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Targeting In-Kind Transfers through Market Design: A Revealed Preference Analysis of Public Housing Allocation†

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Public housing benefits are rationed through wait lists. Theoretical work on public housing allocation has debated how much choice applicants should have over units, identifying a possible trade-off between efficiency and redistribution. This paper empirically establishes the existence and economic importance of this trade-off using wait list data from Cambridge, Massachusetts. I estimate a model of public housing preferences in a setting where heterogeneous apartments are rationed through waiting time. Eliminating choice would improve targeting but reduce tenant welfare by more than 30 percent. Such a change is only justified on targeting grounds by a strong social preference for redistribution. (*JEL* D47, H75, I38, R38)

In the United States, more than one million low-income households live in public housing. Beneficiaries receive a permanent, place-based entitlement to a rent subsidy that often exceeds $10,000 per year. However, due to limited funding, assistance is rationed: in 2012, 1.6 million US households were on a public housing wait list (Collinson, Ellen, and Ludwig 2016). Given this scarcity, public housing authorities (PHAs) in each city use a wide variety of rules to allocate available apartments. Theoretical work on public housing allocation has debated how much choice applicants should have over their assigned units, identifying a possible trade-off between efficiency (maximizing the welfare gains for tenants) and redistribution (targeting the most economically disadvantaged applicants) (Arnosti and Shi 2020, Leshno 2019). Yet, there has been little empirical work quantifying how public housing wait list policies affect who receives benefits or how much beneficiaries value their assistance.

This paper empirically quantifies the trade-off between efficiency and redistribution in public housing allocation. I use wait list data from Cambridge, Massachusetts to estimate the distribution of preferences for public housing developments based on

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applicants' decisions while on the wait list. A central idea is that waiting time acts as a price; some applicants face a trade-off between waiting for less time and being assigned to their preferred housing development. In counterfactual simulations, the trade-off between efficiency and redistribution exists and is quantitatively significant. Eliminating choice would allocate housing to applicants with significantly worse outside options. However, the efficiency loss due to lower match quality is only justified on targeting grounds by a strong preference for income redistribution.

To gain intuition for how wait list design might affect efficiency and redistribution, imagine applying for public housing in New York City and Miami. In New York City, you are asked to choose your preferred housing development and wait until an appropriate apartment becomes available. In Miami, you are offered the first available apartment from any development when you reach the top of the wait list, and removed from the list if you decline. Theoretical work has argued that not allowing choice, as in Miami, leads to lower match quality because applicants must accept mismatched offers in order to be housed (Thakral 2016, Leshno 2019). However, not allowing choice has a potential benefit; it may improve targeting if applicants with unobservably better outside options are more likely to reject, self-selecting out of the application process and making room for more disadvantaged applicants (Arnosti and Shi 2020). The existence and magnitude of this trade-off depend on applicant preferences: how much applicants differ in where they want to live, how much they value assistance compared to their outside options, and sensitivity of their development choices to waiting time.

The first part of this paper develops a method to estimate applicant preferences using wait list data. The data, provided by the Cambridge Housing Authority (CHA), record which households applied for public housing in Cambridge, Massachusetts over a five-year period and contain rich development choice information. This provides a direct measure of which households expressed demand for assistance and their willingness to wait for specific developments.

To recover the distribution of preferences from applicant decisions, I build a structural model of application and development choice based on the structure of the CHA's allocation mechanism—hereafter, the Cambridge Mechanism. Since applicants choose their preferred housing development in two stages and receive new information about waiting time in the second stage, they face a portfolio choice problem (Chade and Smith 2006). Second-stage choices are responsive to new information, motivating a development choice model in which applicants know their preferences over housing developments but face waiting time uncertainty. They choose their preferred distributions of assignments and waiting times at each stage of the application process, given their current information.

Estimation proceeds in three steps. First, because applicants may be a selected sample of eligible households, I estimate the distribution of households eligible for CHA public housing using American Community Survey (ACS) data. Second, I construct applicants' beliefs about the distributions of assignments and waiting times. I assume that beliefs match the long-run stationary distribution of the Cambridge Mechanism generated by the empirical distribution of applicants and their decisions. This assumption allows me to construct beliefs from the output of a detailed simulation of the Cambridge Mechanism, using the data to estimate a lower-dimensional set of inputs. Finally, I estimate preference parameters by matching predicted choice patterns to those in the data using the method of simulated moments (McFadden 1989, Pakes and Pollard 1989).

I parameterize preferences in a way that captures the potential trade-off between efficiency and redistribution. Eligible households have a common discount factor, but heterogeneous preferences both for specific developments (*match values*) and for the aspects of public housing that are common across developments (*values of assistance*). The value of assistance is interpreted relative to a household's outside option. To motivate this decomposition and facilitate welfare analysis, I assume a utility model in which households have heterogeneous tastes for specific public housing developments and different levels of income outside of public housing. Importantly, part of the value of the household's outside option is not observed but affects their marginal utility of income. With restrictions on the functional form of utility, indirect utilities can be converted to equivalent variation.

The application data and structure of the Cambridge Mechanism provide crucial information about both dimensions of preference heterogeneity. Application rates by income and demographic groups are informative about differences in values of assistance. Because CHA applicants choose up to three developments in the first stage, initial choices reveal heterogeneity in tastes for specific development characteristics, including waiting time, as well as idiosyncratic tastes. Sensitivity of second-stage development choices to waiting time information allows me to estimate the discount factor in addition to the parameters governing flow payoffs. The moments used in estimation capture these features of application decisions and development choices.

Estimates show that applicants are patient and exhibit substantial heterogeneity in values of assistance and match values. While observed characteristics strongly predict the value of assistance, particularly income and race, the standard deviation of the unobservable among applicants is equivalent to more than $9,000 of annual income. Applicants also have strong preferences for specific developments, and as a result, some applicants are quite selective. One in six applicants would only be willing to live in three or fewer developments, while one in four prefers any development to their outside option. Applicants in the latter group have much lower observed incomes and unobservably worse outside options. In contrast, because applicants are patient, development choices provide little information about need. It may therefore be possible to increase redistribution by inducing rejections.

Using the estimated model, I predict equilibrium allocations in CHA public housing under two development choice systems: asking applicants to choose their preferred development when they first apply ("Choose One"), and fully eliminating choice ("No Choice"). These two choice systems are common in practice and respectively maximize match quality and targeting under certain conditions (Arnosti and Shi 2020). Under each policy, I solve for a fixed point between applicants' optimal decisions and their endogenously generated waiting time distributions, holding the public housing stock and other market primitives fixed.

Choice restrictions involve a dramatic trade-off between efficiency and redistribution. Under the current CHA priority system, moving from Choose One to No Choice targets assistance to applicants with 19 percent worse outside options. Meanwhile, the fraction of tenants living in their first-choice development falls from 58 to 9 percent, and equivalent variation per assigned unit falls by 35 percent. This trade-off persists if observed income is used to prioritize lower-income or higher-income applicants, as is done in several cities. However, choice restrictions are only justified on targeting grounds by a very strong preference for redistribution. I use a "constant relative inequality aversion" class of social welfare functions (Atkinson 1970) to compare allocation mechanisms across a range of values of redistribution. Under their current priority system, to justify eliminating choice the CHA would need to be willing to take \$8 from one household to transfer just \$1 to a household with half as much income. The CHA could achieve a similar increase in redistribution without lowering tenant values by prioritizing lower-income applicants while still allowing choice. Unless there is a large behavioral response to income-based priorities,[1] these results suggest that PHAs wishing to increase redistribution should first exploit observed characteristics through the priority system, and only remove choice as a last resort.

This paper contributes to the literatures on centralized matching markets, means-tested housing assistance, and in-kind transfers. The growing literature on revealed preference analysis of centralized matching markets has largely focused on static problems (Agarwal 2015; Abdulkadiroğlu, Agarwal, and Pathak 2017; He 2017; Agarwal and Somaini 2018; Fack, Grenet, and He 2019), with two notable exceptions: Agarwal et al. (2021) studies the allocation of deceased donor kidneys, and Verdier and Reeling (2020) studies the allocation of hunting licenses in Michigan. Both papers use dynamic discrete choice estimation techniques, whereas I study a portfolio choice problem.

This paper also contributes to the literature on means-tested housing assistance by using individual-level wait list data to estimate demand for public housing. Previous work has used data on assignments for this purpose (Geyer and Sieg 2013, Van Ommeren and Van der Vlist 2016, Sieg and Yoon 2020). Other empirical work has argued that there is substantial misallocation in the public and rent-controlled housing sectors (Glaeser and Luttmer 2003, Thakral 2016). A complementary literature evaluates the causal effects of housing assistance on economic and health outcomes (Kling, Liebman, and Katz 2007; Ludwig et al. 2013; Chetty, Hendren, and Katz 2015; Humphries et al. 2018; Collinson and Reed 2019; van Dijk 2019).

The market design trade-off between match quality and targeting has been studied in the theoretical literature on one-sided dynamic assignment (Thakral 2016, Bloch and Cantala 2017, Leshno 2019, Arnosti and Shi 2020). Arnosti and Shi (2020) shows that the relationship between match quality and total welfare depends qualitatively on the distribution of agent preferences. A related literature on the targeting of public assistance has highlighted the tension between providing valuable assistance to those who receive it and restricting assistance to the households that need it most (Akerlof 1978, Nichols and Zeckhauser 1982). Several recent papers empirically study this trade-off in the context of means-tested transfer programs of homogeneous benefits (Alatas et al. 2016, Deshpande and Li 2019, Finkelstein and Notowidigdo 2019, Lieber and Lockwood 2019).

The rest of the paper is organized as follows. Section I provides institutional background and describes the CHA dataset. Section II presents descriptive facts

[1] To my knowledge, there is no evidence on behavioral responses to changes in a priority system in a dynamic matching mechanism, and the data and setting here were not suitable to provide evidence.

that motivate a model of development choice and a microfoundation of preferences, presented in Section III. Section IV describes the parametric model and the estimation procedure used to recover the distribution of preferences for public housing developments. Section V presents the estimation results, and Section VI analyzes the effects of alternative choice and priority systems. Section VII concludes.

I. Institutional Background and Data

Section IA provides an overview of the US public housing program, surveys allocation policies used in practice, and discusses design trade-offs. Section IB describes the CHA and the mechanism it used to allocate public housing during the period of study. Section IC describes the applicant dataset and sample criteria.

A. *Public Housing in the United States*

The US public housing program subsidizes the rents of 1.2 million low-income households at an annual cost of $8–10 billion. A PHA in each city maintains the stock of public housing developments located in its jurisdiction using funds allocated by Congress and distributed by the US Department of Housing and Urban Development (HUD). A public housing tenant pays 30 percent of pretax income toward rent, and is entitled to assistance as long as they meet the continued eligibility requirements, remain in their assigned apartment, and comply with other lease terms. Public housing and its private market counterpart, the Housing Choice Voucher program, are unusual in their benefit generosity: in 2013, participants received an average annual subsidy of $8,000 (US Department of Housing and Urban Development 2015).[2]

Due to the combination of limited federal funding, generous per-household benefits, and broad eligibility criteria, demand for public housing greatly exceeds supply. Congress does not set funding levels to assist all eligible households, but rather to maintain existing services. New public housing is not being built.[3] The income limit for eligibility is 80 percent of area median income (AMI), a regional income measure adjusted for household size, which includes lower-middle income households as well as the very poorest (US Department of Housing and Urban Development 2016). As a result, in 2012 there were approximately 1.6 million households on public housing wait lists nationwide, and nearly 3 million applicants on voucher wait lists (Public and Affordable Housing Research Corporation 2015).

Public Housing Allocation Mechanisms and Design Trade-Offs.—The limited supply of public housing creates a dynamic assignment problem for each PHA. When tenants move out, the PHA must assign vacant apartments to applicants on a wait list. PHAs have substantial autonomy over allocation policy, including whether applicants may choose their assigned developments and how applicants are ordered on the wait list. I call these policy levers the *development choice system* and the *priority*

[2] Based on per-household subsidy from tenant-based vouchers reported in HUD Congressional Justification for Fiscal Year 2015. Public housing serves a population with similar incomes.

[3] The majority of new affordable housing is built through the Low-Income Housing Tax Credit (LIHTC), a federal tax expenditure that subsidizes private sector construction of new affordable housing. LIHTC tenants with very low incomes receive a smaller effective rent subsidy than they would in public housing.

system, respectively. To my knowledge, no resource systematically documents the wait list policies of the 3,300 US PHAs. I examined administrative plans of 24 PHAs falling into two categories: (i) those with the largest public housing stocks, and (ii) those similar to Cambridge, Massachusetts in terms of public housing stock and city population. The development choice and priority systems used by these PHAs are summarized in online Appendix Table 8.

The allocation policies of surveyed PHAs share several common features. Applicants are ordered by priority and then by date of application. If an applicant rejects an offer without good cause, they are removed from the list, though some PHAs allow one or two rejections prior to removal. Applicants living or working in the jurisdiction have priority over other applicants. There are also federally mandated priorities, such as for veterans and natural disaster victims, that affect relatively few applicants.

Despite these similarities, existing choice and priority systems exhibit important differences. The key difference across priority systems is whether households with higher or lower socioeconomic status receive priority. Some PHAs, including those in New York City and Los Angeles, prioritize households that have a working member, are economically self-sufficient, or have incomes above 30 percent of AMI. Others do the opposite: the Seattle Housing Authority prioritizes households below 30 percent of AMI, and several PHAs prioritize households that are severely rent burdened or at risk of being displaced. One goal of the empirical exercise is to quantify how strongly observed characteristics predict need, and whether the priority or development choice system more effectively improves targeting.

The range of development choice systems is equally wide. Several PHAs, including those in New York City, Seattle, New Haven, and Cambridge, require applicants to choose a limited number of developments (Limited Choice). Systems allowing choice tend to achieve good match quality because applicants with the highest values of oversubscribed developments are more likely to apply for and occupy them. Other PHAs do not allow applicants any choice over their assignment (No Choice), including large cities such as Miami, Los Angeles, and Minneapolis.[4]

For No Choice to improve targeting relative to Limited Choice, the decision to reject a random offer must screen out more low-need applicants than the choice of how long to wait under Limited Choice. If all applicants would accept any public housing offer, then No Choice offers no targeting benefit. Allowing choice may achieve better match quality *and* targeting if high-need applicants choose developments with shorter waiting times, increasing the probability they are eventually housed. The existence and magnitude of the trade-off between efficiency and redistribution therefore depend on waiting time differences across developments, the correlation between applicants' chosen waiting times and levels of need, the rate at which applicants depart the wait list, and the correlation between need and the decision to reject a random offer.

[4] Other PHAs use intermediate systems. For example, Chicago allows applicants to select a neighborhood but not a specific development, while in Boston, applicants may choose any subset of developments, providing the option to hedge against waiting time uncertainty. Online Appendix Table 16 presents results from simulations of these intermediate choice systems and finds that they produce intermediate allocations in terms of efficiency and redistribution.

B. *The Cambridge Housing Authority and Cambridge Mechanism*

The CHA administers the Public Housing and Housing Choice Voucher programs in Cambridge, Massachusetts.[5] During the period of study—January 1, 2010 to December 31, 2014—the CHA maintained about 2,450 public housing units, with half reserved for elderly or disabled applicants (Cambridge Housing Authority 2007). The wait list for vouchers was closed from 2008 until 2016, while public housing wait lists were open from 2008 until 2015. For this reason, I study the public housing program in isolation.

In the Cambridge Mechanism, applicants select their preferred development in a two-stage process.[6] Each development is a building, complex, or collection of apartments in a distinct geographic location. Apartments with the same number of bedrooms are mostly homogeneous within a development. All applicants with a household member living or working in Cambridge receive equal priority. At initial application, a household is assigned a program (Elderly/Disabled or Family) and bedroom size and makes an initial choice of up to 3 developments from between 9 and 13 alternatives. The initial choice forms the applicant's choice set later on, and the applicant is placed on a wait list for each chosen development. At a later date, the CHA sends the applicant a letter asking them to make a final development choice. The letter informs the applicant of their current position on each list in their choice set. After making their final choice, the applicant remains on the wait list for that development until the CHA makes a single, take-it-or-leave-it offer of an apartment. If the applicant rejects, they are removed from the wait list and cannot reapply for one year. The applicant may also be removed if they fail to attend a screening appointment, produce required documentation, or respond to mail from the CHA. Online Appendix C.2 provides a formal description of the Cambridge Mechanism, including when the CHA sends final choice letters and how it calculates list position.

The two stages of choice in the Cambridge Mechanism differ from the one-stage development choice systems used by many other PHAs.[7] Sections III and IV carefully model the two stages of choice in the Cambridge Mechanism in order to recover the correct market primitives. However, theory suggests that the number of stages of choice is not fundamental to the trade-off between efficiency and redistribution in wait list design (Arnosti and Shi 2020). Instead, the key feature of the Cambridge Mechanism is that applicants must commit to one development.

[5] Although Cambridge has a low poverty rate compared to other US cities, its public housing residents are comparable to those nationwide in terms of socioeconomic status and demographics. In 2014, 74 percent of Cambridge public housing tenants earned less than 30 percent AMI and 48 percent were headed by an African American, compared to 72 percent and 48 percent nationwide.

[6] Every year, each housing authority is required to publish an Admissions and Continued Occupancy Policy (ACOP). The following description is based on the CHA's 2014 ACOP as well as conversations with several CHA employees.

[7] The New York City Housing Authority, which administers 15 percent of the nation's public housing stock, uses a similar two-stage development choice system. Applicants first choose a preferred borough, and later choose their preferred development from a subset of the developments in that borough.

C. *Data and Sample Selection*

The main dataset used in this study contains anonymized records of all CHA public housing applicants on the wait list between October 1, 2009 and February 26, 2016. The CHA maintains a database of applicants to manage operations and comply with HUD regulations. For each applicant, the dataset records household characteristics, development choices, and the timing and outcome of events during the application process.

I restrict the analysis sample to applicants who had priority for Cambridge public housing; who applied for two- and three-bedroom apartments in the Family Public Housing program; and who submitted an application between 2010 and 2014. Applicants without priority had virtually no chance of being housed. Family Public Housing applicants are a more homogeneous group than Elderly/Disabled applicants. I restrict to two- and three-bedroom apartments because within Family Public Housing, there are few apartments of and applicants for other bedroom sizes. Analyzing new applications between 2010 and 2014 avoids selection issues because not all pre-2010 applicants were still on the wait list in 2010. After omitting a small number of irregular applications, 1,725 applicants remain.

To estimate the distribution of households that could have applied during the sample period, I augment the CHA dataset with a sample of likely eligible households from the ACS (US Census Bureau 2010–2014). I also use data provided by the CHA on Cambridge public housing tenants between 2012 and 2014. Online Appendix A provides details of the CHA and ACS datasets, and Section IVA explains how they are used to estimate the distribution of potential applicants.

Online Appendix Table 11 shows that relatively few households reach the later stages of the Cambridge Mechanism due to the five-year sample window and heavy attrition from the wait list. Of the 1,725 applicants, 573 made a final choice and only 163 applicants in the sample received an offer of housing before the end of 2014. Since almost all offers of housing were accepted, my empirical strategy focuses on the 6,818 eligible households, the 1,725 applicants who made an initial choice, and the 573 who made a final choice.

II. Descriptive Evidence

This section presents descriptive statistics of Cambridge public housing developments, applicants, and their development choices. These patterns suggest that applicants have heterogeneous preferences for public housing developments, and that their choices are sensitive to waiting time information.

A. *Cambridge Public Housing Developments*

Applicants for Family Public Housing in Cambridge chose among up to 13 developments that differ primarily in size, location, and expected waiting time. The location of each development is shown in online Appendix Figure 3. There are three developments in East Cambridge, three in North Cambridge, and seven near Central Square. Table 1 presents other characteristics of these developments. The smallest developments contain just a few apartments that blend in with the

Table 1—Characteristics of Family Public Housing Developments

List name	Mean waiting time (years)	No. housed applicants	No. units	Neighborhood	Tenant income ($)	% Black tenants	Applicant income ($)
Roosevelt Mid-Rise	1.58	18	77	East	18,258	42	13,930
Woodrow Wilson	1.98	2	68	Central	20,380	73	15,662
Jefferson Park	2.16	62	284	North	27,454	62	16,025
Newtowne Court	2.33	95	268	Central	24,132	63	16,619
Washington Elms	2.92	26	175	Central	32,198	62	16,237
Putnam Gardens	2.98	36	122	Central	22,864	61	16,896
Corcoran Park	3.05	45	153	North	26,605	65	17,923
Scattered	3.52	11	88	N/A	25,269	61	17,064
Roosevelt Low-Rise	3.55	21	124	East	28,906	63	18,040
Lincoln Way	3.72	2	70	North	32,360	62	17,960
Jackson Gardens	3.75	9	45	Central	21,593	48	17,322

Notes: Characteristics of CHA Family Public Housing developments available between 2010 and 2014. Mean waiting time is the mean waiting time for applicants who were housed during the sample period. Tenant characteristics reflect active tenant certifications on January 1, 2014. Applicant characteristics reflect all applicants who selected the list as an initial choice. The scattered list aggregates three lists: Mid-Cambridge, East Cambridge, and River Howard Homes.

surrounding housing stock,[8] while the largest developments are complexes of several buildings containing hundreds of apartments. Average waiting times for housed applicants range from 1.58 to 3.75 years across developments, with smaller developments tending to have longer waits. Some applicants therefore faced a trade-off between their preferred assignment and a shorter expected wait. Tenant characteristics, such as income and racial/ethnic composition, are fairly similar across developments.[9]

B. *Application Decisions and Initial Development Choices*

Eligible households who would be expected to have higher values of public housing relative to their outside options are more likely to apply. The first two columns of Table 2 show that only one in four eligible households applied for Cambridge public housing during the sample period. The average income of eligible households is $42,308, while that of applicants is $18,465. This is not surprising; since rent is 30 percent of pretax income, lower-income households receive a larger effective subsidy from public housing. Differences by race are also striking: half of applicant households are headed by an African American, while only one in five eligible households are. Despite these strong correlations, online Appendix Figure 4 shows that some of the lowest-income eligible households did not apply, while some higher-income households did. Similarly, more than one in four eligible households headed by an African American did not apply.

[8] The scattered wait list represents three lists: one for scattered sites in Mid-Cambridge (Central), one for East Cambridge, and one for River Howard Homes (Central). In July 2013, the CHA combined Mid-Cambridge, River Howard Homes, and Woodrow Wilson with Putnam Gardens, and also combined East Cambridge with Roosevelt Low-Rise. Only Putnam Gardens and Roosevelt Low-Rise were options thereafter, reflecting units from the combined lists.

[9] There are outliers. Roosevelt Mid-Rise has an unusually low average tenant income and a small fraction of African American tenants. This is because it is a mixed development, with some apartments for Elderly and Disabled households. Its tenants are older, and as a result have lower incomes and are more likely to be White.

Table 2—Characteristics of Eligible and Applicant Households

	All		By year of initial application				
	Eligible	Applied	2010	2011	2012	2013	2014
Number of applicants	6,818	1,725	187	417	404	368	346
Income ($)	42,308	18,465	16,994	18,030	18,730	18,149	19,834
2 bedrooms (%)	76.3	69.2	67.4	67.9	69.6	68.2	72.5
3 bedrooms (%)	23.4	29.7	27.8	30.5	30.0	31.8	27.2
Lives in Cambridge (%)	42.9	57.2	61.5	55.2	62.1	52.4	56.9
Works in Cambridge (%)	60.5	40.1	29.9	37.2	40.1	44.8	44.2
Age youngest member	10.5	8.5	8.9	8.1	8.0	8.8	9.1
Age oldest member	40.0	36.6	34.5	35.7	36.4	37.7	37.7
Number of children	1.26	1.27	1.22	1.40	1.28	1.24	1.16
Child under 10 (%)	60.9	60.9	56.1	57.1	63.4	62.0	64.7
Household head White (%)	55.8	36.1	36.9	32.6	38.4	38.6	34.4
Household head Black (%)	19.6	50.4	56.7	54.2	47.8	47.0	49.1
Household head Hispanic (%)	17.9	19.3	16.6	20.6	17.3	20.9	19.9

Notes: The applicant sample consists of Family two- and three-bedroom priority applicants who made their initial development choices between 2010 and 2014. Application date is defined as the first date an applicant appears on a wait list in the status log. Family Public Housing wait lists were closed during the second and third quarters of 2010. The eligible population is estimated using the 2010–2014 ACS. Households already living in Cambridge public housing, as well as households that applied before 2010 and were still on the wait list during the sample period, are not counted as eligible.

The remaining columns of Table 2 show that most applicant characteristics are stable over time. However, there are a couple of moderate trends. The annual rate of new applications fell from 417 in 2011 to 346 in 2014.[10] Over time, new applicants had higher incomes and were more likely to work in Cambridge, consistent with improving local economic conditions. Though only one in four eligible households applied for public housing during the sample period, there were five new applicants for each of the 318 applicants who were housed. Demand greatly exceeded supply in this market.[11]

Initial development choices are consistent with heterogeneity in tastes for specific developments and overall selectivity. The first row of Table 3 shows that the majority of applicants (85 percent) exhaust their initial choice set and select 3 housing developments. This rate is lower for applicants with incomes over $32,000 (panel A): only 79 percent select 3 lists, compared to 86 percent for lower-income applicants. Higher-income applicants also select developments with slightly longer average waiting times. Both patterns are consistent with better outside options leading higher-income applicants to be more selective. Applicants that already live in Cambridge are more likely to select developments in their own neighborhoods (panel B).

[10] The CHA closed its Family Public Housing wait lists during the second and third quarters of 2010. As a result, 2010 saw fewer new applications than subsequent years.

[11] The number of vacancies is below the long-run average because the CHA began renovating its public housing stock during the sample period. For a plausible upper bound on the long-run average, an annual turnover rate of 10 percent per unit would raise the expected number of vacancies to 540 over a 5 year period.

Table 3—Initial Development Choices

Subgroup	Number of applicants	Selectivity: 2 initial choices (%)	Selectivity: 3 initial choices (%)	Selectivity: Mean waiting time (years)	Selectivity: Number of units	Location: No. Central Cambridge	Location: No. East Cambridge	Location: No. North Cambridge
All	1725	12.1	84.6	2.89	145	1.50	0.52	0.79
Panel A. Household income								
\$0–\$8,000	467	11.1	85.2	2.86	149	1.50	0.53	0.79
\$8,000–\$16,000	411	10.9	86.1	2.88	145	1.52	0.54	0.77
\$16,000–\$32,000	553	10.8	85.9	2.89	145	1.50	0.50	0.82
Over \$32,000	294	17.7	78.9	2.98	141	1.50	0.49	0.77
Panel B. Neighborhood of current residence								
Central Cambridge	517	10.1	86.7	2.90	140	1.69	0.51	0.63
East Cambridge	132	12.1	85.6	2.94	137	1.48	0.89	0.47
North Cambridge	338	19.2	77.2	2.93	147	1.26	0.37	1.11
Outside Cambridge	738	10.3	86.3	2.87	150	1.49	0.52	0.82

Notes: Initial choice characteristics are first averaged across each applicant's chosen developments, and then averaged across applicants. Sample is family two- and three-bedroom priority applicants who made their initial choices between 2010 and 2014. Neighborhood is based on the zip code of the applicant's contact address. East contains zip codes 02141 and 02142; Central contains 02139; North contains 02138 and 02140; and Outside Cambridge contains all other zip codes.

C. *Response to Waiting Time Information*

This section presents evidence that applicant choices are sensitive to information about waiting time. Between 2010 and 2014, the CHA sent final choice letters to applicants who were near the top of the list for one of their initial choice developments. The letter informed applicants of their position on each list and asked them to make a final development choice. Fluctuations in relative list lengths over time and the CHA's algorithm for calculating list position and sending final choice letters caused applicants who made the same initial development choices but applied on different dates to receive different position information.

I test the null hypothesis of no response to waiting time information by running a conditional logistic regression that predicts an applicant's final choice as a function of list position or expected continued waiting time. The sample is applicants who made a final choice during the period of study. Since each applicant's choice set is determined by their initial choice, I include as controls fixed effects for the interaction between each development and choice set. This isolates the natural experiment in which applicants who made the same initial choices—and whose development preferences are therefore drawn from the same distribution—receive different waiting time information for the same alternatives. In this specification, choice probabilities are

$$\Pr(j \mid C_i) = \frac{\exp\{\beta x_{ij} + \xi_{j,C_i}\}}{\sum_{k \in C_i} \exp\{\beta x_{ik} + \xi_{k,C_i}\}}, \tag{1}$$

where C_i is applicant i's set of initially chosen developments, conditioning on bedroom size; x_{ij} is the position number or expected continued waiting time for development j; and ξ_{j,C_i} is a fixed effect for the interaction between development j and initial choice C_i.

TABLE 4—FINAL DEVELOPMENT CHOICE

	No controls		Development controls		Choice set controls	
	(1)	(2)	(3)	(4)	(5)	(6)
Position on waiting list	−0.0186		−0.0206		−0.0299	
	(0.0032)		(0.0037)		(0.0065)	
Expected waiting time (years)		−0.265		−4.031		−5.411
		(0.289)		(0.755)		(1.335)
Development fixed effects			X	X		
Development choice set fixed effects					X	X
Implied own-price elasticity	−0.707	−0.121	−0.817	−3.270	−1.332	−4.136
	(0.149)	(0.145)	(0.182)	(0.637)	(6.486)	(1.946)
Observations	573	573	573	573	343	343

Notes: Estimates from a conditional logistic regression of final development choice on waiting time information from the applicant's final choice letter. The sample consists of applicants who made a final development choice between 2010 and 2014. List position is calculated for each applicant/list on the date the CHA sent the final choice letter. Continued waiting time is estimated from realized waiting times after applicants made their final choices. Columns 1 and 2 have no controls. Columns 3 and 4 include fixed effects for each development. Columns 5 and 6 include as fixed effects a full set of interactions between the development and the applicant's choice set.

Table 4 presents coefficient estimates and implied elasticities from specifications with no controls; with development fixed effects; and with the full set of development and choice set interactions. The coefficient estimates consistently show a strong negative response to list position and continued waiting time. The response grows stronger with additional controls: with full controls, the elasticity of final choice is -1.3 with respect to list position and -4.1 with respect to continued waiting time.

Two conditions are sufficient for position information to be uncorrelated with development preferences among applicants with the same choice set who made a final choice. The first is that the development preferences of applicants who applied on different dates but made the same initial choice are drawn from the same distribution. Since waiting time fluctuations are determined by randomness in when apartments become vacant and the decisions of other applicants, these fluctuations are difficult to predict or influence. The second condition is that response to the final choice letter is uncorrelated with the specific information in the letter, conditional on the elapsed time since application. This will be true if applicants become unresponsive for exogenous reasons. Online Appendix B shows that applicants' initial choices are not predicted by list lengths on the specific date they applied, and that their observable characteristics are not predicted by the information they receive in the final choice stage.

III. Model of Preferences and Development Choice

Section IIIA presents a development choice model that predicts how eligible households behave at each stage of the Cambridge Mechanism given their preferences and information. This model is sufficient for positive analysis of alternative wait list policies. To quantify welfare and distributional impacts, Section IIIB provides a microfoundation of preferences that links development preferences to households' marginal utilities of income.

A. *Development Choice Model*

The development choice model provides a rational benchmark through which to interpret the application decisions of eligible households and development choices of applicants. It captures the trade-off between spending less time on the wait list and being assigned to a preferred housing development.

In the model, an applicant solves a single-agent problem taking the strategies of other applicants as given. The applicant enjoys flow indirect utility depending on where they live—outside of public housing, or in a specific public housing development—and discounts future payoffs. They face waiting time uncertainty because they do not know exactly who is on the wait list or how it will evolve in the future. The applicant forms beliefs about the joint distribution of assignments and waiting times given the structure of the Cambridge Mechanism, and chooses their preferred distribution at each stage of the application process, updating their beliefs given position information in the second stage.

The following sections specify the sequence of decisions, payoffs, information and beliefs about how choices affect future states, and the resulting portfolio choice problem.

Sequence and Timing of Decisions.—An eligible household, indexed by i, makes decisions in the following sequence:

(i) *Application Decision*: i receives the opportunity to apply on a random date.

(ii) *Initial Choice*: If i applies, they immediately choose up to three developments, denoted $C \subset \{1, \ldots, J\}$ with $|C| \leq 3$. These developments form i's choice set in the final choice stage, and i is placed on a wait list for each development $j \in C$.

(iii) *Final Choice*: After s years have elapsed, i learns their wait list positions $\mathbf{p} \equiv \{p_j\}_{j \in C}$ and makes a final choice $f \in C$. If i chooses f, they remain on the wait list until receiving a take-it-or-leave-it apartment offer in f.[12]

Applicant i may become unresponsive while on the wait list, and is removed from the wait list if this occurs. I assume that attrition is exogenous to the model; that an applicant cannot anticipate the date they will be removed; and that removal occurs at a Poisson rate α that is equal across applicants.[13] Applicants may not fully anticipate

[12] In principle, the applicant also decides whether to accept their offer of housing. In the model presented here, an applicant will always accept an offer from the Cambridge Mechanism because it is never optimal to choose a development that is worse than their outside option in the final choice stage, and apartments are homogeneous within a development. Rejections are rare in the CHA data.

[13] This model of applicant attrition is consistent with the evidence in the CHA dataset. After controlling for time since initial application, attrition is not predicted by initial choices (which should reflect applicant preferences)

the possibility of attrition, and have a subjective attrition probability $\tilde{\alpha} \leq \alpha$. This allows an applicant's effective discount rate to be lower than the rate of attrition.

Preferences over Assignments and Waiting Times.—Household i receives a payoff that is realized continuously over time and depends on where they live. Specifically, i's per-period flow indirect utility from living in development j is v_{ij}, and their flow indirect utility from not living in Cambridge public housing is v_{i0}. I will refer to these flow indirect utilities as flow payoffs. Assignments are believed to be permanent, and anticipated flow payoffs are not time dependent. This rules out learning about characteristics of the developments over time or changing household circumstances. When making development choices, the household discounts future payoffs at exponential rate $\rho = r + \tilde{\alpha}$. This includes both the household's rate of time preference r, and beliefs about the exogenous attrition rate $\tilde{\alpha}$. There is no direct cost of remaining on the wait list, and no fixed cost of beginning or continuing the application process.[14] The present discounted value to i of being assigned to development j in t years is

$$e^{-\rho t}\frac{1}{\rho}\left(v_{ij} - v_{i0}\right). \tag{2}$$

Applicant Information and Beliefs.—An applicant's optimal initial and final choices will depend on their beliefs about how each possible choice affects the joint distribution of assignments and continued waiting times. Based on institutional features of the Cambridge Mechanism as well as descriptive evidence, I assume that applicants do not know the exact state of the queue when they first apply, but update their beliefs based on the position information in their final choice letters.[15] Applicant i makes their initial choice with beliefs about the likely date s and position information $\mathbf{p}$ of the final choice, whose joint distribution depends on i's initial choice. Let $G_C(s, \mathbf{p})$ denote the probability that the final choice letter is sent less than s years after initial application and that the applicant's list position is no greater than p_j for each development $j \in C$. At the final choice stage, s and $\mathbf{p}$ are realized, and i updates their beliefs about the continued waiting time for each development $j \in C$. Let $F_{j,C}(t \mid \mathbf{p})$ denote the probability that continued waiting time for list $j \in C$ is less than t years given position vector $\mathbf{p}$. Importantly, these distributions depend on the full set of initial choice lists C. Due to the algorithm by which the CHA sent out final choice letters, described in online Appendix C.2, the full set of lists in C could affect the date and information at the final choice stage. Furthermore, because applicants make their final choices based on new position information, the full set of list positions $\mathbf{p}$ may be informative about the expected continued waiting time for each development $j \in C$.

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or the waiting time information in applicants' final choice letters (which should affect the value of continuing the application process). Details available upon request.

[14] Estimating an application cost would require exogenous variation in either the value of the application process or the cost of applying. Unfortunately, neither source of variation was available in the CHA dataset.

[15] Online Appendix B presents evidence that applicants are unaware of short- and medium-term fluctuations in list lengths when they make their initial choices. This finding is also consistent with the information they are given at initial application, and with conversations with the CHA. CHA staff knew which developments had longer waiting times than others but were unaware of fluctuations in the lengths of particular lists.

Choice Problem.—Given beliefs and payoffs, an applicant solves the two-stage development choice problem backwards. In the final choice stage, applicant i with initial choice C learns their list positions $\mathbf{p}$ and solves

$$\max_{j \in C} \int \frac{1}{\rho} e^{-\rho T_j} \big(v_{ij} - v_{i0}\big)\, dF_{j,C}\big(T_j \,|\, \mathbf{p}\big). \tag{3}$$

Applicant i's initial choice maximizes the expected discounted value of the final choice:

$$\max_{C \in \{0,1,\ldots,J\}^3} \int e^{-\rho S} \max_{j \in C} \left[\int \frac{1}{\rho} e^{-\rho T_j} \big(v_{ij} - v_{i0}\big)\, dF_{j,C}\big(T_j \,|\, \mathbf{P}\big) \right] dG_C\big(S, \mathbf{P}\big). \tag{4}$$

Since there is no direct cost of applying or remaining on the wait list, an eligible household applies for public housing if and only if some development is preferred to their outside option: $\max_j v_{ij} > v_{i0}$. An applicant will also continue the application process unless they depart for exogenous reasons. As a result, counterfactual mechanisms will affect development choices and waiting times, but not which households apply or when they would depart before being offered an apartment.

The development choice model above and the beliefs model in Section IVB assume applicants are sophisticated and fully account for the complexity of the portfolio choice problem and wait list dynamics in the Cambridge Mechanism. To assess robustness to these assumptions, online Appendix D presents results from three alternative models in which applicants are less sophisticated or have different beliefs. The qualitative trade-offs between efficiency and redistribution are the same as under the model presented in the main text. Equations (2)–(4) also abstract away from changes in applicants' preferences or household circumstances, such as income or family structure, after they make their development choices. One may interpret the flow payoffs defined above as expected payoffs that incorporate an applicant's beliefs at the time of their decision about possible changes. The key assumption is that these beliefs, and therefore preferences, are similar at the initial and final choice stages.

B. *Microfoundation of Flow Payoffs*

Development choices reveal the distribution of flow indirect utilities $\mathbf{v}_i = \big(v_{i1} - v_{i0}, \ldots, v_{iJ} - v_{i0}\big)$. This section provides a microfoundation for these payoffs in order to compare changes in utility to the value of cash transfers. In estimation, I add a restriction on the functional form of utility to parameterize the distribution of v_i and obtain a measure of equivalent variation for welfare analysis.

Household i receives utility from consumption of housing h and a numeraire c. The utility function is additively separable in the two goods:

$$u(c,h) = u_1(c) + u_2(h).$$

Both u_1 and u_2 are strictly increasing, concave functions. The household has three characteristics: observed income y_i; unobserved income η_i; and development-specific preferences summarized by hedonic indices $\mathbf{h}_i = \big(h_{i1}, \ldots, h_{iJ}\big)$. Outside of public housing, a household chooses how much to spend on each good given its budget $y_i + \eta_i$. The prices of both goods are normalized to 1. The household's flow indirect utility from its outside option is

$$v_{i0} \equiv \max_{c,h} u_1(c) + u_2(h) \tag{5}$$

$$= v_0(y_i + \eta_i), \tag{6}$$

subject to

$$c + h \leq y_i + \eta_i.$$

One can think of unobserved income as capturing resources that relax or tighten the household's budget constraint, shifting the value of their outside option. An extensive literature has shown that social ties and alternative living arrangements are important economic resources for many low-income households (Stack 1974, Desmond and An 2015). By modeling these resources as part of the budget constraint, I assume that they are substitutable between housing and the numeraire.

In public housing, i only has access to observed income y_i. If assigned to development j, i pays a fixed fraction τ (30 percent) of observed income in rent, spends the rest on the numeraire, and enjoys housing consumption h_{ij}. The flow indirect utility from living in development j is

$$v_{ij} \equiv u_1((1-\tau)y_i) + u_2(h_{ij}). \tag{7}$$

The difference in flow payoffs is given by

$$v_{ij} - v_{i0} = \underbrace{u_1((1-\tau)y_i) - \overbrace{v_0(y_i + \eta_i)}^{\text{outside option}}}_{\text{value of assistance}} + \underbrace{u_2(h_{ij})}_{\text{match value}}. \tag{8}$$

This expression decomposes the difference in flow payoffs into two components: the household's value of assistance and its match value. The value of assistance is common across developments and depends only on household i's observed and unobserved income. It can be thought of as the household's value of the homogeneous aspects of Cambridge public housing. In estimation, the value of assistance will also be allowed to depend on demographic variables such as race/ethnicity and household size. The match value depends on i's taste for the characteristics of development j; it comes from the heterogeneous nature of public housing. These two terms capture the mechanism design trade-off between providing better match quality for housed applicants and housing applicants who want public housing the most. A mechanism that does not allow choice may induce low-value applicants to reject mismatched offers. If this occurs, more high-value applicants will be housed, with the potential cost that tenants enjoy lower match values. In the empirical specification, values of assistance are highly—though imperfectly—correlated with marginal utilities of income.

This utility model embeds two key assumptions. First, utility is additively separable in housing and the numeraire. This rules out complementarity between housing and nonhousing consumption and assumes that the match quality a tenant enjoys from their apartment does not affect the value of consuming other goods. Second, unobserved income is only available outside of public housing, where it is substitutable between housing and the numeraire. This implies that unobserved differences in the value of assistance are driven by outside options rather than the value of public housing itself, and that households with the highest values of assistance also have the highest marginal utilities of income.[16] This assumption has the attractive feature that it maximizes the ability of the development choice system to reveal a household's level of need. Therefore, the targeting gains from removing choice in Section VI are likely an upper bound on what would actually be achieved. The finding that removing choice can only be justified by a very high value of income redistribution would be strengthened if choice behavior were less strongly correlated with a household's marginal utility of income.

IV. Empirical Strategy

This section describes the three steps in estimation. The first step (Section IVA) estimates the distribution of potential applicants, including eligible households who did not apply. The second step (Section IVB) estimates applicants' beliefs about how their choices affect the joint distribution of assignments and waiting times. The third step (Section IVC) estimates preferences over assignments and waiting times by matching application decisions and development choices using the method of simulated moments, taking beliefs and the distribution of potential applicants as inputs (McFadden 1989, Pakes and Pollard 1989). Additional estimation details are provided in online Appendix C. Finally, Section IVD converts estimates from the utility model to equivalent variation.

By constructing waiting time distributions in a first step and estimating the preference parameters in a second step, the estimation procedure avoids computing equilibria of the Cambridge Mechanism. This feature is shared by many estimators used for models of dynamic decision making and dynamic games (Rust 1987; Hotz and Miller 1993; Bajari, Benkard, and Levin 2007). While a "full-solution" approach that solves for a fixed point between applicants' optimal decisions and their implied waiting time distributions given preference parameters would have better efficiency properties (Aguirregabiria and Mira 2007), it would be computationally infeasible. The estimator proposed here avoids this costly step and yields consistent preference estimates if the waiting time distributions correctly describe applicant beliefs.

A. *Distribution of Potential Applicants*

Application rates by income and demographic groups reveal heterogeneity in the value of assistance. If not all eligible households apply, preference estimation must account for selection into the applicant pool since applicants will tend to have unobservably worse outside options. The CHA dataset includes the households who applied during the sample period, as well as those who were CHA public housing tenants or already on the wait list at the beginning of 2010. However, it does not

[16] Additional data on applicants' outside options would be needed to separately identify unobserved tastes for public housing.

record eligible households who could have applied during the sample period, but did not.

To estimate the distribution of characteristics among eligible nonapplicants, I combine a sample of likely eligible households from the ACS with the CHA dataset.[17] I assign a probability to each ACS household for whether it appears in the CHA dataset, either as a tenant or as a past or current applicant. These probabilities are a parametric function of household characteristics. I estimate the parameters by minimum distance, matching the characteristics of households in the CHA dataset. Finally, I use the ACS sample and estimated probabilities to simulate a sample of eligible nonapplicants. The combined sample of applicants and eligible nonapplicants is the set of potential applicants used in preference estimation. Online Appendix C.1 provides details of the data construction, minimum distance estimator, and construction of the full sample of potential applicants.

B. *Belief Distributions over Assignments and Waiting Times*

The information about preference heterogeneity contained in applicants' development choices depends on their beliefs about how their choices affect future payoffs. An applicant solving the two-stage development choice problem of Section IIIA has beliefs about how each initial choice affects the date and position information at the final choice stage, and about continued waiting times for each development given list positions: $\left\{G_C(S,\mathbf{P}), \left\{F_{j,C}(T_j \mid \mathbf{p})\right\}_{j,\mathbf{p}}\right\}_{C\in\mathcal{C}}$. Because the final choice stage of the Cambridge Mechanism generates interdependence in waiting times across developments, each possible initial choice may induce a different joint distribution of final choice states and continued waiting times. A major challenge is that data on realized waiting times are sparse, while beliefs are high-dimensional. To address this issue, I assume applicants have beliefs of a particular form: their beliefs are consistent with the long run stationary distributions that the Cambridge Mechanism would generate given empirical vacancy rates, applicant arrival and departure rates, and initial and final choice frequencies. These empirical quantities can be estimated directly from application data. Combining these estimates with knowledge of the Cambridge Mechanism, I simulate a stationary distribution of outcomes for each possible sequence of choices. The specifications reported in the main text assume applicants have these beliefs when simulating the development choice model in the final step of estimation.

Online Appendix C.2 describes the formal model of the Cambridge Mechanism, the construction of simulation inputs, and the construction of belief distributions from simulation outputs. The simulation places additional structure on the stochastic evolution of the wait list. Apartment vacancies, applicant arrivals, and departure prior to assignment are each assumed to follow independent, exogenous Poisson processes. Consistent with the empirical evidence presented in online Appendix B, initial choice probabilities also do not depend on the current wait list state. However, the final choice stage does depend on the wait list due to both the CHA's policy for

[17] To my knowledge, no large survey asks households whether they are on a *wait list* for public housing. The ACS does ask whether a household receives housing assistance. However, these questions tend to understate program participation (Meyer and Mittag 2019).

sending final choice letters and the responsiveness of final choices to position information. By accounting for this state dependence, the simulation captures the sources of interdependence across lists in a flexible, albeit reduced-form, way.

C. *Preferences over Assignments and Waiting Times*

Parameterization of Flow Payoffs.—For estimation, I assume a Cobb-Douglas utility function,

$$u(c,h) = \gamma \log c + (1-\gamma)\log h, \tag{9}$$

where γ is the fraction of a household's disposable income that it would spend on the numeraire if unconstrained.[18] I also parameterize the distribution of unobserved income η_i and development-specific tastes h_i. Let $\mathbf{Z}_i$ represent observed household characteristics, $\mathbf{X}_j$ observed development characteristics, and $\mathbf{X}_{ij}$ interactions between applicant and development characteristics. Flow payoffs take the form

$$\begin{aligned} v_{ij} - v_{i0} = \delta_j + &\underbrace{\phi_1 \log y_i - \overbrace{\phi_2 \log(y_i + \eta_i)}^{\text{outside option}} + g(\mathbf{Z}_i)}_{\text{value of assistance}} \\ &\underbrace{+ \sum_k X_{ijk}\beta_k^o + \sum_m X_{jm}\nu_{im}\beta_m^u + \epsilon_{ij},}_{\text{match value}} \end{aligned} \tag{10}$$

where $(\boldsymbol{\nu}_i, \boldsymbol{\epsilon}_i)$ are individual-specific taste parameters not observed by the econometrician. Note that $\phi_1/\phi_2 = \gamma$. The unobserved characteristics are parameterized as

$$\eta_i \overset{iid}{\approx} \begin{cases} TN\left(0, \sigma_\eta^2, \underline{c} - y_i, \infty\right) & w.p.\ 1 - \Phi\left(\frac{\underline{c} - y_i}{\sigma_\eta}\right) \\ \underline{c} - y_i & w.p.\ \Phi\left(\frac{\underline{c} - y_i}{\sigma_\eta}\right), \end{cases} \quad \nu_{im} \overset{iid}{\approx} N(0,1), \quad \epsilon_{ij} \overset{iid}{\approx} N(0,1). \tag{11}$$

In addition to placing structure on match values and values of assistance, this parameterization adds development fixed effects and demographic shifters to equation (8). The development fixed effect δ_j captures the component of development quality that is common across households. The value of assistance may depend on other household characteristics $\mathbf{Z}_i$ in addition to income. The matching type contains standard terms in discrete choice demand estimation: tastes for observed development characteristics that depend on observed and unobserved household characteristics (ν_{im}), and idiosyncratic tastes for each development (ϵ_{ij}).

Unobserved income η_i is parameterized so that observed income is an imperfect predictor of a household's marginal utility of income. With probability $1 - \Phi\left((\underline{c} - y_i)/\sigma_\eta\right)$, η_i follows a truncated normal distribution with parameters $\left(0, \sigma_\eta^2\right)$, and with probability $\Phi\left((\underline{c} - y_i)/\sigma_\eta\right)$ it is bottom-coded at $\underline{c} - y_i$. The

[18] Cobb-Douglas utility implies that households spend a constant fraction of their income on rent. However, survey data show that higher-income households tend to spend a lower fraction of income on rent. Online Appendix D presents results from a specification in which households are constrained to a minimum annual housing expenditure of $10,000. The primary effect of this change is that equivalent variation is lower than in the baseline specification. The qualitative trade-off between efficiency and redistribution is similar.

parameter σ_η determines how strongly observed income predicts need: perfectly for $\sigma_\eta = 0$, and not at all as $\sigma_\eta \to \infty$. This parameterization has several attractive features. First, the minimum consumption level $\underline{c}$ outside of public housing is consistent with the presence of other social safety net programs. Second, bounding applicants' marginal utilities of income guarantees that social welfare calculations will not be dominated by a single simulation draw. Third, for each observed income y_i, total income $y_i + \eta_i$ has support on the interval $[\underline{c}, \infty)$. Thus, some low-income households can have low marginal utilities of income while some high-income households can have high marginal utilities. Finally, $E(y_i + \eta_i \mid y_i)$ increases in y_i, an intuitive condition that is consistent with the data.

The parametric restrictions in equation (11) assume independence between values of assistance and match values conditional on observed characteristics. An implication is that, other things equal, applicants with greater willingness to wait have unobservably better outside options. The parameterization also places restrictions on the correlation structure of match values across developments. In Section VC, I find that key parameter estimates are robust to more flexible specifications of match value heterogeneity.

Moments and Objective Function.—The parameters to be estimated are the discount factor and the parameters governing flow payoffs:

$$\boldsymbol{\theta} \equiv \{\rho, \boldsymbol{\delta}, g(\cdot), \boldsymbol{\phi}, \boldsymbol{\beta}, \sigma_\eta\}.$$

I estimate $\boldsymbol{\theta}$ based on moment conditions,

$$E\big[(\mathbf{m}_i - E(\mathbf{m}_i \mid \mathbf{Z}_i, \boldsymbol{\theta}_0)) \mid \mathbf{Z}_i\big] = 0,$$

where $\boldsymbol{\theta}_0$ is the true parameter vector, $\mathbf{m}_i$ contains features of household decisions, and $\mathbf{Z}_i$ contains household characteristics and choice conditions that are determined outside the model. The method of simulated moments captures these conditions in a set of moments, indexed by $q \in \{1, \ldots, Q\}$, for specific choice features $m_i^{(q)}$ and household characteristics $Z_i^{(q)}$:

$$\hat{g}^{(q)}(\boldsymbol{\theta}) = \frac{1}{N}\sum_{i=1}^{N}\Big(m_i^{(q)} - \hat{E}\big[m_i^{(q)} \mid \mathbf{Z}_i, \boldsymbol{\theta}\big]\Big)Z_i^{(q)}.$$

The conditional expectation $\hat{E}(\mathbf{m}_i \mid \mathbf{Z}_i, \boldsymbol{\theta})$ is estimated by simulation. The parameter estimate $\hat{\boldsymbol{\theta}}_{MSM}$ solves

$$\min_{\boldsymbol{\theta}} \hat{\mathbf{g}}(\boldsymbol{\theta})'\mathbf{A}\hat{\mathbf{g}}(\boldsymbol{\theta}),$$

where $\hat{\mathbf{g}}(\theta) = \big(\hat{g}^{(1)}(\boldsymbol{\theta}), \ldots, \hat{g}^{(Q)}(\boldsymbol{\theta})\big)'$ and $\mathbf{A}$ is a symmetric, positive-definite weight matrix. I match the following choice features $(m_i^{(q)})$ and applicant characteristics $(Z_i^{(q)})$ in the data to those predicted by the simulated model:

(i) Application rates by income and demographic groups:

$$m_i^{(q)} = \mathbf{1}\{C_i \neq \varnothing\}; \quad Z_i^{(q)} = \mathbf{1}\big\{(y_i, \mathbf{Z}_i) \in \mathcal{Y}^{(q)} \times \mathcal{Z}^{(q)}\big\}.$$

(ii) Development shares among applicants' initial choices: for each list j,

$$m_i^{(q)} = \mathbf{1}\{j \in C_i\}, \quad Z_i^{(q)} = 1.$$

(iii) Covariances between applicant characteristics and characteristics of their initial development choices:

$$m_i^{(q)} = \mathbf{1}\{C_i \neq \varnothing\}\frac{1}{|C_i|}\sum_{j\in C_i} X_j^{(q)}; \quad Z_i^{(q)} = \mathbf{1}\left\{(y_i, \mathbf{Z}_i) \in \mathcal{Y}^{(q)} \times \mathcal{Z}^{(q)}\right\}.$$

(iv) Means and variances of initially chosen development characteristics within and between applicants. An important characteristic is $\bar{T}_j$, the expected waiting time for development j from initial application if an applicant's initial choice was only j. Formally,

$$m_i^{(q)} = \frac{1}{|C_i|}\sum_{j\in C_i} X_j^{(q)}, \quad \left(\frac{1}{|C_i|}\sum_{j\in C_i} X_j^{(q)}\right)^2, \quad \frac{1}{|C_i|}\sum_{j\in C_i}\left(X_j^{(q)}\right)^2;$$

$$Z_i^{(q)} = \mathbf{1}\left\{(y_i, \mathbf{Z}_i) \in \mathcal{Y}^{(q)} \times \mathcal{Z}^{(q)}\right\}.$$

(v) Final choice moments. For all of these, $Z_i^{(q)} = 1$, and $m_i^{(q)}$ depend on the final choice made and the expected continued waiting times of all options in the applicant's choice set $\left(f_i, \{t_j\}_{j\in C_i}\right)$. I match the fraction of eligible households who made a final choice, the expected continued waiting time of their final choices, the average and maximum difference in expected continued waiting time between the chosen and alternative developments, and a "price index" that measures the waiting time of the final choice relative to other options in the applicant's choice set. The last two sets of moments are intended to capture the response to position information at final choice documented in Section IIC.

Intuition for Identification.—While a formal identification argument is beyond the scope of this paper, it is useful to consider how the moments described in the previous section are related to features of the preference distribution. Application rates by income and demographic groups reveal observed heterogeneity in values of assistance. Lower-income and non-White households are more likely than other groups to apply for public housing, suggesting that these groups tend to value public housing more relative to their outside options. However, observed characteristics do not fully explain who applies, suggesting some unobserved heterogeneity. Initial choices reveal heterogeneity in match values and values of assistance by arguments similar to those in Berry, Levinsohn, and Pakes (2004). Covariances between applicant and chosen development characteristics reveal which applicants systematically prefer which types of developments, and the second moments of chosen development characteristics capture unobserved heterogeneity in tastes for those characteristics. The number of and expected waiting times for initially chosen developments reveal unobserved heterogeneity in the value of assistance. Some high-income applicants initially choose developments with short waiting times, while others choose long waiting times or select just one or two developments. To the extent that this cannot be explained by observed applicant or development characteristics, or idiosyncratic taste shocks, these differences in behavior suggest that applicants differ in their values of assistance. Development shares at the initial and final choice stages reveal the relative desirability of different developments. Moments capturing the sensitivity of the final choice to waiting time information separate the discount factor from heterogeneity in flow payoffs.

While these arguments are tailored to the two-stage structure of the Cambridge Mechanism, much of the logic could be adapted to data generated by a one-stage mechanism. The main requirement is exogenous waiting time variation at the time development choices are made. This variation would reveal sensitivity of applicants' development choices to waiting time and substitution patterns across developments, which could be decomposed into unobserved heterogeneity in match values and values of assistance. Application rates and development shares by household type would identify observed heterogeneity in development quality, match values, and values of assistance. Thus, this paper's empirical strategy is likely relevant for other PHAs that allow applicants some degree of choice.

D. *Equivalent Cash Transfers*

The microfoundation of preferences provides a way to interpret estimates from the utility model in terms of the value of cash transfers. I use equivalent variation (EV), the cash transfer that would produce a welfare change equal to that of a public housing assignment, to quantify the welfare gains from alternative allocations.

If applicant i is assigned to development j, the equivalent variation EV_{ij} is implicitly defined by

$$v_{ij} - v_{i0} = v_0\big(y_i + \eta_i + EV_{ij}\big) - v_0\big(y_i + \eta_i\big), \tag{12}$$

where $v_0(\cdot)$ is the indirect utility function defined in equations (5) and (6). For the Cobb-Douglas utility function in equation (9), EV has the closed-form expression

$$EV_{ij} = \big(y_i + \eta_i\big)\big(e^{v_{ij} - v_{i0}} - 1\big). \tag{13}$$

It is worth noting that although applicants do not make explicit financial trade-offs in their application and development choices, the conversion from estimated utilities to EV has empirical content because a household's public housing rent depends on income. Differences in application rates by income are therefore informative about households' willingness to pay. If expressed demand for public housing is highly income dependent, applicants must have low willingness to pay for specific development characteristics, and EV will primarily depend on the financial subsidy a household receives by living in public housing. If income only weakly predicts who applies, this suggests considerable preference heterogeneity relative to the value of the public housing subsidy.[19]

[19]This argument conditions on a particular degree of unobserved heterogeneity in values of assistance (σ_η). This is in part why development choice information is crucial for distinguishing heterogeneity in match values and values of assistance, and why parametric restrictions on the joint distribution of the two objects are needed.

Nevertheless, this reasoning is not sufficient to obtain an exact conversion. Even if indirect utilities are known, identifying the marginal utility of income outside of public housing requires knowing agents' underlying utility functions. In the present application, the exact conversion depends on the parametric structure placed on the joint distribution of match values and values of assistance, the Cobb-Douglas functional form of utility, and the assumption that η_i only enters the value of the outside option.

V. Estimation Results

This section presents estimates of the distribution of potential applicants, applicants' waiting time beliefs, and preferences over assignments and waiting times.

A. *Eligible Population*

Online Appendix Table 13 presents the probit model coefficient estimates predicting the probability that an ACS household is in the CHA dataset as an applicant or tenant. The probabilities depend on household income, the household head's race and ethnicity, and whether the household already lives in Cambridge. The minimum distance estimator matches the total number of households in the CHA dataset, the number of households in six income groups, and the numbers of households from Cambridge and with African American or Hispanic household heads. The point estimates reinforce the discussion of application rates in Section IIB, with lower-income and non-White households much more likely to appear in the CHA dataset. Though the parameter estimates are noisy due to a small sample of eligible ACS households, online Appendix Figure 4 shows that the estimated pattern of falling application rates by income is stable across bootstrapped ACS samples.

B. *Applicant Beliefs*

Selected parameters governing inputs to the Cambridge Mechanism simulation are shown in online Appendix Table 12. The annual vacancy rate per unit is calibrated to 10 percent. The applicant arrival rate was 345 per year during the sample period. Based on responses to final choice letters, 23.9 percent of applicants become unresponsive immediately, and attrition occurs at an annual rate of 22.2 percent thereafter. Consistent with the analysis in Section IIC, applicants are less likely to choose a development with a higher list position at the final choice stage.

Online Appendix Table 14 shows that the development means and standard deviations of simulated waiting times are qualitatively similar to those in the data. Simulated waiting times are constructed by averaging realized waiting times across applicants housed during the simulation. The largest developments (Jefferson Park, Newtowne Court, Roosevelt Low-Rise, and Washington Elms) have simulated average waiting times between 1.2 and 2.6 years. The smaller developments, including Mid- and East Cambridge, Lincoln Way, and Jackson Gardens, have longer simulated waiting times of 4.3 to 6.8 years. The simulation also broadly matches the degree of waiting time variability in the data, which ranges from about six months to two years across developments.

Although the simulation broadly captures which developments have longer waiting times, the simulated average waiting times are more dispersed and larger on average than those observed in the data. The main reason for this is that the Cambridge Mechanism was not fully in steady state during the sample period. List closures before and during the sample period allowed some applicants to be housed quickly. In addition, since some developments housed only a few applicants, observed average waiting times have considerable sampling noise. Since applicants had limited information about list closures and current and future fluctuations in list lengths, it would have been reasonable to form beliefs based on the long-run stationary distribution of outcomes in the Cambridge Mechanism. Online Appendix D presents results from a version of the structural model in which applicants' beliefs approximately follow the empirical distribution of waiting times in the data. The qualitative trade-off between efficiency and redistribution does not change.

C. *Preferences over Assignments and Waiting Times*

This section presents estimates from three preference specifications (corresponding with the three columns in Table 5). All specifications include fixed effects for each development, the race and ethnicity of the household head, and whether the household lives in Cambridge; the two terms that depend on observed income and the random effect η_i; and an indicator for whether the household lives in the same neighborhood as each development. The minimum consumption level $\underline{c}$ is set to \$10 per day for both estimation and counterfactuals. Specification 2 allows for additional observed heterogeneity: indicators for a three-bedroom household, household income below \$20,000, and children below age 10, as well as interactions between development size and Hispanic household head, children under 10, and income below \$20,000. Specification 3 allows for additional unobserved heterogeneity in match values by adding random coefficients for development size and location. Counterfactuals use the estimates from specification 3.

Parameter Estimates.—Applicants are patient in their development choices. In the first row of Table 5, the estimated annual discount factor is between 0.966 and 0.977 across specifications. The estimates are precise and reject moderate to high degrees of impatience. While applicants exhibit some willingness to substitute towards developments with shorter waiting times, many are willing to wait years for their preferred option. The high annual discount factor suggests applicants do not fully anticipate that they might exit the queue before they are housed. It is also lower than the discount rate implied by many financial instruments available to lower-income households.[20]

Panel A of Table 5 shows that while income and demographic variables strongly predict the value of assistance, there is substantial unobserved heterogeneity. Consistently across specifications, households headed by an African American have much higher values of assistance. Other variables predicting higher values of assistance are intui-

[20] In results not reported here, I found that the estimated discount factor tends to be lower when some applicants are assumed to be naive and choose their preferred developments without considering waiting time. Details available upon request.

Table 5—Parameter Estimates

	Baseline specification (1)		Richer observed heterogeneity (2)		Unobserved taste for size and location (3)	
Annual discount rate	0.977	(0.011)	0.977	(0.008)	0.966	(0.009)
SD development fixed effects	0.352		0.415		0.432	
Panel A. Value of assistance						
Head is Black	0.933	(0.092)	0.838	(0.061)	0.839	(0.082)
Head is Hispanic	0.032	(0.043)	0.138	(0.046)	0.083	(0.062)
Lives in Cambridge	0.528	(0.065)	0.384	(0.045)	0.381	(0.036)
Youngest member < 10 years			0.005	(0.041)	−0.018	(0.037)
3-bedroom household			0.258	(0.047)	0.259	(0.053)
Household income < \$20,000			0.321	(0.068)	0.320	(0.059)
log of observed income	0.164	(0.08)	0.158	(0.058)	0.166	(0.066)
log of observed and unobserved income	−1.000	—	−1.000	—	−1.000	—
Scale of unknown income (\$10,000)	1.115	(0.11)	1.115	(0.109)	1.090	(0.081)
Panel B. Match values						
Applicant and development same neighborhood	−0.137	(0.065)	−0.196	(0.031)	−0.193	(0.058)
Applicant head is Hispanic × development size			0.022	(0.033)	0.043	(0.043)
Youngest member < 10 years × development size			0.000	(0.016)	−0.006	(0.021)
Household income < \$20,000 × development size			0.000	(0.022)	−0.003	(0.021)
SD unobserved taste for development size					0.039	(0.011)
SD unobserved taste for North Cambridge					0.035	(0.019)
SD unobserved taste for East Cambridge					0.039	(0.013)
SD idiosyncratic shock	0.161	(0.013)	0.155	(0.01)	0.156	(0.015)

tive: for example, a three-bedroom household faces higher rents on the private rental market than a two-bedroom household with equal income, but pays the same rent in public housing. The value of assistance falls rapidly with observed income: the estimated coefficient on log of observed income implies households would like to spend more than 80 percent of their incomes on housing. Though large, this estimate is consistent with very high rent burdens among low-income households.

Unobserved income makes a substantial contribution to the value of assistance. In specification 3, the point estimate of σ_η implies a standard deviation of approximately \$10,380 in the outside options of eligible households, and \$9,700 among applicants.[21] These large estimates are driven by the fact that applicants differ greatly in their selectivity. Some low-income applicants behave as though they can afford to wait a long time for their preferred development, while some high-income applicants appear desperate. These differences cannot be fully explained by observed characteristics or unobserved match value heterogeneity. Due to the high variance in unobserved income, 22 percent of applicants' outside options are at the consumption minimum.

Estimates of match value parameters (panel B) show substantial heterogeneity in applicants' preferred developments. Location is a source of predictable heterogeneity, and conditional on other observed characteristics, applicants who already live in Cambridge would actually prefer to move to a different neighborhood. Other

[21] Recall that σ_η parameterizes a truncated normal distribution to guarantee a minimum consumption level.

Table 6—Features of Preference Distribution

	All applicants		African American household head		Household income below $15,000	
	Median ($)	Mean ($)	Median ($)	Mean ($)	Median ($)	Mean ($)
Panel A. Value of assignment to preferred development						
First choice instead of second	891	2,028	1,136	2,465	526	1,082
First choice instead of third	1,894	3,344	2,493	4,111	1,047	1,807
	Percent of applicants	Outside option ($)	Percent of applicants	Outside option ($)	Percent of applicants	Outside option ($)
Panel B. Number of acceptable developments						
1–3 acceptable	16.2	30,547	12.0	45,150	4.9	21,091
4–10 acceptable	23.2	24,888	22.1	34,431	11.9	17,525
11–12 acceptable	36.5	13,327	35.8	18,825	42.8	11,001
13 acceptable	24.1	4,710	30.1	5,230	40.4	4,510

Notes: Statistics are averaged across a simulated sample of eligible households that would apply for Cambridge public housing, using estimates from specification 3. Panel A presents equivalent variation of reassigning applicants from a less preferred development to their first choice. Panel B summarizes the percentage and mean outside option of applicants based on the number of developments they would accept as a take-it-or-leave-it offer. The outside option includes both observed and unobserved income. Household income below $15,000 refers to observed income, and includes approximately half of the applicant sample.

interactions between development size and household characteristics are small in magnitude. Specification 3 estimates a modest degree of unobserved heterogeneity in tastes for development size and location. A substantial component of match values are explained by idiosyncratic tastes, with estimated standard deviations between 0.155 and 0.161. Importantly, estimates governing values of assistance—particularly the importance of observed and unobserved income—are stable across specifications of match value heterogeneity.

Features of the Preference Distribution.—This section summarizes two features of the preference distribution that drive the trade-off between efficiency and redistribution: the value of being assigned to a preferred development, and the number of developments preferable to the outside option. Statistics are based on a sample of applicants drawn from the preference distribution estimated in specification (3).

There are large welfare gains from matching applicants to their preferred developments. Panel A of Table 6 displays medians and means of the EV from moving an applicant from a lower-ranked choice to their first choice, calculated using equation 13. Across all applicants, the median EV between an applicant's second and first choice is $891 per year. The mean is even larger, driven by a long right tail in the distribution. These strong preferences for specific developments may be driven by the desire to live in a specific location, for example near a school or workplace, or by other amenities such as building or neighborhood character. These values are slightly higher among African American applicants, but much lower for applicants with annual incomes below $15,000.

Because there is substantial heterogeneity in match values, many applicants are only willing to live in a subset of the CHA developments and would reject some take-it-or-leave-it offers of housing. Panel B of Table 6 summarizes applicants by the number of developments they find acceptable. Some applicants are quite selective—16 percent would only be willing to live in 3 or fewer developments—while

24 percent of applicants would be willing to live in any development, and 60 percent would live in at least 11. Applicants who would accept more developments have worse outside options than more selective applicants. Patterns are qualitatively similar for African American and very low-income applicants, but these groups are less selective overall. Thirty percent of African American applicants and 40 percent of applicants with incomes below \$15,000 would accept any take-it-or-leave-it-offer.

These statistics suggest that allocation mechanisms that affect match quality and targeting may have large welfare and distributional consequences. A development choice system in which an applicant cannot choose where they live will induce some applicants to reject offers. However, any targeting improvement is likely to come at substantial cost due to lower match quality.

VI. Evaluating Design Trade-Offs

Using the estimates from Section V, I perform counterfactual simulations to evaluate how the development choice and priority systems commonly used to allocate public housing would perform if implemented in Cambridge. These simulations hold all market primitives fixed, including the stock of public housing apartments available to the CHA, and only vary allocation policy. Section VIA defines a class of one-stage choice mechanisms and describes the specific mechanisms considered. Section VIB presents results from counterfactual simulations.

A. *Space of Mechanisms*

This section formalizes a class of dynamic assignment mechanisms that capture the key features of public housing choice and priority systems used in practice. Applicants make development choices in one stage at initial application, and are ordered on the wait list lexicographically by priority group and then application date. Compared to the two-stage development choice mechanism used by the CHA, one-stage choice greatly simplifies equilibrium computation and is also more common in practice. To isolate long-run effects, I abstract away from transition dynamics following a change in the mechanism and analyze stationary equilibria. The remainder of this section formalizes one-stage choice mechanisms, defines equilibrium, explains how allocations are evaluated, and describes the mechanisms explored in counterfactual simulations.

One-Stage Choice Mechanisms.—A one-stage choice mechanism φ is defined by two objects:

(i) A development choice system $\mathcal{C}_\varphi \subseteq 2^{\{1,\ldots,J\}}$. Each element of $\mathcal{C}_\varphi$ is a subset of developments from which an applicant may receive apartment offers.

(ii) A priority system $\psi_\varphi : \mathcal{Z} \to \{1,\ldots,B\}$ maps applicant characteristics to a priority group. Applicant i has higher priority than applicant i' in φ if $\psi_\varphi(\mathbf{Z}_i) < \psi_\varphi(\mathbf{Z}_{i'})$.

The mechanism operates on sequences of apartment vacancies, applicant arrivals, and exogenous applicant departures. Each vacancy $\nu \in \{1,\ldots,V\}$ has a date t_ν and development j_ν. Each applicant $i \in \{1,\ldots,N\}$ has arrival date t_i, departure date r_i, observed characteristics $\mathbf{Z}_i$, and payoff vector $\mathbf{v}_i = (v_{i0}, v_{i1}, \ldots, v_{iJ})$. The mechanism φ runs according to the following algorithm. On each date t:

(i) Each arriving applicant $(t_i = t)$ chooses a set of developments $C_i \in \mathcal{C}_\varphi$ and is placed on the wait list for each development $j \in C_i$. On each list, applicants are ordered by $(\psi_\varphi(\mathbf{Z}_i), t_i)$.

(ii) Each vacancy ν with $t_\nu = t$ is offered to the first applicant on list j_ν. If the applicant accepts, they are housed and removed from all lists $j \in C_i$. If the applicant rejects, they are removed from all wait lists and cannot reapply. This step is repeated until an applicant accepts or the wait list is empty. If the latter occurs, the vacancy is held until the next day.

(iii) Departing applicants $(r_i = t)$ are removed from all lists $j \in C_i$.

Development Choice Problem, *Information*, *and Equilibrium*.—An applicant's choice problem in a one-stage mechanism involves choosing a subset of developments for which to wait. The applicant simply considers, for each possible subset $C \in \mathcal{C}_\varphi$, which development is likely to arrive first, and when. Let T_j be the random variable for the waiting time for development j if an applicant were only on the wait list for j. The realization of T_j will depend on applicant i's date of application. The joint distribution $F_{T_1,\ldots,T_J}$ may depend on the applicant's priority $\psi_\varphi(\mathbf{Z}_i)$. The applicant solves the following choice problem:

$$\max_{C \in \mathcal{C}_\varphi} \sum_{j \in C} w_j^C(\psi_\varphi(\mathbf{Z}_i))(v_{ij} - v_{i0}), \tag{14}$$

$$w_j^C(\psi_\varphi(\mathbf{Z}_i)) = \frac{1}{\rho} E_{\psi_\varphi(\mathbf{Z}_i)}\Big[e^{-\rho T_j} \,|\, T_j = \min_{k \in C_i} T_k\Big] \times P_{\psi_\varphi(\mathbf{Z}_i)}\Big[T_j = \min_{k \in C_i} T_k\Big]. \tag{15}$$

In equilibrium, beliefs are consistent with the long-run distributions generated by the mechanism given the distribution of potential applicants, the preference distribution $p(\mathbf{v}_i \,|\, \mathbf{Z}_i, \hat{\boldsymbol{\theta}}_{MSM})$, and applicants choosing developments according to equation (14). As in the Cambridge Mechanism, I assume applicants do not know the state of the queue when they apply, and instead have a common prior over the outcome distribution under each possible choice $C \in \mathcal{C}_\varphi$ given their priority group $\psi_\varphi(Z_i)$ and the mechanism's stationary equilibrium.

Online Appendix C.4 provides details of how the equilibrium is computed under each mechanism. The algorithm iteratively updates applicant choices and their implied waiting time distributions until a fixed point is reached. The departures and vacancy models are the same as in the Cambridge Mechanism simulation. Applicant arrivals are generated using the distribution of potential applicants and preferences estimated in Section V. Potential applicants choose to apply if any development is preferable to their outside option. Each applicant's choice solves equation (14) given preferences and beliefs.

Evaluating Allocations.—To summarize the welfare and distributional impacts of a mechanism, I average characteristics of assigned applicants and their values over assigned apartments. If tenants vacate apartments exogenously at a common Poisson rate, then this provides consistent estimates of the characteristics of public housing tenants at any given time. A social planner interested in maximizing the expected discounted sum of future payoffs would be interested in these statistics.

Given sequences of inputs, a mechanism φ produces an assignment $j_\varphi(i) \in \{0, 1, \ldots, J\}$ for each applicant, with $j_\varphi(i) = 0$ if applicant i is never assigned an apartment. Let $f(\mathbf{Z}_i, \mathbf{v}_i, j_\varphi(i))$ be a function of the assigned development, applicant characteristics $\mathbf{Z}_i$, and their indirect utility vector $\mathbf{v}_i$. This function can describe positive characteristics of the allocation (e.g., tenant characteristics $\mathbf{Z}_i$), or normative ones such as tenants' equivalent variation $EV_{i, j_\varphi(i)}$ from their assignments. It also allows the social planner to apply different welfare weights to different types of households.

One can also adjust welfare gains under different mechanisms by the total cost of the public housing program. Since rent in public housing is proportional to a tenant's income, the CHA will receive lower rent payments if it houses lower-income applicants. As a result, changing the allocation mechanism may not be budget neutral even if the set of items remains fixed. Estimating the fiscal cost of public housing is challenging for a variety of reasons.[22] Instead, I use market rents in Cambridge, Massachusetts during the sample period as a proxy for the fiscal opportunity cost of the public housing program. Between 2010 and 2014, a conservative estimate of the market rent for a modest 2- to 3-bedroom apartment was \$2,000 per month, or $c \equiv \$24{,}000$.[23] Adjusted for cost, welfare gains generated by an allocation mechanism are

$$\tilde{W}(\varphi; f) = \frac{\sum_{i=1}^{N} f\left(\mathbf{Z}_i, \mathbf{v}_i, j_\varphi(i)\right)}{\sum_{i=1}^{N} \mathbf{1}\left\{j_\varphi(i) \neq 0\right\}\left(c - 0.3\, y_i\right)}. \tag{16}$$

This benefit-cost ratio shares the spirit of welfare measures commonly used in public economics, such as the marginal value of public funds (Mayshar 1990, Hendren and Sprung-Keyser 2020). However, rather than quantifying the welfare impact of an incremental change in spending on an existing program, equation (16) quantifies the total welfare gains produced by all assignments. This is appropriate for comparing allocation mechanisms for a fixed set of heterogeneous items. Equation (16) also does not incorporate fiscal externalities generated by any behavioral responses (e.g., labor supply changes) to the mechanism.

Simulated Mechanisms.—To quantify the effects of development choice on efficiency and redistribution, counterfactual simulations consider development choice and priority systems motivated both by theory and by the systems PHAs are using

[22] See Olsen (2009) for a detailed discussion. Since public housing is a durable good that depreciates over time and requires lumpy investment to maintain, maintenance and administrative costs in a particular year may under- or overstate long-run average costs. In addition, they will not capture the opportunity cost of alternative uses of a PHA's land and buildings.

[23] Based on the Zillow rent index: https://www.zillow.com/cambridge-ma/home-values/. Median rents ranged from about \$2,200 to \$2,600 for 2-bedroom units, and \$2,600 to \$2,900 for 3-bedroom units.

in practice, described in Section IA. I computed the counterfactual equilibrium that would arise in Cambridge under each pair of development choice and priority systems.

I focus on two development choice systems that, under certain conditions, respectively maximize match quality and targeting:

(i) Choose One: $\mathcal{C} = \{\{1\},\{2\},\ldots,\{J\}\}$. Applicants select one development at initial application. They only receive apartment offers from their chosen development, and are removed from the wait list if they reject an offer. This is a version of "Limited Choice" discussed in Section IA.

(ii) No Choice: $\mathcal{C} = \{\{1,\ldots,J\}\}$. Applicants must accept the first available apartment in any development; they are removed from the wait list if they reject an offer and cannot reapply.

I also consider how development choice interacts with priorities based on observed applicant characteristics. If a household's marginal utility of income were fully captured by observables, a PHA could simply use priorities to determine which applicants to house. For priority systems, I model priority for higher socioeconomic status households as a priority for higher-income applicants, and lower socioeconomic status or need-based priorities as a priority for lower-income applicants:

(i) Equal Priority: Applicants are treated equally and ordered only by application date.

(ii) Low-Income Priority: Applicants with annual income below \$15,000 receive offers first.

(iii) High-Income Priority: Applicants with annual income above \$15,000 receive offers first.

B. *Welfare and Distributional Impacts of Allocation Policy*

This section analyzes the effect of eliminating development choice under different priority systems, and concludes with a social welfare function exercise to show how distributional preferences determine which mechanism should be adopted.

Effects of Choice and Priority.—The development choice systems used in practice involve a dramatic trade-off between efficiency and redistribution. Columns 1 and 2 of Table 7 summarize allocations under Choose One and No Choice with Equal Priority. Under Choose One, the average tenant values their assignment as much as an annual cash transfer of \$22,318; under No Choice, the value falls by 35 percent to \$14,617. Part of this welfare loss is driven by a reduction in match quality. While 58 percent of tenants are assigned to their first choice development under Choose One, only 9 percent are under No Choice. However, No Choice substantially improves targeting by inducing applicants with higher incomes and better outside options to reject offers. The mean observed income of tenants falls from \$16,953 to

TABLE 7—ALTERNATIVE CHOICE AND PRIORITY SYSTEMS

	Equal priority		Low-income priority		High-income priority	
	Choose one (1)	No choice (2)	Choose one (3)	No choice (4)	Choose one (5)	No choice (6)
Panel A. Welfare gain and cost of allocation						
Equivalent variation ($)	22,318	14,617	24,448	16,328	17,811	13,469
Cost per unit ($)	18,914	19,735	20,856	21,543	17,251	18,426
Equivalent variation per $ cost to government	1.18	0.74	1.17	0.76	1.03	0.73
Panel B. Targeting						
Observed income ($)	16,953	14,217	10,481	8,191	22,496	18,579
Unobserved income ($)	−2,548	−2,615	−482	73	−4,785	−4,762
Observed and unobserved income ($)	14,405	11,602	9,999	8,264	17,711	13,817
% extremely high need	29.7	35.5	37.9	46.1	21.7	27.4
Panel C. Match quality						
% assigned top choice	58.1	8.9	53.6	8.1	54.1	10.0
% assigned top 3	79.7	24.4	76.0	22.6	69.6	25.5
Panel D. Characteristics of housed applicants						
Waiting time (days)	1,688	643	1,110	172	1,310	478
% Black	52.4	55.2	50.6	52.1	56.2	57.7
% Hispanic	18.9	17.0	19.7	19.6	16.2	15.5
From Cambridge	61.4	62.0	61.4	62.3	61.2	62.2
Panel E. Distribution of tenants across developments						
SD observed income ($)	4,378	2,413	4,373	261	8,433	3,811
Range of observed income ($)	[10,774, 25,107]	[8,884, 17,163]	[7,477, 20,159]	[7,774, 8,692]	[6,849, 31,940]	[9,489, 22,277]
SD % Black	15.3	3.5	9.2	4.0	6.5	3.4
Range of % Black	[42.3, 100.0]	[51.6, 64.0]	[35.8, 70.7]	[48.2, 63.8]	[50.1, 75.8]	[54.0, 65.6]
SD % from Cambridge	8.8	2.8	10.1	3.0	8.6	2.7
Range of % from Cambridge	[47.8, 72.1]	[59.1, 69.3]	[42.6, 72.3]	[58.4, 70.4]	[48.4, 75.3]	[57.1, 68.5]

Notes: Statistics averaged across assigned apartments in each counterfactual simulation. Dollar amounts are annual. Cost per unit is calculated based on market rate rental prices in Cambridge, Massachusetts during the sample period. Equivalent variation is the equivalent cash transfer outside of public housing that would generate the same welfare change for a housed applicant as their assignment. Extremely high-need applicants are at the minimum consumption level of $10/day outside of public housing. Low-Income Priority first offers vacant apartments to applicants with incomes below $15,000; High-Income Priority does the same for applicants with incomes above $15,000.

$14,217, and tenants have unobservably worse outside options. Due to lower tenant incomes, the CHA would receive lower rent payments and therefore incur a higher cost per unit under No Choice. Adjusted for cost, Choose One achieves $1.18 of welfare gains per dollar spent, while No Choice achieves 74 cents, a 37 percent decrease.

Columns 3–6 show that these trade-offs are similar under income-based priorities. Eliminating choice causes large welfare losses for tenants due to lower match quality, with cost-adjusted welfare gains falling by 34 percent under Low-Income Priority and 29 percent under High-Income Priority. However, eliminating choice increases redistribution: the average tenant's outside option falls from $9,999 to $8,264 under Low-Income Priority, and from $17,711 to $13,817 under High-Income Priority. There is still scope to elicit applicants' outside options through choice restrictions under the coarse priorities used by PHAs.

In contrast, the CHA could use income-based priorities to increase redistribution without sacrificing match quality. Relative to Equal Priority, Choose One, moving to Low-Income Priority while allowing choice produces similar targeting gains to eliminating choice while keeping Equal Priority. Importantly, however, Low-Income Priority does not sacrifice match quality: 54 percent of tenants are still assigned their first-choice development, and equivalent variation per assigned unit remains high at \$24,448. If behavioral responses to the priority system are not too large, income-based priorities may be preferable to eliminating choice when a moderate increase in redistribution is desired. Choice and priority should both be used to maximize redistribution: under Low-Income Priority, No Choice, 46 percent of tenants are extremely high need. However, due to poor match quality and the additional cost of housing lower-income households, cost-adjusted welfare gains are only 76 cents per dollar under this system.

The methods developed here can also quantify how wait list design affects outcomes of interest to policy makers other than efficiency and redistribution. Geographic concentration of race and poverty is of particular concern in public housing because the program ties financial assistance to living in a specific building and neighborhood (Collinson, Ellen, and Ludwig 2016). Panel E of Table 7 shows that allowing choice consistently leads to increased tenant sorting across developments within Cambridge public housing. For example, under Equal Priority, Choose One, the average income of tenants ranges from \$10,774 to \$25,107 across developments; under Equal Priority, No Choice, the range is smaller, between \$8,884 and \$17,163, and the standard deviation falls by nearly half. Similar patterns arise for racial concentration and for the fraction of tenants who already lived in Cambridge when they applied.

Incorporating a Preference for Redistribution.—Given the trade-off between efficiency and redistribution, how should a PHA decide which mechanism to use? Since public housing is an antipoverty program, a PHA may prefer to make transfers to households with higher marginal utilities of income.[24] In the preference model presented in Section IIIB, there is a one-to-one mapping between a household's marginal utility of income and the value of their outside option, summarized by total income $\tilde{y}_i \equiv y_i + \eta_i$. Any monotonically increasing function $f(\tilde{y}_i)$ corresponds to a social welfare function which penalizes inequality.

To parsimoniously capture a wide range of distributional preferences, I consider a parametric class of social welfare functions proposed by Atkinson (1970):

$$f(\tilde{y}_i, EV; \lambda) = \begin{cases} \frac{1}{1-\lambda}\left[(\tilde{y}_i + EV)^{1-\lambda} - \tilde{y}_i^{1-\lambda}\right] & \text{if } \lambda \neq 1 \\ \log(\tilde{y}_i + EV) - \log(\tilde{y}_i) & \text{if } \lambda = 1. \end{cases}$$

This class of functions exhibits "constant relative inequality aversion," with the degree of inequality aversion parameterized by the scalar λ. It is the criterion function of a utilitarian social planner when all agents have the same constant relative risk aversion utility function over $\tilde{y}_i$, with risk aversion parameter λ. For $\lambda = 0$, the

[24] In the model presented in Section IIIB, the most efficient way to achieve redistribution across observed income groups would be through the income tax schedule (Atkinson and Stiglitz 1976). The present analysis assumes that the tax schedule is not available as a policy instrument; the policy maker can only increase social welfare through the allocation of its existing public housing stock.

planner has no taste for redistribution; for $\lambda = \infty$, the planner only values welfare changes for the worst-off agents; and for intermediate values, transferring \$1 to a household with 1 percent lower income increases social welfare by approximately λ percent. Since public housing allocation operates in the presence of the existing federal, state, and local tax and transfer systems, λ should be interpreted as the social value of redistribution over and above what is achieved by other policies.

Figure 1 shows that under the current CHA priority system (Equal Priority), eliminating choice can only be justified by a strong preference for income redistribution. The figure plots the cost-adjusted welfare gains from equation (16) under Choose One and No Choice, normalized by Choose One at each value of λ. Choose One is preferred with low inequality aversion because it produces the highest EV per dollar spent. With high inequality aversion ($\lambda > 3$), No Choice becomes preferable because it maximizes the proportion of extremely high-need tenants. In this range of the inequality aversion parameter, one would be willing to take \$8 from a household earning \$20,000 in order to transfer only \$1 to a household earning \$10,000. Eliminating choice is a very costly way to increase redistribution.

Figure 2 shows that among the six combinations of choice and priority, only three are preferred for some value of redistribution. With inequality aversion near 0, Equal Priority, Choose One is best because it maximizes equivalent variation per dollar of expenditure. With low to moderate inequality aversion ($\lambda < 2.6$), it is best to prioritize low-income applicants but still allow choice. The additional redistribution to lower-income households justifies the additional cost of housing them. With high inequality aversion, Low-Income Priority, No Choice is best. In this region, housing additional extremely high-need households justifies the large efficiency loss from eliminating choice.

This analysis suggests that the CHA should use choice restrictions to increase redistribution only after exploiting observed characteristics through the priority system. A corollary is that for this class of social welfare functions, some combinations of choice and priority are dominated in Cambridge: for any degree of inequality aversion, there is a better policy. A mechanism that performs particularly badly is High-Income Priority, No Choice. This mechanism produces the worst of both worlds by generating low tenant welfare through choice restrictions and poor targeting through the priority system. Similar systems are used by other PHAs, but they are unlikely to produce desirable outcomes in Cambridge. In contrast, the Cambridge Mechanism—which is most similar to Equal Priority, Choose One—performs well under low inequality aversion.

An important caveat to the conclusion that High-Income Priority mechanisms are dominated is that applicants might adjust their labor supply in response to income-based priorities. This would likely make High-Income Priority more attractive due to its positive fiscal externality. While measuring such behavioral responses is beyond the scope of this paper, any labor supply response to income-based priorities would further motivate using the development choice system to increase redistribution.

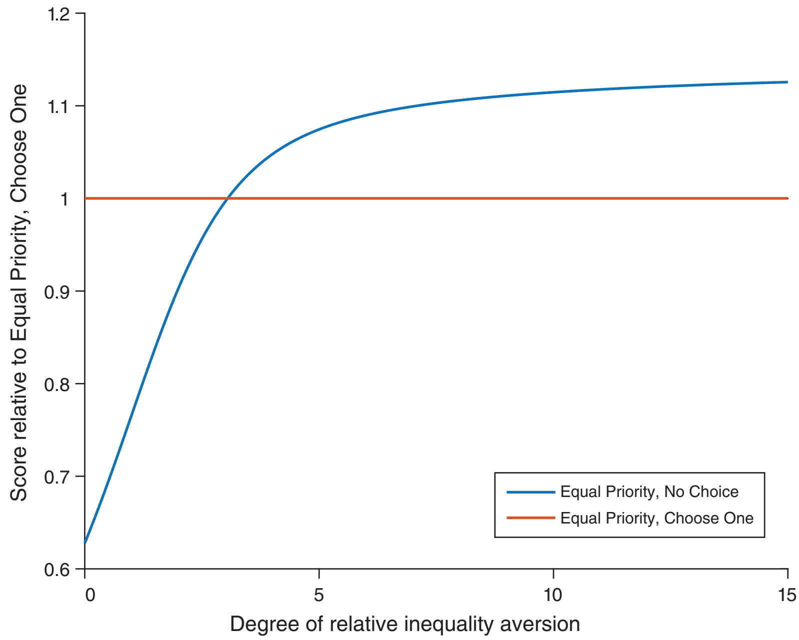

Figure 1. Welfare under Alternative Development Choice Systems

Notes: Cost-adjusted welfare gains under Choose One and No Choice, with Equal Priority. Each point on the x-axis corresponds to a degree of relative inequality aversion. At each point, cost-adjusted welfare gains from each mechanism are normalized by the value under Equal Priority, Choose One.

VII. Conclusion

The allocation of scarce public resources often involves trading off efficiency with other policy goals. This paper empirically studies a trade-off arising in the allocation of public housing between efficiency and income redistribution. Using data on the choices of public housing applicants in Cambridge, Massachusetts, I estimate a model of preferences for public housing that quantifies heterogeneity in applicants' preferred developments and overall values of obtaining assistance. The empirical strategy exploits a trade-off faced by applicants between shorter waiting times and preferred assignments as well as the structure of the allocation mechanism. I use the estimated model to simulate counterfactual equilibria under allocation mechanisms in use across the United States, and ask whether the CHA could redesign its wait list to target assistance to those who need it most.

Mechanisms allowing applicants less choice over where they live can screen out low-need applicants, but only by dramatically reducing efficiency through lower match quality for tenants. Under the current CHA priority system, eliminating choice would significantly improve targeting, but also lower tenant welfare by 35 percent. Such a policy is only justified under extreme distributional preferences: the CHA would have to be willing to take \$8 from one household to transfer only \$1 to another household with half as much income. The CHA could achieve the same increase in targeting without lowering tenant welfare by prioritizing lower-income applicants and allowing choice. A number of papers have argued that ordeals can increase the efficiency of public programs by more effectively targeting intended

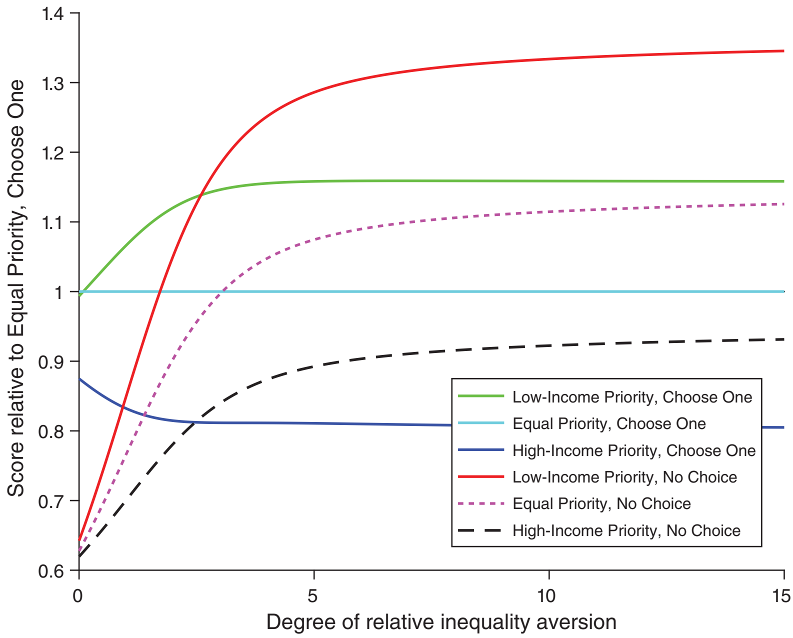

Figure 2. Preferred Mechanisms by Degree of Inequality Aversion

Notes: Cost-adjusted welfare gains under all six combinations of choice and priority analyzed in Table 7. Each point on the x-axis corresponds to a degree of relative inequality aversion. At each point, cost-adjusted welfare gains from each mechanism are normalized by the value under Equal Priority, Choose One.

beneficiaries. The results from Cambridge weigh against using development choice restrictions as an ordeal. In addition, PHAs already collect applicant information that is highly predictive of need, and they can use this information to improve targeting without creating inefficient matches.

These findings raise several questions for future work on affordable housing allocation. The extent to which applicants correctly form beliefs and strategize in wait list mechanisms could affect revealed preference analysis and the impacts of alternative designs, as it has been shown to in static mechanisms (Kapor, Neilson, and Zimmerman 2020). Behavioral responses to the allocation mechanism, such as adjusting labor supply in response to income-based priorities, may also affect these trade-offs. Linking application data with other datasets that directly measure socioeconomic outcomes could yield a more detailed understanding of how wait list behavior is related to short- and long-run economic disadvantage. Finally, an important direction for future work is to understand the extent to which the available public housing stock, housing market conditions, and applicant preferences vary across cities, and whether this variation affects the trade-off between efficiency and redistribution found here. The methods developed in this paper may prove useful in analyzing these contexts, particularly when development choice data are available.

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