PUBLIC HOUSING, WAITING LISTS AND LOTTERIES:

QUASI-NATURAL EXPERIMENTAL EVIDENCE FROM AMSTERDAM

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Abstract

We examine welfare outcomes for non-allocation mechanisms of public housing. We make use of a quasi-natural experiment in Amsterdam where public houses are allocated through lotteries to households already on waiting lists. We demonstrate that a lottery reduces waiting time by 8.5 years and offers benefits to lottery winners. Households in public housing value these benefits at about €875 per year. We demonstrate that the lottery experiment resulted in different – and less efficient – household and public housing matches than those based on waiting time. Using a structural approach, the annual welfare loss associated with lottery due to an inefficient match is estimated to be €275 for each public house. *JEL:* C78 D82 R21 R31.

Keywords: nonmarket allocation mechanisms, waiting lists, lotteries, public housing.

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I. INTRODUCTION

Public house allocation is a classical allocation problem in nonmarket mechanism design, of how to allocate a limited number of houses among a large group of agents.[1] Public house allocation in the presence of rental price controls and therefore excess demand requires nonmarket allocation mechanisms to substitute for market pricing clearing. Typically, public housing is allocated using waiting lists or lotteries. The use of waiting lists imply that public housing associations offer vacant units to registered households based on a households' rank on the waiting list.[2] Lottery allocation mechanisms allocate units randomly to registered households, so independently of their waiting time. The welfare analysis of nonmarket allocation of public housing has received much attention in the theoretical literature.[3] Our paper is the first empirical study which examines welfare outcomes for these two types of non-allocation mechanisms of public housing. We make use of a quasi-natural experiment in Amsterdam where public houses are allocated through lotteries to households already on waiting lists.

In Amsterdam, 55 percent of housing is public rent and low-income households have access to public housing through waiting lists, resulting in mean waiting times of over 10 years. In the current paper, we examine allocation outcomes using matches of households and public housing when households on waiting lists had the opportunity to participate in a temporary lottery experiment. We show that the associations' choice between waiting lists and the use of lotteries has strong distributive consequences.[4] The introduction of lotteries particularly benefits younger households who have short waiting times. Furthermore, the introduction of lotteries resulted in different – and plausibly less efficient – housing-household matches combinations than those based on waiting times.

Different types of allocation mechanisms of public housing have been adopted by cities around the world.[5] Not only the distinction between waiting lists, which are also called first-come-first-served systems (FCFS), and lotteries is fundamental, it is also essential to distinguish

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[1] Allocation mechanism refers to any 'institutional arrangement' by which members of one group of agents is assigned to a unit of a second group (Roth, 1982). Other related assignment problems are the 'kidney allocation problem' (Su and Zenios, 2004; 2005), 'adoption problem' (Doval, 2018), and 'school choice or day care assignment problem' (Kennes et al., 2014).

[2] FCFS non-deferral allocation was the conventional system of The Netherlands till the 1990s, and still in place in large parts of Europe and the U.S.A. In such a system, registered households have limited choice over the unit, and if households reject an offer, they are typically removed from the waiting list.

[3] See Kaplan (1986; 1987), Abdulkadiroglu and Sonmez (1999), Chen and Somnez (2004) Abdulkadiroglu and Loertscher (2005), Ehler and Klaus (2007), Sonmez and Unver (2010), and Sonmez and Unver (2011), Andersson and Svensson (2014) and Andersson et al. (2015).

[4] We show that the type of housing that was supplied by the lottery can be considered as a random draw from the supply of public housing for eligible households.

[5] Many public housing systems are centrally administered. A centralized system matches reported households' preferences with vacant public housing units of different housing associations. The eligibility criteria are set by local governments and vary across jurisdictions.

between allocation mechanisms which allow for *deferral*, i.e. households may reject public housing offers and wait for another unit to arrive, and mechanisms were households upon rejecting an offer are removed from the waiting list. Furthermore, some cities have *choice-based* schemes in which households apply for a unit, whereas other cities use allocation mechanisms which offer public housing units irrespective of households' choice. In Amsterdam, public housing allocation is choice-based with unlimited deferral, which leads to a consistent preference ordering (Thakral, 2014), and allows one to use waiting time to reveal information on the marginal willingness to pay for public housing characteristics (as in Van Ommeren and Van der Vlist, 2016).[6] The lottery experiment included households who were also on a waiting list for a public house within the city.[7] The question we aim to answer is whether such lottery leads to different – and, more interestingly, less efficient – outcomes compared to the waiting list system.

The fundamental allocation problem is that the rent is given (they are rent controlled) and that heterogeneous units are allocated to heterogeneous households (Kaplan, 1986). Preferences for housing characteristics are not observed by the public housing association that allocates housing units to households. The aim is to assign households to units such that the outcomes of housing-household matches are socially desirable. The literature analyse matches and welfare outcomes under varying assumptions regarding assignment rule (e.g. waiting times), households' preferences and specification of welfare functions (Kaplan, 1987; Bloch and Cantala, 2016; Leshno, 2017).

There are very few empirical studies on nonmarket allocation of public housing.[8] Only little is known about housing-household matches as noted by Sieg and Yoon (2017). One of the obvious reasons for this gap in the literature is that detailed information (e.g. on waiting times) is usually unavailable, as noted by Geyer and Sieg (2013). Our study is novel in providing microeconometric evidence on new matches of FCFS and lotteries assignment using waiting times. We first provide evidence that – conditional on the neighborhood of the vacant public house – public houses are randomly assigned to lottery or waiting time allocation. Hence the use of the lottery can be interpreted as a quasi-natural experiment with random allocation, which

[6] Note that this preference ordering holds for new matches but not necessarily for existing matches because of changes in the stages in the life course.

[7] The lottery experiment includes only households who are already in non-shared housing. In Amsterdam, all households with public housing, and who are still eligible for public housing (e.g. income levels) can apply for another public house. The announced justification by the public housing authority for this lottery is to increase turnover in public housing.

[8] By comparison, there is a substantial literature which shows the effect of rent control on market outcomes. For example, in their groundbreaking study, Glaeser and Luttmer (2003) show that the allocation between households and housing is less efficient in rent-controlled New York compared to non-regulated markets in other cities. In this literature, the exact allocation mechanism is usually not discussed.

facilitates a comparison of the outcomes of both allocations mechanisms.[9] We are the first study to use detailed information on housing allocation matches for alternative nonmarket allocation designs. Our setup uses information from a natural counterfactual analysis of outcomes under alternative designs which is usually not available (as observed by Agarwal, 2015).

To interpret our empirical results, we rely on the above-mentioned theoretical literature which analyses the question under which assumptions allocation of public housing based on FCFS is preferred to lottery-based allocation. The theoretical framework we have in mind is one where heterogeneous public housing is sequentially offered to heterogeneous households (at a rent below the market price), but where the alternative market to public housing is not distorted (i.e. rents of private houses are competitively determined). With heterogeneous public housing we mean that there is a given distribution in terms of quality (e.g., public houses differ in size). Heterogeneity of households implies that some households (e.g. those with a higher income) have a stronger preference for high-quality housing than other households. Assuming a static economy, one can show then that the use of lotteries, i.e. random allocation, results in a welfare loss compared to the first-best allocation. For example, low-quality houses may be allocated to households with a strong preference for high-quality houses (e.g. Glaeser and Luttmer, 2003).

To analyze FCFS allocation, one has to introduce an element of time, see Leshno (2017), Thakral (2016) and Bloch and Cantala (2016).[10] In general, the use of waiting times generates efficiency gains compared to lotteries (Bloch and Cantala, 2016). The intuition is that the waiting time of a specific public house reflects households' preferences regarding its housing characteristic. For example, FCFS induces households with a strong preference for large houses (e.g. those with children) to wait longer for large houses so there will be a positive relation between the size of the house and duration of waiting. Consequently, waiting times under FCFS provides important information on the willingness to pay for public housing characteristics. Following Thakral (2015), FCFS allocation can be treated as an efficient nonmarket allocation benchmark to evaluate allocation mechanisms such as lotteries.

We emphasize that the assumption that the use of FCFS generates efficiency gains compared to lotteries only holds given two fundamental assumptions – low public housing vacancy rates and identical discount rate for households – which are difficult to test empirically, but which seem to hold in the context of Amsterdam.[11] The main consequence is that one may

[9] The main advantage of this setup is that we avoid a comparison of different allocation mechanisms used in different (geographical) markets, which makes the analysis less straightforward, see for example, Glaeser and Luttmer (2003).

[10] One common assumption is to assume that eligible households are born at the start of a certain period with a demand for public housing for two periods.

[11] The first assumption – that public housing vacancy rates are essentially zero – is needed because lotteries can be argued to improve welfare as they accelerate turnover in the queue, as household are less

interpret the observed differences in allocation outcomes between FCFS and lotteries as distortionary.

We evaluate the welfare outcomes of FCFS, i.e. allocation through waiting times, and lotteries for Amsterdam using a sample of new matches between households and public housing for the period of 2008 - 2011. Our identification strategy is based on information from a quasi-natural experiment where public houses are allocated through lotteries to households who are already on waiting lists. We have access to information on household, public housing characteristics and, waiting time at the time of signing the new rental contract. While lotteries do not assign public housing to households based on waiting time, we observe the waiting time of lottery winners.

We demonstrate that the experiment using lotteries resulted in very different – and arguably less efficient – household and public housing matches combinations than those based on waiting time. Using a structural approach we show that the annual welfare loss due to lotteries is substantial.

The rest of the paper is as follows. Section 2 gives the theoretical background to evaluate outcomes of allocation mechanisms. Section 3 describes the institutional context and data. Section 3 discusses the empirical approach. We present our findings in Section 5. Section 6 concludes.

II. THEORETICAL BACKGROUND

We consider a housing market in which eligible heterogeneous households wish to move to public housing.[12] These households enter a queue and are placed on a centralized waiting list. Over time, households in line receive a public housing offer when one of the existing tenants moves out, creating a housing vacancy. We assume a housing market in steady state, so the queue is of constant length and in which the queue is never empty (Kaplan, 1987).[13]

Public housing is offered by a public housing authority which task is to assign public housing units to households. The public housing stock is exogenously determined and is

selective in rejecting housing offers which reduces vacant public housing. In Amsterdam, public housing vacancy rates are essentially zero, hence this assumption holds. The other assumption – that households have identical discount rates – is needed because lotteries change the time ordering that households receive housing. Why we think this assumption is reasonable in our context, will be discussed in detail later.

[12] In our application of Amsterdam, we focus on households which are already in public housing and who wish to move to a more preferred public house. Households who move into a public house, are automatically queueing for a more preferred public house.

[13] Leshno (2017) refers to this as 'overloaded' queues. Given long waiting times, households with very high waiting costs will not sort for public housing.

heterogeneous in quality (which includes the level of the rent, which is controlled).[14] Given the assumptions that tenants randomly move out, the housing quality of the vacant unit is a random draw from a given quality distribution.[15]

Public housing units which become vacant are posted, while households on the waiting list apply for these units. Units are assigned to households according to a specific allocation mechanism with unlimited deferral, which we will discuss shortly hereafter. Upon receiving an offer, the household subsequently has to decide whether or not to accept.[16] If the household rejects the offer after considering the housing quality, the unit is offered to another household. Households may reject the housing offers unlimited and are not removed from the waiting list. Households who accept are removed from the waiting list.

The behavior of a household can be formulated as a dynamic optimization problem in which the decision to accept the housing unit by a risk neutral agent can be written as a reservation rule.[17] This decision depends on the state-specific payoffs (e.g. the payoff while waiting, during service, and when exiting the queue, see Su and Zenios, 2004). The expected payoff of a public house is conditional on its quality exceeding the reservation value.

The household's utility of its position in the queue depends on the probability that an offer is rejected by a higher-ranked household, and the value when the specific household receives a unit above the reservation value, and a continuation value when the unit is below the reservation value which depends on the waiting costs. Households with a long waiting time are ranked high, but also have a high continuation value and can be said to be "patient" (Schummer, 2016).

Following Thakral (2016), we assume that households have *identical* time-invariant waiting costs, hence they have identical preferences of the timing of receiving public housing. If the household accepts the offer, the household will experience a constant per unit time value over the remaining lifetime and leaves the queue. All other households ranked after the specific household will move up in rank while households ranked before the specific household will keep their rank. Note that households are not affected by the behavior of households ranked lower (Su and Zenios, 2004; Bloch and Cantala, 2016). Hence, acceptance of a housing unit by a lower

[14] In the specific housing market we consider, the controlled rent is fully determined by an *administrative* measure of housing quality, so that the rent level can be considered random from a household perspective.

[15] In the specific housing market considered, public housing tenants also move to other public housing units. Hence the draw is from a conditional quality distribution, where the condition is that the quality of the house accepted exceeds the quality of the current house. This complication does not change the insight of our theoretical background.

[16] In our application, when the household accepts the offer, eligibility in terms of income is checked.

[17] We refer here to a large theoretical literature on household behavior and residential mobility (see Arnott, 1989).

ranked household yields a Pareto efficient allocation (Doval, 2018; Thakral, 2016).[18] The waiting time at the time of accepting an offer, in conjunction with information about housing characteristics and rent, provides information on household's preferences about these housing characteristics and can be exploited to elicit information on the willingness to pay for public housing (Van Ommeren and Van der Vlist, 2016).

Now, consider a situation with a lottery where a small fraction of households, while waiting in the queue, unexpectedly, receive a public housing offer during a short period (independent of their queueing time).[19] Houses offered by the lottery are randomly chosen from the quality distribution of housing (we will show that this assumption holds in our data). Winners from the lottery who accept the public housing offer will lose their rank on the waiting list (they will be automatically ranked last) and therefore will only accept the offer when the public housing offer is more attractive than the public house they would get through their current rank on the waiting list. Furthermore, because they lose their ranking on the waiting list after accepting, the public house offered through the lotteries must be *much* more than the public house they would get through their current rank on the waiting list.[20] Furthermore, when winners from the lottery reject the public housing offer, they remain on the waiting list. When a household receives and accepts an offer through the lottery, the house on offer is not necessarily rejected by all higher-ranked households, so household's utility of accepted offer does *not* depend on the probability that an offer is rejected by any household ranked higher (the utility depends on the value of the unit on offer when above a reservation value, and a continuation value when the value of the offer is below the reservation value). Now, since households with short waiting times have lower continuation values (and will be less patient), they are more likely to accept the offer, resulting in a higher rate of lottery acceptance and different housing-household matches. Contrary to waiting lists does acceptance by a lower-ranked household in a lottery not necessarily imply rejection by higher-ranked households. Acceptance of a housing unit by such a lower-ranked household than implies that the outcome is *not* Pareto efficient,

[18] This follows from the assumption that households are homogeneous with respect to the cost of waiting, because the higher-ranked household would never have preferred to get this public house.

[19] The probability of receiving several lottery offers is negligible, and can be assumed away.

[20] For example, let us suppose that a household who occupies a house of 100 m2 is 10 years of waiting-list. Furthermore, suppose that every year of waiting increases the size of the house by one square meter, but all the other characteristics remain constant including the rent. Given the household's duration of waiting, the household may get a house of 110 m^2. Suppose that for this household it is optimal to wait another five years receiving a house of 115 m^2. But now the household wins the lottery. Clearly, any house offered by the lottery larger than 115 m^2 will be accepted. However, a house of 111 m^2 might be rejected: it is more attractive for the household to wait longer.

implying welfare losses (Bloch and Cantala, 2016; Schummer, 2016).[21] We aim to evaluate these welfare losses for lottery relative to waiting lists.

In our empirical analysis, we aim to test for welfare losses of lotteries in *three* ways. First, we will test for welfare losses by examining whether lotteries induce reductions of waiting time for winners.[22] A small reduction in waiting times suggests that welfare losses will be small. In contrast, we will demonstrate that lottery assignment leads to a reduction in waiting times of about 6 years, suggesting that these welfare losses might be substantial. Note that these welfare losses will only be substantial when households attach substantial economic value to reductions in waiting time, i.e winning the lottery. We therefore apply two different – and approximate – methods to estimate the household's benefit of winning a lottery (one method uses the increase in the market value of the public house due to winning the lottery, the other method uses the reduction in waiting time and multiplies this with the marginal valuation of the waiting time in terms of the market value of the public house). Both methods provide similar results and suggest that the winners gain considerable. These large gains for winners provide *suggestive* evidence of substantial welfare losses.[23]

Second, to make these welfare losses salient, we will test whether the distribution of household characteristics for winners of lotteries differs from this distribution for households that obtain public housing through waiting. For a lottery to be as efficient as waiting list, a necessary (but not sufficient as discussed in Chiappori and Salanie, 2016) condition is that there is no (or little) difference in these two distributions of household characteristics. We will show however that – due to important differences in the probability of accepting lottery offers by different households – there is a *substantial* difference in the distribution of observed household characteristics. We will demonstrate that lottery winners have higher income levels and less children, but the difference is particularly extreme with respect to age: the household head of lottery winners is 12 years younger.[24]

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[21] This result assumes that households do not differ in their waiting costs, implying that they do not differ in their preferences of the timing of receiving public housing or in their discount rates (see Leshno, 2017). In general this assumption may not hold as household within a population are extremely heterogeneous. There are reasons to believe that this assumption is not too unreasonable in our context. We focus on a sample of households who occupy public housing and who are still waiting for another public house (and therefore who are still eligible for public housing), which strongly reduces heterogeneity of households.

[22] This assumes away the effect of lotteries on vacancy rates, as in Leshno (2017). Lotteries increase acceptance probability, which may result in lower vacancy rates and therefore welfare gains (Bloch and Cantala, 2016). In Amsterdam, however, most vacant public houses are occupied within one month, resulting in a vacancy rate which is close to zero, so a lottery system may not decrease vacancies.

[23] We emphasise that given homogeneous households *or* homogeneous houses, there will be no welfare losses.

[24] These results make sense: houses with higher income levels are more likely in the near future to surpass the eligibility threshold given income growth and are therefore more likely to accept lottery offers. Furthermore, younger households have less waiting time, and households with shorter waiting times are more likely to accept lottery offer.

Third, in a more structural approach we estimate the size of the welfare loss of lotteries in terms of *yearly* income. In essence, we are inspired by the work of Sieg and Yoon (2017) that makes explicit assumptions about the form of the utility function. We allow for heterogeneous housing – based on the market value of the public house – and heterogeneous households – who differ in terms of household income and household size.[25] We show that the income that households, a priori, require to compensate for the loss in consumer surplus, because of the introduction of the lottery is €275 per year (or associated life time compensation at 5 percent of about €5,500).

III. THE DATA

III.1 Institutional Context

In Amsterdam, about 70 percent of the rental market is supplied by housing associations. Housing associations are not-for-profit organizations which aim to provide homes for those in housing need, to maintain and manage property properly, to keep rents at affordable levels, and to invest in communities and neighborhoods.[26] Housing associations list public housing units for which households apply. This includes information regarding the allocation mechanism (lottery or waiting time), as well as information regarding address, and housing characteristics, and restrictions on which type of household can apply (minimum or maximum income; number of members in the household). All public housing units are assigned to households using a nonmarket allocation mechanism. For the majority of public housing units, a waiting list is used which is centralized for the whole of Amsterdam.[27] In the current paper we focus on households who already occupy a house and who are on a waiting list for another public house.[28] For these households, waiting time is defined by the elapsed time since moving into the current house.[29]

[25] The main disadvantage however is that this calculation makes potentially restrictive assumptions on the form of the utility function (and makes restrictive assumptions on the time horizon of households). The other disadvantage is that by limiting heterogeneity of households (it only allows for heterogeneity in terms of income and age) as well as of housing (only allows for heterogeneity in terms of market value, but ignores other variation), and therefore underestimates the welfare loss.

[26] Non-regulated rents (per square metre) vary between €10 and €25, whereas public housing rents vary between €3 and €13 (with a mean of €8).

[27] We exclude mainly houses allocated to households with a priority status. Priority holds for households in urgent need of a house, mainly divorced females with small children and households who have to move because of an urban regeneration project.

[28] Van Ommeren and Van der Vlist (2016) focus on a group of households who are on public housing waiting-lists for the first time and who are not eligible for lotteries.

[29] Our sample may include a few households who owned a private house before moving into public housing, but this has no consequence for our analysis. Note that the waiting times cannot be compared to those reported in Van Ommeren and Van der Vlist (2016), because the latter study included 'starters', households not creating any vacancy chain, for which the waiting time is defined differently (based on the day of registering with the housing authority), resulting in much shorter waiting times.

Over 2008-2011, during a period of a few weeks, a small share of public houses is assigned to households who are on a waiting list using a lottery. Hence, units are assigned randomly and irrespective of their waiting time (Rigo, 2008). Households are notified of the houses which are part of the lottery, and can then apply for this lottery. Accepting the offer of a public house obtained through the lottery implies that one is removed from the current waiting lists (or to be more precise, the new waiting time is reduced to zero). An important characteristic of our data, is that only 20 percent of lottery winners accepts the offer. This is important because it implies that households frequently reject offers (even when the house on offer is better than the currently occupied one), because they lose their position in the waiting list which guarantees them in the (near) future even better one (or, more formally, for households who reject the lottery offer, the utility derived from their current house plus the value attached to the position in the waiting list exceeds the utility derived from lottery offer).

III.2 Descriptives of households and allocated public housing

Our data refer to the period 2008-2011 and come from 5 different housing associations in Amsterdam.[30] We have 1,243 observations of public houses allocated during that period of which 318 have been allocated through lotteries and 925 through waiting time.[31] We have information on structural housing characteristics (e.g., number of rooms), rent and market value (as estimated by property tax authorities), the exact residential location, as well as household characteristics (e.g. household size, type and income). The main descriptive statistics are given in Table 1. We distinguish between *allocation characteristics* (e.g. lottery or waiting time), *housing characteristics* (e.g. number of rooms) and *household characteristics* (e.g. household income).

[30] In 2008, Amsterdam had 10 housing associations participating in the public housing matching authority (AFWC, 2008). In 2011, Amsterdam had 8 housing associations of which one association is specifically for student housing, another one for senior households (AFWC, 2011). Out of the 6 remaining housing associations we have data for 5 associations (as for one housing association we were not able to merge new rental contracts to house units).

[31] The large majority of lottery observations come from one association. In the sensitivity analysis, we show that our results are robust when we select only observations from this association.

TABLE 1: DESCRIPTIVE STATISTICS

	All		Waiting list		Lottery	
	mean	st.dev.	mean	st.dev.	mean	st.dev.
Allocation characteristics						
Lottery (1=yes)	0.256				1	
Waiting time (in years)	12.08	8.571	14.26	8.407	5.746	5.268
Rejections (number)	7.931	10.73	9.142	11.13	4.689	8.808
Housing characteristics						
Rent (in € per month)	481.1	101.1	487.1	99.52	463.5	103.6
Unit rent (Rent-to-market value)	0.0297	0.00903	0.0296	0.00907	0.0302	0.00894
Market value (in €)	205,974	56,500	209,920	56,645	194,495	54,560
Apartment (1=yes)	0.522		0.583		0.346	
Building year	1956	33.84	1957	35.03	1953	29.91
Number of rooms	2.973	0.871	2.892	0.918	3.208	0.665
Size (in sq.m)	55.92	12.79	55.32	13.39	57.66	10.68
Year	2010	1.287	2010	1.227	2009	1.258
Month	5.953	3.352	6.438	3.445	4.544	2.600
Neighborhoods in Amsterdam						
City-centre	0.12		0.14		0.05	
West	0.16		0.18		0.09	
Nieuw-west	0.09		0.10		0.05	
Noord	0.24		0.17		0.44	
Oost	0.16		0.17		0.13	
Zuid	0.11		0.14		0.03	
Zuid-oost	0.13		0.10		0.21	
Household characteristics						
Age (in years)	44.37	13.82	47.81	13.23	34.36	10.13
Household income (in € per year)	21,091	10,090	20,259	9,672	23,513	10,876
Household size (number)	2.260	1.376	2.190	1.430	2.462	1.185
Number of adults	1.359	0.529	1.329	0.529	1.447	0.523
Number of children	0.901	1.142	0.862	1.177	1.016	1.025
	1,243		925		318	

Notes: descriptive statistics refer to data on rental contracts of public housing units. St.dev is standard deviation.

It appears that mean waiting time (when accepting a house) is substantial and equal to 12.08 years (with a standard deviation of about 9). Importantly, lotteries show considerably shorter waiting times. Households who accept public housing through a lottery reduce their waiting time by 8.5 years. Given the assumption that lotteries are random (to be investigated later on) this indicates that households with longer waiting times are much less likely to accept public housing assigned using lottery. As explained in the previous section, this reduction in waiting time for winners implies that lotteries reduce welfare.

In Amsterdam, households first have to apply and then after inspection immediately have to decide whether to accept or not. Public houses are frequently rejected after being offered to households: only one out of nine houses is accepted when it is offered through a waiting list, while it is accepted almost twice as often when it is offered through a lottery. The latter is in line with the idea that lottery winners are much less selective (Schummer, 2016).

The average public house is small: it is a 56 square meter, two-bedroom apartment. The average monthly rent is equal to €481. The market value (when the house would have been sold in the market) equals €205,974. The unit rent, or rent-to-market value, is low (2.97 percent) which is in line with the idea that rents are controlled below rental market value (DTZ reports 5.2 percent).

These households are poor: it has an annual household income of €21,091 (about 40 percent below average household income in the Netherlands during that period), despite having 2.26 members on average. The head of the household (signing the rental contract) is 44.37 years, on average.

III.3 Information about previous housing

The above information is about the characteristics of the public house allocated to households. Importantly, we do *not* have individual level data about their previous house, but we have aggregate information about the public houses occupied by similar households. To be more precise, we have individual level data of matches allocated to households who obtain public housing *for the first time*. Given the – we believe reasonable – assumption that the previous houses have been allocated to first-time occupiers, we have accurate information at the aggregate level. It appears that the average market value of the previous house is about €154,000. Hence, on average, winning and accepting a lottery (after 5.7 years of waiting) or accepting a public house through the waiting list (after 14.2 years of waiting) generates a lifetime benefit equivalent to a reduction of waiting time of 8.5 years for a consumption benefit of €50,000 (206,000 - 154,000), on average.

III.4 Lottery as a quasi-natural experiment

In order to interpret the lottery as a quasi-natural experiment, it is important that houses included in the lottery experiment are a random sample from the full sample of houses offered to households. This is unlikely to hold, because the bulk of the lottery observations come from one association and associations are dominant in different neighborhoods.[32] Because neighbourhoods differ in terms of type of housing (e.g, apartments versus single family homes), type of housing will differ between lottery and waiting time offers. Consequently, the main

[32] Furthermore, housing associations may – on purpose, or accidentally – select certain types of houses for the lottery. Note that the latter is not so likely, because housing associations particularly offer houses in lotteries during certain short periods. It is reasonable to assume that the period that types of houses which become available during a certain period is more or less random.

question is not whether lotteries are unconditional random, but the question is whether lotteries are random *conditional on housing association* and *on the location in certain neighbourhood fixed effects*.

In Table 1, it is shown that the difference in most housing characteristics is small between the allocation mechanisms. For example, in our data we have an administrative measure of housing quality which has an identical average for both allocation mechanisms. Moreover, the market value of the property, which we believe is the most accurate economic measure of differences in housing quality, and which is also a measure of societal cost of public housing, is only slightly lower for lotteries than for waiting time (€195,000 versus €210,000). Also the rent, which is controlled, is only slightly different for lotteries, suggesting that there are no strong differences in the type of quality of housing, and if anything, houses chosen for lotteries are at most only slightly less attractive than those for waiting times. If the latter is true then the main consequence for our analysis is that we tend to underestimate welfare losses if we make the assumption that the selection of housing characteristics is random.

Nevertheless, the univariate data reveal important differences in *three* types of housing characteristics, as shown in Table 1. The main eye-catching difference is the *neighbourhood* of the property, but there are also suggestive differences in *number of rooms*, and particularly *share of apartments*. To investigate this further we have run a range of analyses, which all indicate that the use of the lottery is random *conditional on housing association* and *on neighbourhood fixed effects*.

Hence, the relevant question is to what extent lotteries can be considered random, conditional on neighbourhood fixed effects. For example, we have estimated a probit model of lottery as a function of housing characteristics and neighborhood fixed effects. These results are reported in Appendix A. It appears that given these fixed effects, there is no effect of any housing characteristic on the probability that the house is offered through a lottery. Hence, the lottery draws randomly from the supply housing, conditional on neighbourhood fixed effects, and is therefore conditionally random.[33]

III.5 Lottery reduces waiting time

Table 1 indicates that lottery winners have a much shorter waiting time. We are interested in the *causal* reduction in waiting time for lotteries. It is then possible to interpret the reduction in waiting time, τ, observed both for lottery winners and non-winners, as a counterfactual to

[33] This conclusion is also supported by another (reversed) analysis, where we have estimated the effect of lottery on individual housing characteristics (e.g., market value), conditional on housing association fixed effects, neighbourhood fixed effects and time fixed effects. We do not find any evidence that the type of housing characteristics offered to households is different (e.g. higher market value, number of rooms, apartment) when a lottery is used, conditional on housing association (see Appendix A).

evaluate the lottery. Given that we have shown that housing units are randomly assigned conditional on neighbourhoods and time fixed effects, we estimate a model where we aim to estimate the *causal* effect of a lottery of a house i at time t on the natural logarithm of waiting time, conditional on housing association fixed effects θ_m, neighbourhood fixed effects, η_j and, time fixed effects, μ_t.

(1) $$log\tau_{it} = \alpha + \delta Lottery_{it} + \theta_m + \eta_j + \mu_t + \varepsilon_{it,}$$

where α and δ are coefficients to be estimated and ε is random error. The results are reported in Table 2. We find that δ is about -1. This implies that lotteries reduce waiting time by more than 50 percent (exp(-1) -1). In this setup, efficiency can potentially be improved by controlling for a range of housing characteristics. As one can see, efficiency hardly improves by adding these housing characteristics. We emphasise here that the reduction in waiting time does *not* necessarily have any effect on efficiency of the allocation mechanism. In particular given the assumption that households have identical discount rates there are no welfare losses (as the reduction in waiting times through winning a lottery is compensated by the increase in waiting time by non-winners). On, a priori, grounds, identical discount rates seem a reasonable starting point, because we have a relatively homogeneous sample of poor households who live in the same city.[34]

[34] Moreover, our sample excludes households that are in distress (e.g. through a divorce or for medical reasons) who can avoid waiting-lists and frequently get priority.

TABLE 2: LOG WAITING TIME

	(1)	(2)	(3)	(4)	(5)
Lottery (1=yes)	-1.052***	-1.075***	-1.027***	-0.928***	-0.928***
	(0.0614)	(0.0614)	(0.0645)	(0.169)	(0.170)
Year	y	y	y	y	y
Month	y	y	y	y	y
Housing Association		y	y	y	y
Neighborhood			y		
Street				y	y
Property characteristics					y
Observations	1,243	1,243	1,243	1,243	1,243
R^2	0.255	0.258	0.276	0.841	0.843

Note: dependent variable is log waiting time. Standard errors in parentheses. ***, **, * at 1, 5 and 10 percent

III.6 Does the lottery change the match between household characteristics and housing?

We have shown in section III.4 that the lottery offers random housing (conditional on neighbourhood, housing association and time fixed effects) to households. We have argued in the previous section that the lottery-induced reduction in waiting time does not necessarily imply welfare distortion. In contrast, any lottery-induced change in the distribution of household characteristics implies a different – i.e. distortionary as argued in the introduction – match between households and housing. We emphasise that, because we have a quasi-experimental setup, we can draw this conclusion, while this is not possible with nonexperimental data as argued, for example, by Glaeser and Luttmer (2003), because of differences in housing supply.

It is, in principle, possible to examine first-order as well as second-order distortions in matches. The first-order distortion would be that mean household characteristics are different between lotteries and waiting time. For example we can examine whether households are younger, on average, in the lottery. The second-order distortion is that the distribution of household and house characteristics matches changes. For example, it may be the case that younger households tend to have larger houses due to the lottery. The literature focuses on the second-order distortion (Glaeser and Luttmer, 2003). Here, we analyse first-order distortions due to the use of lotteries using reduced form models, and we ignore, for now, second-order distortions, which will be estimated using structural models.

To examine first-order distortions, we estimate a set of linear models, where we examine the effect of lotteries (relative to waiting time) on five different households characteristics – age of the head of the household, household size (i.e. number of members), number of children and number of adults – conditional on housing neighbourhood and time fixed effects. To improve the efficiency of the estimates, we also control for four relevant house characteristics (the market value, the number of rooms, the size of the house, apartment or not). Results are reported in Table 3.

TABLE 3: HOUSEHOLD CHARACTERISTICS

	(1) Age	(2) Household income	(3) Household size	(4) Number of adults	(5) Number of children
Lottery (1=yes)	-11.56***	2,083***	-0.140*	0.0328	-0.173***
	(0.997)	(803.9)	(0.0774)	(0.0395)	(0.0666)
Log market value (in €)	3.638	3,532*	-0.223	0.0821	-0.305**
	(2.248)	(1,813)	(0.175)	(0.0892)	(0.150)
Log rooms	-1.328	-646.1	1.397***	0.137**	1.261***
	(1.632)	(1,316)	(0.127)	(0.0647)	(0.109)
Log size (in sq.m)	-10.03***	5,383***	3.058***	0.773***	2.285***
	(2.459)	(1,984)	(0.191)	(0.0976)	(0.164)
Apartment (1=yes)	-0.429	-667.0	-0.140**	-0.0428	-0.0977*
	(0.830)	(669.2)	(0.0645)	(0.0329)	(0.0554)
Year	y	y	y	y	y
Month	y	y	y	y	y
Housing Association	y	y	y	y	y
Neighborhood	y	y	y	y	y
Observations	1,243	1,243	1,243	1,243	1,243
R^2	0.234	0.066	0.534	0.179	0.500

Notes: the dependent variable is a household characteristic. Standard errors in parentheses. ***, **, * at 1, 5 and 10 percent.

Lotteries appear to have a strong effect on household-public housing matches. As reported in column (1) we find that lotteries induce substantially younger households: the age of the household is on average *12 years* younger. Young households clearly find lotteries attractive. This makes sense: young households do not have yet the long waiting times to be ranked high in first-come first-served allocation mechanisms, and lotteries offer them the chance to improve their housing. This is particularly so for permanent rental contracts which make young households with high earning capacity more willing to accept a public housing offer before they become non-eligible while waiting. As is well known, households that remain eligible for social housing at older age are an increasingly selective group of poor households.

Further, column (2) suggests that income levels are higher (€2,083, about 10 percent of mean income). Furthermore, column (4) shows that lotteries lead to smaller households with fewer children (-0.173, about 20 percent of mean number of children). In other words, lotteries induce young households, with fewer children and higher incomes to accept the lottery.

Pulling together, these findings are consistent with observations of Glaeser and Luttmer (2003) who suggest losses of misallocation under random allocation being non-negligible. Although suggestive, these reduced form estimates do not provide an exact measure of the welfare loss (and ignore second-order distortions as discussed above). We will therefore estimate a structural model following Sieg and Yoon (2017) to estimate this welfare loss.

III.7 The value of winning a lottery to winners

We have shown that lottery winners reduce their waiting time by about 60 percent (from 14.2 to about 5.7 years) and that the average increase in market value is about €50,000 (204,000 - 154,000). Given a discount rate of 0.05, this suggests that the gain to winners is about 35 percent of €50,000 = €17,500 ($1 - 0.95^{8.5} = 0.35$), equivalent to about €875 per year (at 5 percent). Hence, winning a lottery is very beneficial, roughly equal to about 3.5 percent of annual household income.

One objection to this calculation is the monetary benefit may be less because the winner does not own this house, but can only use the house until the household voluntarily leaves (or dies). Furthermore, the household may not value a house at market value, because it is not obtained through the market. To address this issue, the households' value of winning a lottery is defined by the households' willingness to pay for receiving an increase of €50,000 in market value in terms of housing. To derive this willingness to pay we employ a methodology, introduced in Van Ommeren and Van der Vlist (2016), where we show that the households' *marginal* annual monetary benefit of the market value, *X,* can be derived by estimating the effects of the market value *X* and of the annual rental price *r* on waiting time for household *h* that obtains public housing through waiting.:

(2) $$log\tau_{ht} = \rho + \beta logX_{ht} + \gamma logr_{ht} + \mu_t + \varepsilon_{ht},$$

where ρ, β, γ and μ are coefficients to be estimated and ε is random error. By assumption, the *ratio* of the marginal effect of X on household utility and the marginal effect of r on household utility, defines the (negative value of) the household's marginal willingness to pay for X, denoted as MWP_X. It can be a result shown that MWP_X equals the ratio of - $\partial log\tau/\partial logr$ and $\partial log\tau/\partial logX$. Hence, given estimates of β and γ, MWP_X can be calculated as:

(3) $$MWP_X = -\frac{\beta}{\gamma}\frac{r}{X}.$$

The annual willingness to pay for *an increase in* market value, WP_X, from *x* to *X,* and hence the households' value of receiving an increase in market value, can be obtained by integrating from *x* to *X* and is hence equal to: [35]

[35] The standard error of the estimate of MWP_X and WP_X will be calculated using the delta method (Wooldridge, 2008).

(4) $$WP_X = -\frac{\beta}{\gamma} r[log\ (X/\mathrm{x}\ )\ ].$$

Consequently, WP_X can be calculated using information on the relative increase in market value *(X/x)*, the annual rent, *r*, and the ratio of two coefficients, i.e. ratio of the marginal effect of log market value on log waiting time and the marginal effect of log rent on log waiting time.

TABLE 4: QUEUING TIME AND WILLINGNESS TO PAY FOR WAITING LIST ALLOCATION MECHANISM

Panel A: coefficients		
Log market value (β)	0.377	***
	(0.110)	
Log rent (γ)	-0.204	*
	(0.119)	
Observations	925	
R^2	0.036	

Panel B: WTP estimates		
$-\beta/\gamma$	1.848	*
	(1.029)	
MWP_x	0.0514	*
	(0.0287)	
WP_x	16,564	*
	(8,200)	

Notes: dependent variable is log waiting time. Controls for year, month and housing association dummies. Standard errors in parentheses. ***, **, * at 1, 5 and 10 percent.

We have estimated equation (2) while also controlling for time (month and year) and housing association fixed effects. The implied estimates are reported in the lower panel B of Table 4. Using the average values for the annual rent and market value, we find that the *marginal* willingness to pay, MWP_X, is 0.051 or 5.1 percent of market value.[36] So, households in public housing are willing to pay €0.051 per year, when the market value of their house is increased by €1.00. Based on these estimates, and a mean reduction of waiting time by about 60 percent, we find that winning a lottery offers yearly benefits of €1,070 (0.35 · 1.848 · (12 · €480) · ln(200,000/150,000)) and a lifetime benefit of €21,500, which is similar to our earlier estimate which is based on market estimates. Hence, we conclude that winning a lottery offers substantial individual benefits to winners. Public housing in Amsterdam is considerably cheaper compared to nonregulated rents. Also as rental contracts are permanent in Amsterdam these benefits hold

[36] Note that this estimate of 0.051 aligns with capitalization rates of the private rental market which ranges between 0.047 and 0.052 in the same period (DTZ, 2011).

for longer periods of time and, in actual fact, increase with tenure because of the cap on annual rent increases in public housing. So our results give empirical support for earlier findings of large individual benefits for households that have access to public housing. For example, Sieg and Yoon (2017) indicate benefits of up to $55,000 for access to public housing relative to unregulated rental housing in New York based on simulation results.

Sensitivity analyses

Most of our lottery observations come from one housing association. This raises the question to what extent our results are robust as we mix observations of several housing associations which are not equally likely to be involved in lotteries, and which public housing units are not equally spread over the city. To investigate this, we use information from one single housing association, the association which was extremely dominant in using the lottery. This selection reduces the number of observations from 1,243 to 861, mainly by reducing the number observations of housing allocation through waiting lists. We have repeated all the analysis. These results are reported in the Appendix B. In essence, all our results are extremely robust except that the point estimates of MWP_x and WP_x are now imprecisely estimated, which is not too surprising given that the number of observations for waiting times was strongly reduced.

IV STRUCTURAL MODEL

Our above estimates indicate that lotteries are distortionary, but do not provide evidence of the induced welfare losses. For example, we have noted that younger households are more likely to be matched to public housing given lotteries. Although this finding has severe distributional consequences, it does not imply welfare losses if the willingness to pay for housing does not depend on age. Here, we evaluate welfare outcomes of lotteries using a *structural model* approach based on a standard two-goods static consumer choice model (Sieg and Yoon, 2017).[37]

Our methodology has two key characteristics. First, we allow for *household-specific* Cobb-Douglas utility function of housing and another good, where we estimate household-specific utility parameters for households in the public sector using information about housing choices of counterfactual households in the nonregulated sector (as in Glaeser and Luttmer, 2003).[38]

[37] Using a static model seems reasonable given the assumption that discount rates are identical for different households. Given this assumption we assume away that lotteries may affect welfare through a change in the timing of housing consumption.

[38] An important criticism of the Cobb-Douglas utility function assumption is that it implies that in (non-regulated) markets, the share of household income spent on housing is a constant, whereas it is usually found, as confirmed in our data, that this share is a decreasing function of household income. This issue will be addressed by allowing the key Cobb-Douglas parameter to be a function of household income (and other household characteristics).

Second, a key characteristic of housing is that it is heterogeneous, which is difficult to deal with in a structural approach. For example, Glaeser and Luttmer (2003) analyse rent-control-induced distortions in number of rooms, but this ignores that houses differ in location and house sizes strongly related to location. We improve upon this by using the market value of the property (when sold in the private property market) as a measure of housing, denoted by X.[39]

We assume that household i with income of y_i has a Cobb-Douglas utility function of housing, X, and one other good, with a price normalised to one, and hence flow utility, v_i, is written as:

$$v_i = X_i^{\alpha_i}(y_i - p_X \cdot X_i)^{(1-\alpha_i)}, \tag{5}$$

where p_X refers to the unit rent (i.e., the rent per unit of X) and $0 < \alpha < 1$.[40]

Households are assumed to freely choose housing consumption in the nonregulated market by maximising their utility. When they are in the nonregulated market, it follows that their housing demand is equal to:

$$X_i^* = \frac{\alpha_i \cdot y_i}{p_X} \tag{6}$$

which determines v^*. We emphasise that p_X and α_i is unknown, but will be estimated in a procedure where we take a number of sequential steps, such that:

In the first step, we estimate p_X as the unit price in the non-regulated housing market. Specifically, we regress p_X on the market value X. The estimates then, with market value observed for households in the public sector we are able to predict $\hat{p}_X(X)$ (see Appendix C for details).

In the second step, we estimate α_i as the share of income spent on housing in the *non-regulated* housing market. We aim to estimate α_i for households in public housing, which will be denoted as α_i^p. This step again contains two phases. In the first phase, using our sample of households in the nonregulated market, we regress $\hat{\alpha}_i$ on a range of household characteristics Z_i (e.g. income, age of head of the household, number of adults, number of children; interactions between these variables) using the following regression:

[39] Because our measure of housing is comprehensive (i.e., it does not measure one dimension of housing, i.e. the number of rooms), we avoid a restrictive assumption that unobserved housing quality in public housing and the non-regulated market is similar (Sieg and Yoon, 2017).

[40] Note that the unit rent is not a constant, but is a function of housing. This is important for two reasons. In the public housing market, housing corporations determine the controlled rent using a range of indicators (e.g. number of rooms), but location hardly influences the rent. As a consequence, the unit rent tends to decrease in the market value of the public house. But also in the nonregulated market, we observe that unit rents tends to decrease with their market value (e.g. due to fixed cost of letting by real estate agents). Hence, it is essential to allow the unit rent to be a function of housing consumption. <u>We leave this for now but going to address this issue.</u>

(7) $$\hat{\alpha}_i = \delta Z_i + \varepsilon_i.$$

where ε_i is random error. We estimate eq. (7) with OLS. In the second phase, given (7) combined with household characteristics Z_i observed for households in the public sector we are able to predict $\alpha_i^p(Z_i)$.

In the third step, we aim to estimate welfare counterfactuals for the use of lotteries as well as waiting time using a standard equivalent income measure, i.e., the income households have to receive to obtain the same utility level given a different allocation of houses to households. Arguably, the individual measures, y_l^{eq} and y_w^{eq}, are potentially *not* appropriate measures of efficiency differences, because these measures are only valid given a range of a restrictive assumptions, while these assumptions are relaxed by focusing on the difference. To be precise, we calculate the equivalent income measurement for lotteries, y_l^{eq}, as well as waiting time, y_w^{eq}, and are then interested in the difference between these two equivalent income measurements: $\Delta y^{eq} = y_l^{eq} - y_w^{eq}$.[41]

The individual measures are valid given that: *i)* the assumption on the form of utility function strictly holds, *ii)* α is known for each household in the public housing, and, *iii)* we observe rent as well as household income is measured without measurement error (for households in public housing).[42] These assumptions are very restrictive, and when they do not hold, the individual equivalent measures will most likely systematically be biased upwards. To give an example, when all the assumptions strictly hold, and choices of public housing are identical to those in the non-regulated market, but we measure household income with some measurement error, we will find that the equivalent measure is positive. As a result, we focus on the difference between both measurements, so that it is plausible that most of the systematic bias is removed. Further, by focusing on the difference, we do not make any ex-ante assumptions on the efficiency of waiting list compared to lottery allocation, as this measure can be positive or negative. A positive difference between the equivalent income measurements implies then that lotteries are less efficient than waiting lists. Such a finding would be consistent with the theoretical notion that lotteries induce lottery winners to accept houses preferred by other households with longer waiting times which induces inefficiencies.[43]

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[41] $y_i^{eq} = (v_i^*/X_i^{\alpha})^{1/(1-\alpha)} + p_X \cdot X_i$.

[42] Note that while we measure the rent and household income likely more precisely compared to most studies (we use administrative data), household income can still have some measurement error.

[43] Lottery winners with low queueing times are more likely to accept offers, because of a lower continuation value upon when rejecting the offer. Consequently, according to theory, a reduction in waiting time for lotteries is a necessary, but not a sufficient, condition for misallocation.

The structural model approach is based on the notion of identical utility functions for households across allocation mechanisms (Glaeser and Luttmer, 2003). The most straightforward approach is to ignore household heterogeneity in α, and assume that the average estimate of α can be applied to all households in the public housing.[44] This will be our starting point. By assuming households with identical utility functions (but who have different incomes), it is likely that we underestimate welfare differences (in absolute magnitude). To allow for heterogeneity in utility functions, we focus on groups of homogeneous households, i.e. we assume that the utility of households in subgroup k is identical. Heterogeneity across households relates then to observable characteristics like the size of the household (one, two, or more than two members).

IV. EMPIRICAL RESULTS

We estimate the share of housing (α) in the non-regulated housing market using housing survey WOON. WOON is a survey on housing needs representative for the entire nation. The survey includes self-reporting housing needs and, specifically important for our aim here, registration data on household income, tenure, rent and, property market value. Also, information on respondents' addresses on city-level is given. We use 2009 and 2012 waves (BZK, 2009; 2012). We select all households in the private rental sector in Amsterdam with rents net of service charges above the €631.73 per month (2008) and €652.52 per month (2011).[45]

For our calculations, it is important to have information on households in private rental housing because this provides information on structural parameters in non-regulated and presumed non-distorted markets (Glaeser and Luttmer, 2003). Data from WOON provides information on the stock of households in non-regulated, private rental housing. The confounding issue however is that households in private rental may differ in observed characteristics from households in public rental. For example, households in private rental housing have mean incomes of €53,269 relative to €21,415 in public rental housing. What we need is a sample of similar households in private rental housing with housing share and unit rent information in unregulated rental markets. First, we collect information on the share of housing from WOON to predict expected share of housing for households in our sample.[46] This gives for our sample of households the respective distribution of share of housing. Second, we

[44] Note that it is not possible to use the full distribution of α as measured in the non-regulated housing sector, because households differ in income and the value of α is negatively correlated to the income level.
[45] Amounts refer to maximum rents for public housing.
[46] WOON (2009 and 2012) includes 2,241 full information observations for Amsterdam, of which 2,002 are in social rental housing and 239 in private rental housing. WOON provides information on household size, age head of household and, household income.

exploit information on the relationship between unit rent and market value in unregulated markets to predict counterfactual unit rent (rent-to-market value ratio) for our stock of public housing.

The estimate for share of housing is provided in Table 5 column (1). The estimate for waiting lists 0.55 with a standard error of 0.29, and for lottery 0.50 with a standard error of 0.24. Hence, 55 percent of income is spent on housing if households were in unregulated markets. Our estimate is consistent with low income households spending larger shares on housing. Also, these estimates are in line with estimates reported in the literature. For example, Sieg and Yoon (2018) report estimates for share of housing anywhere between 0.43 and 0.50 for renters in Manhattan, New York.

Public housing offers substantial benefits to public housing renters. The mean estimate for unit rent in private rental markets is in waiting lists 0.059 with a standard error of 0.01, while in lotteries 0.062 with a standard error of 0.01.[47] The unit rent in public housing (0.0297, see Table 1) is 50 percent lower than the estimate for private rental housing for our sample of households. As unit rent in private rental is substantially different and higher we expect optimal housing consumption to be different from observed housing consumption.

The outcomes for both waiting time and lottery allocation are reported in Table 5 (for details see Appendix C). Our estimates reported in Table 5 imply a welfare loss for lottery relative to waiting lists. Specifically, we find an annual welfare loss of €273 for each public house assigned by lottery.

TABLE 5: ESTIMATED PARAMETERS BY ALLOCATION MECHANISM

	Allocation mechanism			
	Waiting list		Lottery	
Unit rent (p_X)	0.059	(0.010)	0.061	(0.009)
Adjusted share of housing (α)	0.554	(0.029)	0.502	(0.237)
Welfare loss lottery (Δy^{eq})	€273 per year			

Note: For details see Appendix C

V. CONCLUSIONS

Public housing allocation is one of the classical problems in nonmarket design. This is because the presence of price controls prevents households from revealing their marginal willingness to pay for housing through market prices. The theoretical literature considers

[47] Note that while our estimated discount of 30 percent is lower than the 51 percent reported by Sieg and Yoon (2017) for NY, they cannot fully control for housing service flows as we do. We have precise information on housing service flows as we have property-specific market value as estimated by property tax authorities.

allocation mechanisms based on random or non-random mechanisms. We focus on the public housing sector, where houses are supplied by non-profit housing associations that use queuing time to allocate houses. We are the first to empirically compare the outcomes of waiting lists and lotteries for public housing. We use data from public housing in Amsterdam where lotteries, as part of a temporary housing policy to increase turnover for movers, co-existed with waiting lists or first-come first-served (FCFS) allocation based on waiting time. The data is rather unique as both allocation mechanisms co-existed within the very same housing market during the very same weeks of public housing units listings.

We use the FCFS allocation to estimate the households' marginal willingness to pay for public housing when eligible households are allocated using waiting lists. For Amsterdam City, we show that the estimate of the households' marginal willingness to pay for public housing is 5 percent of market value. We use this information to elicit information on the value of winning a lottery. Winning a lottery reduces waiting time by 8.5 years, which has a value of about €850 per year in Amsterdam City (or €17,500 over the lifetime).

We also show that the introduction of lotteries resulted in different household-housing match combinations than those based on waiting times. Our descriptive analysis conjectures hat lotteries lead to households with fewer children in otherwise similar public housing. Furthermore, we find that lotteries lead to renters with greater income potential given their younger age and already higher mean income for otherwise similar public housing. We test these conjectures using a structural approach in which counterfactuals are based on structural parameters of the model. We find that lotteries, while a benefit to the individual households winning a lottery, create a welfare cost above and beyond waiting time allocation mechanisms of about €275 per year (or €5,500 over the lifetime).

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APPENDIX A: EXOGENEITY OF HOUSING UNITS TO LOTTERIES

One of the assumptions underlying our analysis relates to the exogeneity of housing units to lotteries. Here in Appendix A we explore the restrictiveness of our assumption. As we show below, our analysis confirms exogeneity by and large.

First, in Figure A1 we map the distributions of waiting time (left panel), rent (middle panel) and market value (right panel). The most remarkable difference in distribution by allocation mechanism is for waiting time. For FCFS allocation based on waiting time longer waiting times can be observed compared to lotteries. Lotteries are associated with households with shorter waiting times.

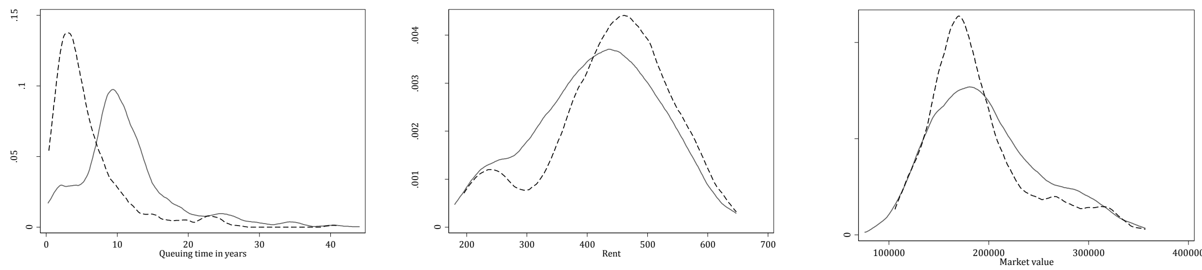

FIGURE A1: WAITING TIME, RENT, MARKET-VALUE BY ALLOCATION MECHANISM FCFS (SOLID LINE) AND LOTTERY (DASHED LINE).

From the distribution of waiting times in Figure A1 one already observes that the distributions are rather different. The difference in behaviour is also reflected in Figure A2 which maps unit rent (rent-to-market value) and waiting time.

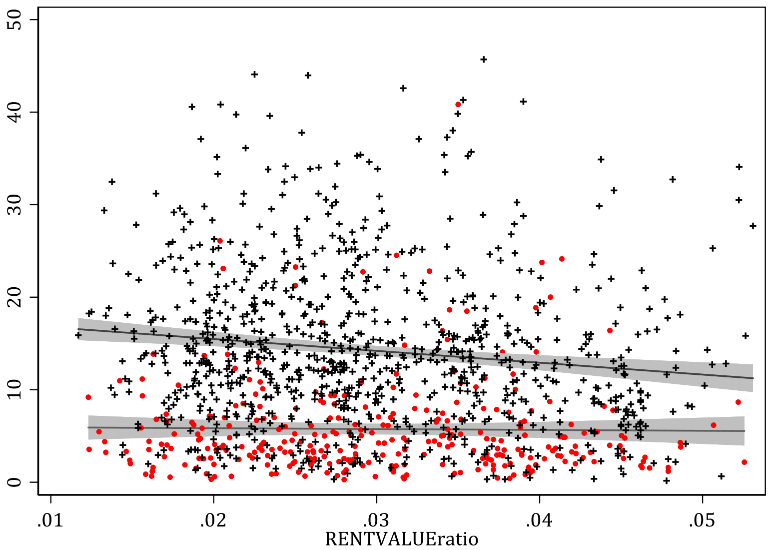

FIGURE A2: UNIT RENT AND WAITING TIME BY ALLOCATION MECHANISM FCFS (BLACK +) AND LOTTERY (RED DOTS).

Now given the shorter waiting times for lotteries, we in Table A1-A2 explore whether lotteries relate to different (less attractive) properties. For this we regress the logarithm of market value on lottery and a set of characteristics. From Table A1-A2 we observe that lotteries are not associated with structurally different public housing.

TABLE A1: LOTTERY AND MARKET VALUE, LINEAR MODEL RESULTS

	(1)	(2)	(3)	(4)	(5)	(6)
Lottery (1=yes)	-0.092***	-0.116***	0.0199	-0.142***	-0.00552	-0.00358
	(0.0205)	(0.0203)	(0.0161)	(0.0196)	(0.0125)	(0.0184)
Log rooms				-0.0192	0.0667***	0.0739*
				(0.0309)	(0.0226)	(0.0445)
Log size (sq.m)				0.377***	0.557***	0.547***
				(0.0388)	(0.0302)	(0.0802)
Apartment (1=yes)				-0.00994	-0.0646***	0.00930
				(0.0153)	(0.0111)	(0.0210)
Year	y	y	y	y	y	y
Month	y	y	y	y	y	y
Housing Association		y	y	y	y	y
Neighborhood			y		y	
Street						y
Observations	1,243	1,243	1,243	1,243	1,243	1,243
R^2	0.050	0.096	0.449	0.187	0.682	0.984

Note: dependent variable is log market value. Standard errors in parentheses. ***, **, * at 1, 5 and 10 percent.

TABLE A2: LOTTERY AND HOUSING CHARACTERISTICS, MARGINAL EFFECTS PROBIT

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log rent (in €)	0.117**	-0.0248	0.148**	-0.000175	-0.0174	-0.0376	-2.580
	(0.0491)	(0.0509)	(0.0586)	(0.0612)	(0.0619)	(0.0618)	(1.745)
Log market value (in €)	-0.192***	0.147***	-0.309***	0.102	-0.357***	-0.0813	-3.252
	(0.0400)	(0.0547)	(0.0481)	(0.0686)	(0.0457)	(0.0818)	(3.493)
Log rooms					0.209***	0.151**	1.565
					(0.0620)	(0.0644)	(1.656)
Log size (sq.m)					0.290***	0.148	2.033
					(0.0860)	(0.0943)	(2.873)
Apartment (1=yes)					-0.114***	-0.0778***	0.392
					(0.0253)	(0.0290)	(0.730)
Year	y	y	y	y	y	y	y
Month	y	y	y	y	y	y	y
Housing Association		y	y	y	y	y	
Neighborhood		y		y		y	y
Street							y
Observations	1,243	1,243	1,243	1,243	1,243	1,243	1,243

Note: dependent variable is Lottery (1=yes). Probit model results. Standard errors in parentheses. ***, **, * at 1, 5 and 10 percent.

APPENDIX B: SENSITIVITY ANALYSIS

Results for one large housing association

Recall that we control for neighborhoods fixed effects, because housing associations are not equally likely to be involved in lotteries, and housing associations are not equally spread over the city. To investigate this, we use information from one single housing association, the association which was dominant in using the lottery. This selection reduces the number of observations to 861, of which 299 for lottery. Hence, the reduction in data is mostly for allocation using waiting times. Table B1 gives descriptive statistics. Table B2-B4 give estimation results. From Table B2 we observe that the reduction in queueing time is identical to what we found before. Also, from Table B3, we find that lottery is associated with different households in public housing. In Table B4, we find a marginal willingness to pay for public housing that is somewhat lower, and equal to 0.0238, but given the smaller number of observations for waiting time allocation and larger standard errors this effect is not statistically significant. Note however that the estimate using all housing associations is within the confidence interval of the new estimate.

TABLE B1: DESCRIPTIVE STATISTICS FOR ONE LARGE HOUSING ASSOCIATION

	All		FCFS		Lottery	
	mean	st.dev.	mean	st.dev.	mean	st.dev.
Allocation characteristics						
Lottery (1=yes)	0.347	0.476	0	0	1	0
Waiting time (in years)	11.60	8.346	14.63	8.054	5.889	5.368
Rejections (number)	7.267	10.05	8.851	10.47	4.428	8.543
Housing characteristics						
Rent (in € per month)	457.50	99.88	457.60	98.15	457.30	103.2
Rent-to-market value	0.0274	0.0083	0.0262	0.0078	0.0297	0.0087
Market value (in €)	211,478	58,652	220,451	58,749	194,612	54,706
Apartment	0.468	0.499	0.536	0.499	0.341	0.475
Building year	1953	35.28	1954	37.77	1952	30.07
Number of rooms	2.992	0.775	2.891	0.810	3.181	0.666
Size (in sq.m)	55.70	11.94	54.79	12.40	57.41	10.82
Year	2009	1.167	2,009	1.139	2009	1.201
Month	5.806	3.297	6.441	3.473	4.612	2.544
Neighborhoods in Amsterdam						
City-centre	0.13		0.17		0.05	
West	0.06		0.06		0.05	
Nieuw-west	0.28		0.19		0.45	
Noord	0.18		0.21		0.13	
Oost	0.13		0.16		0.09	
Zuid	0.09		0.12		0.03	
Zuid-oost	0.13		0.09		0.20	
Household characteristics						
Age (in years)	42.87	13.43	47.27	12.88	34.61	10.16
Household income (in € per year)	21,560	10,957	20,461	10,712	23,625	11,130
Household size (number)	2.271	1.351	2.183	1.426	2.435	1.184
Number of adults	1.373	0.505	1.335	0.491	1.445	0.524
Number of children	0.898	1.118	0.849	1.167	0.990	1.015
	861		562		299	

Notes: descriptive statistics refer to data on rental contracts of 1 large public housing in Amsterdam of households who transfer between public housing units. St.dev is standard deviation.

TABLE B2: LOG WAITING TIME FOR ONE LARGE HOUSING ASSOCIATION

	(1)	(2)	(3)	(4)
Lottery (1=yes)	-1.047***	-1.073***	-0.901***	-0.900***
	(0.0651)	(0.0688)	(0.164)	(0.164)
Year	y	y	y	y
Month	y	y	y	y
Neighborhood		y		
Street			y	y
Property characteristics				
Observations	861	861	861	861
R^2	0.339	0.361	0.830	0.832

Note: dependent variable is Log waiting time. Standard errors in parentheses. ***, **, * at 1, 5 and 10 percent

TABLE B3: HOUSEHOLD CHARACTERISTICS FOR ONE LARGE HOUSING ASSOCIATION

	(1) Age	(2) Household income	(3) Household size	(4) Number of adults	(5) Number of children
Lottery (1=yes)	-11.59***	1,978**	-0.145*	0.019	-0.164**
	(1.029)	(941.7)	(0.083)	(0.040)	(0.072)
Log market value (in €)	2.886	4,720*	-0.268	0.016	-0.424**
	(2.717)	(2,485)	(0.219)	(0.106)	(0.189)
Log rooms	0.777	1,105	1.261***	0.257	1.235***
	(2.101)	(1,922)	(0.170)	(0.082)	(0.146)
Log size (in sq.m)	-10.82***	4,122	3.545***	0.912***	2.633***
	(3.107)	(2,842)	(0.251)	(0.121)	(0.216)
Apartment (1=yes)	-0.124	-565.5	-0.171**	-0.060	-0.111
	(0.986)	(902)	(0.079)	(0.038)	(0.069)
Year	y	y	y	y	y
Month	y	y	y	y	y
Neighborhood	y	y	y	y	y
Observations	861	861	861	861	861
R^2	0.259	0.068	0.523	0.204	0.482

Notes: the dependent variable is a household characteristic. Standard errors in parentheses. ***, **, * at 1, 5 and 10 percent.

TABLE B4: QUEUING TIME AND WILLINGNESS TO PAY FOR FCFS ALLOCATION MECHANISM FOR ONE LARGE HOUSING ASSOCIATION

Panel A: coefficients	(1)	(2)
Log rent	-0.179	-0.289
	(0.119)	(0.233)
Log market value	0.153	0. 245
	(0.110)	(0.266)
Observations	562	246
R^2	0.035	0.053
Panel B: WTP estimates		
$-\beta/\gamma$	0.856	0.845
	(1.029)	(0.947)
MWP_x	0.024	0.0240
	(0.018)	(0.0269)
WP_x	6,834	6,739
	(5,212)	(7,545)

Notes: dependent variable is log waiting time. Specifications (1) controls for year and month dummies. Standard errors in parentheses. ***, **, * at 1, 5 and 10 percent.

Results for rent-subsidy eligible households

The analysis heretofore ignored the fact that some households receive a rent-subsidy. Low-income households receive rent-subsidy up to an income threshold (depending on household size, and household age class) for specific public housing (within a specific rent-range).[48] To consider this, we calculate whether the household is eligible for a rent-subsidy using their income and household characteristics. The selection reduces the number of observations to 246 observations. Estimation results are reported in Table C4 column (2) and reveal a marginal willingness to pay for public housing of 2.4 percent of market value.

[48] The mean subsidy for renters receiving subsidy is €170 per month given a rent of €421 per month. One out of 3 renters receives rent-subsidy (CBS, 2012).

APPENDIX C: STRUCTURAL MODEL ESTIMATION

Structural model estimation as discussed in Section IV is based on WOON. WOON is the Dutch household survey held every 3 years. WOON is representative for Dutch households. Here we use two waves of 2009 and 2012. Descriptive statistics are in Table C1.

TABLE C1: DESCRIPTIVE STATISTICS RENTAL HOUSING AMSTERDAM, WOON HOUSEHOLD SURVEY

	Public rental housing		Private rental housing	
	mean	st.dev.	mean	st.dev.
Housing characteristics				
Rent (in € per month)	358.4	121.5	889.4	284.4
Rent-to-market value	0.0239	0.011	0.0422	0.0263
Market value (in €)	201,114	87,306	296,382	140,320
Apartment (1=yes)	0.90		0.85	
Number of rooms	3.02	0.95	3.464	1.02
Size (in sq.m.)	65.36	26.88	92.10	28.34
Household characteristics				
Age (in years)	54.13	17.77	45.77	17.02
Household income (in € per year)	25,696	11,345	53,899	24,135
Household size (number)	1.68	1.08	1.97	0.99
Adults (number)	1.27	0.45	1.60	0.49
Children (number)	0.41	0.87	0.38	0.76
Observations	2,002		239	

Note: descriptive statistics relate to the stock of households and housing living in rental housing in Amsterdam. Public housing relate to housing units with a maximum net rent of €631.73 (2008) and €652.52 (2011) per month. Public housing is offered by both housing associations and investors. We removed observations with rents below €180 per month to remove any shared units. We include observations with information on *net* rent.

We use WOON to obtain structural parameters according to the discussion in Section IV. We selected households in private rental housing with similar income and market value. Specifically, we select households with household income up to 50,000 euro. Also, we selected observations with market value between p(1) and p(99) of the distribution. Since WOON is stock-data we used households who recently moved (specifically in the last 2 years). This leaves us with 97 observations.

We first obtain estimates for p_X using information about the unit rent and market value. We regress unit rent on log value for households in private rental housing. These results are in Table C2.

TABLE C2: ESTIMATION RESULTS UNIT RENT, WOON

	Private rental housing	
	mean	st.dev.
Log value	-0.035	(0.003)
Constant	0.475	(0.035)
R^2	0.63	
Observations	97	

We use these parameter estimates to obtain expected unit rent for our sample of households in public housing. The predicted unit rent for our sample of households in public housing are reported in Table 5.

Next, to infer the relationship between share of housing and household characteristics in unregulated markets, we regress household characteristics on share of housing in private rental housing. These results for equation (8) are in Table C3.

TABLE C3: ESTIMATION RESULTS SHARE OF HOUSING α, WOON

	Private rental housing	
	mean	st.dev.
Age	-0.00079***	(0.00038)
Household size	-0.0087	(0.0078)
Log household income	-0.318	(0.023)
Constant	3.67	(0.236)
R^2	0.70	
Observations	97	

These estimates are used to predict share of housing for our sample of households. These estimates are input for our structural model discussed in Section V.

Next, we estimate the welfare counterfactuals and calculate Δy^{eq}. The estimation results are reported in Table C4 and summarized in Section V Table 5.

TABLE C4: ESTIMATED PARAMETERS BY ALLOCATION MECHANISM

		Allocation mechanism			
		(2) Waiting list		(3) Lottery	
Share of housing	α	0.55	(0.29)	0.50	(0.24)
Household income	y	20,259	(9,672)	23,513	(10,876)
Market value	X	209,920	(56,645)	194,495	(54,560)
Annual rent	$p_o \cdot X$	5,845	(1,194)	5,561	(1,243)
Utility	v_o	57,927	(10,991)	54,514	(7,311)
Market value in optimum	X^*	164,978	(44,913)	163,917	(45,803)
Annual rent in optimum	$p_X \cdot X^*$	9,383	(1,857)	9,774	(1,976)
Utility in optimum	v^*	43,657	(5,226)	43,241	(5,369)
Income equivalence	y^{eq}	5,203	(1,387)	5,476	(1,458)
Welfare measure	Δy^{eq}	-273			