interactions between Household and Development Characteristics	
Household Head African American * Development Size	-0.13
Household Head Elderly * Development Size	0.49
Household Has Children * Development Size	0.67
Household Fraction AMI * Development Size	1.11
Household Head African American * Tract Poverty Rate	-0.27
Household Head Elderly * Tract Poverty Rate	-1.08
Household Has Children * Tract Poverty Rate	0.05
Household Fraction AMI * Tract Poverty Rate	-0.11
Household Head African American * Tract Pct Minority	-1.50
Household Head Elderly * Tract Pct Minority	-2.70
Household Head Has Children * Tract Pct Minority	-1.62
Household Fraction AMI * Tract Pct Minority	-0.79
Household Head Elderly * Family Development	-7.13