The Demand for and Impacts of Government Housing: Evidence from Ethiopian Lotteries

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Abstract

The case for government supply of housing hinges on two key questions: do intended beneficiaries value it more than the cost to the state of providing it, and does relocation to remote housing sites impose unintended costs for movers or society? I study a large-scale lottery in Addis Ababa, Ethiopia, which randomly assigned slum residents to housing on the city's outskirts. Leveraging eight years of low-attrition panel survey data alongside market rents, construction costs, and land values, I find that willingness to pay exceeds per-unit production costs for a substantial share of slum households. There is no evidence that housing negatively affects labour market outcomes, education, or household consumption—suggesting that there are neither unanticipated drawbacks for movers nor broader negative externalities. Multiple surveys allow me to track how households adjust to moves and how new mega-neighbourhoods evolve. Although social networks and neighbourhood amenities initially deteriorate for winners, they significantly improve after 8 years. The results differ significantly by randomly assigned location, implying a weaker case for centrally located housing given its higher cost relative to benefits.

*Queen Mary University London (s.franklin@qmul.ac.uk). This paper was previously circulated as an earlier LSE working paper (Franklin, 2019) which contained only the three-year follow-up data, under the title "The demand for government housing: evidence from a lottery for 200,000 homes in Ethiopia". I gratefully acknowledge funding from the International Growth Centre (IGC), including for the 8-year follow-up. IRB approval from LSE REC Ref. 000632 & QMERC Ref. QMERC22.238. For useful comments I thank Clement Imbert, Doug Gollin, Gharad Bryan, Robin Burgess, Ed Glaeser, Benjamin Marx, Vernon Henderson, Alexander Rothenberg, Nina Harari, Guy Michaels, Martina Kirchberger, Pascaline Dupas, Marcel Fafchamps, Simon Quinn, Henry Overman, Stefano Caria, Kate Vyborny, Julien Labonne, Sam Asher, Harris Selod, Girija Borker, Julia Bird, Vimal Balasubramaniam, and Lucie Gadenne. Giulio Schinaia and Nolawi Tadesse provided valuable research assistance.

1 Introduction

Governments around the world intervene directly in the supply of new-build housing, aiming to address shortages in wealthy countries and move people out of slums in developing countries.[1] Standard economic theory suggests that these large supply-side interventions are likely to be highly inefficient. By choosing to live in central slums or other low-cost housing, poor households arguably reveal a preference for location over the improved but often distant housing that governments typically provide (Glaeser and Gyourko, 2008; Glaeser, 2011). If so, willingness to pay for government housing will fall below the costs of construction for most of its intended beneficiaries. Yet in housing markets with constrained supply—particularly in many African cities where housing markets function poorly (Marx et al., 2013; Collier and Venables, 2014)—government-supplied housing may address unmet demand that private markets are unable to satisfy. Designed appropriately, such housing could serve as a second-best solution to housing shortages, even if it falls short of the efficient-market optimum.

Even if unmet demand exists, governments may build in the wrong locations or at the wrong scale or quality, leading to a mismatch between what is provided and what is desired. Moreover, even when households readily move in at prices above costs, it does not guarantee welfare gains. Relocating households farther from the city may sever social networks, reduce labour market access, or create low-social-capital neighbourhoods. This could mean households have misjudged the long-run consequences of moving (violating the logic of revealed preference), and generate social or fiscal externalities that undermine the overall return on public funds (Finkelstein and Hendren, 2020).

Assessing the rationale for government housing, therefore, requires understanding both demand for and the effects of housing. Measuring demand means determining whether households' willingness to pay exceeds construction costs and, if so, how many households meet that criterion.[2] This is challenging, however, because governments commonly fix rents, restrict resale and subletting, and allocate public housing through non-random processes, leaving market prices unobserved and making uptake decisions representative only of a narrow population. On the other hand, estimating relocation effects requires exogenous variation in who moves, which is rare.

In this paper, I study a large-scale housing lottery in Addis Ababa, Ethiopia, where over 200,000 government-subsidized condominiums have been allocated to lottery winners. This setting provides a unique opportunity to examine both willingness to pay for formal housing and the impacts of relocating, in a city with constrained urban land markets and widespread informal settlements.[3] I leverage a key feature of Ethiopia's program: while lottery winners own their homes, they are allowed to rent them out freely.[4] This then allows me to measure the market value of the condominiums and esti-

[1] In developing countries, large government housing programs—like Brazil's and South Africa's millions of homes—are typically sold or given away rather than rented. See Table A1.

[2] Ideally, a representative sample would be randomly offered various prices, including the unsubsidised market rate or the marginal cost of production. See Lee et al. (2020) for an example with electricity.

[3] Section 2 compares slums and housing supply in Ethiopia and Africa. The weak correlation between housing quality and wealth underscores pervasive supply problems across the continent.

[4] Almost all lottery winners purchase their units and cannot sell for five years. The ability to rent freely contrasts with programs where rent subsidies (e.g., in Europe and the US; Van Dijk, 2019) or ownership (e.g., in Brazil; Belchior et al., 2023) require occupants to live in the unit.

mate the share of randomly selected winners—who live in slums and are representative of a large segment of the population—who choose to move in at the market rental price that they would otherwise earn. I then exploit the randomized nature of the lottery to measure the causal effects of winning the housing.

I collect detailed panel survey data on a random sample of households entered into the government-run lottery, following up with them 3 and 8 years after they won. By tracking households over two post-lottery time periods, I analyse the dynamics of how households adjust to moving and how new neighbourhoods evolve. My study incorporates several features that overcome identification challenges in this literature. Tracking households since baseline yields unusually high response rates (92% after 3 years and 87% after 8 years), reducing concerns about differential attrition, and having baseline data allows me to demonstrate balance across a wide range of *outcomes* as well as household demographics. With two endlines, I can use later-lottery movers (defined in the second endline) as a counterfactual for those who moved by the first endline, to separately identify effects for movers and non-movers; a common selection challenge in this literature.[5] Finally, I leverage random allocation of households to locations across the city to understand the relative returns to building in the centre versus the outskirts.

The paper proceeds in two main parts: demand and treatment effects. In Section 4, I analyze demand for government housing. In the first step, I characterize market prices and construction costs for the condominiums at four main locations. I collect a large representative dataset of market rents in the newly built condominiums. I combine this with government financial data and land auction prices to impute the cost of building on government-owned land and household survey data to estimate maintenance and rental transaction costs. My analysis shows that rents exceed production costs on average, using a simple internal rate of return calculation, although returns vary by location and are slightly negative for housing near the city center. These results suggest modest but positive social returns: the equilibrium price of housing exceeds its cost of supply, even after 200,000 units have built, indicating that formal housing was underprovided prior to the state's intervention.[6] However, this willingness to pay is associated with the marginal tenant of public housing, who may be drawn from the wealthier segment of the population with a higher willingness to pay than the average intended beneficiary.

The second step of the demand analysis examines the housing choices of lottery applicants to assess how broadly this demand extends. Lottery applicants represent roughly 70% of all households in the city, minimizing concerns about selection bias. I find that more than half of lottery winners move into their government-provided homes, a rate that remains constant after 8 years, paying an implicit price given by the rents identified in the first step. This finding highlights significant demand for owner-occupied formal housing among households who would otherwise reside in slums and at a price above cost. Using detailed data on household consumption choices, I provide six pieces of evidence that these housing choices reflect a preference for housing quality over location, rather than a large permanent income effect from winning subsidized housing (Andersen

[5] Under certain reasonable assumptions, this separately identifies the effect of moving from the wealth effect of winning. This identification relies on partly testable assumptions, in particular that selection into moving was the same across lotteries.

[6] Glaeser et al. (2005) argue that the private supply of building height is inefficient based on the same price-to-cost principle in Manhattan.

et al., 2023). The key result is that winning the lottery leaves total consumption, income, and housing consumption unaffected, but leads households to trade housing quality for location almost one-to-one in market-value terms: giving up low-quality housing in the centre for good housing further away. I use detailed baseline data to characterise household preferences for consumption versus location and to show how preferences, rather than wealth, shapes the decision to occupy the housing.

In Section 5, I test for costs of moving households to new locations, such as reduced labour market access, severed social networks, or poor neighbourhood conditions. If these costs are unanticipated by moving households, the principle of revealed preference may overstate the benefits they derive from government housing. Even if such costs are anticipated, they could raise the true costs of housing beyond construction expenses, by generating fiscal externalities (Banerjee et al., 2024). I find no effect of winning government housing on non-housing consumption, employment, income, or children's education. These results hold when analyzing movers and non-movers separately. Although commuting times are higher, movers are well-connected to jobs via private minibuses, while others find employment near the new sites.[7] I find no evidence of heterogeneous impacts by gender or seniority within households.

Neighbourhood and social outcomes exhibit a striking "reversal of fortune" dynamic. Note that for majority of sites, built on the periphery, there was no pre-existing neighbourhood character– the housing was built on farmland. Three years after moving, lottery winners report weaker local social networks and a perceived lack of support, though their satisfaction with their networks remains unchanged. After eight years, these initial negative effects have largely diminished or reversed. Households experience persistently reduced conflict with neighbours, increased participation in community groups, and modestly higher satisfaction with their social lives. Similarly, some measures of amenities and public goods look worse after three years, but after eight these effects are reversed. Compared to non-lottery winners, access to public goods is comparable, while amenities and neighbourhood satisfaction are significantly improved.

Finally, I analyse heterogeneity in outcomes by housing location. Households allocated to central locations—where market rents are higher—are more likely to rent out their units. Despite smaller sample sizes assigned to central sites, I detect significantly smaller improvements in housing quality for this group. They also reduce labour supply and earnings, consistent with an income effect from receiving higher-value housing. Since subsidies for central locations are larger (they pay the same cost but receive a more valuable house), building housing in these areas appears less cost-effective for improving housing access at scale.

In sum, the central finding of this paper is building large-scale government housing can meet substantial unmet demand without inducing distortions among beneficiary households.[8] While this does not mean such policies will always succeed, the findings provide a proof of concept that well-designed interventions can effectively address hous-

[7]For example, there is no long-term effect on the likelihood of winners (and movers) working close to home, despite differences in their distance from central areas.

[8]These programs may have broader spillover or equilibrium effects, such as reducing rents throughout the city, inducing more migration into the city, or reducing negative externalities from dense slums. Estimating these is beyond the scope of this paper. I also do not take a stand on whether the deep subsidies to beneficiary households are appropriate or egalitarian.

ing shortages, which are evidently widespread. This finding contributes to two distinct areas of the literature.

First, this paper contributes to our understanding of housing preferences among people living in slums. There is relatively little evidence on demand for government housing to date. Barnhardt et al. (2017) report low take-up rates for a smaller program in India, where households forfeited rental or ownership subsidies if they did not occupy the home, suggesting willingness to pay well below market rates even among those who moved in.[9] My results challenge the hypothesis that slum persistence reflects household preferences for informality and central locations (Glaeser, 2011). Instead, it supports the view that market and regulatory failures constrain the supply of affordable housing, leaving households in slums (Collier and Venables, 2014; Marx et al., 2013).[10] A number of papers highlight the constrained potential of slum households to invest in better living conditions. Devoto et al. (2012) show that households exhibit willingness to pay for tapped water in their homes when provided access to credit to finance these investments. Michaels et al. (2021) find that improved urban planning and serviced plots can unleash substantial private investment in better housing. Low levels of housing investment in slums have also been linked to institutional barriers, including the lack of property rights (Galiani and Schargrodsky, 2010; Collin et al., 2015) and limited access to finance for fixed investments (McIntosh et al., 2011). However, until now, there has been little direct evidence that households living in central slums would be willing to pay for formal housing if it were made available.

My second contribution is to understanding how housing programs affect labour markets and neighbourhood outcomes, with two endline surveys providing a novel dynamic view of how households adjust to government housing. Prior studies report mixed employment effects, including increases (Franklin, 2020; Kumar, 2021), decreases (especially in developed countries) (Picarelli, 2019; Jacob and Ludwig, 2012; Alzúa et al., 2016; Van Dijk, 2019), and no change (Barnhardt et al., 2017; Belchior et al., 2023; Armentano et al., 2024). Like Belchior et al. (2023), I exploit random assignment to identify differential treatment effects by housing location, but I find no evidence that moving to the outskirts negatively affects labour market outcomes, even relative to housing in central areas. My two rounds of follow-up data allow me to analyze how outcomes evolve over time, revealing how households adjust their place of work and commutes in response to the new locations. I also provide novel evidence on neighbourhoods that emerge endogenously in large-scale government housing. The positive effects on neighbourhood quality and null effects on education contrast with studies linking public housing to poor outcomes for children (Chyn, 2018; Chetty et al., 2016; Currie and Yelowitz, 2000; Chetty and Hendren, 2018), particularly when relocations are farther

[9]There is little direct evidence on demand for government housing in rich countries, though Collinson et al. (2015) notes, "the belief that government-supported housing programs are needed to address supply-side problems and stimulate housing production has also waned over time." See Apgar (1990) for an alternative view, and Van Ommeren et al. (2016), who estimate that WTP for public housing applicants exceeds production costs.

[10]A growing literature looks at how slums are affected by neighbourhood-level programs such as infrastructure, planning, and slum upgrading (Michaels et al., 2021; McIntosh et al., 2017; Harari and Wong, 2018; Gechter and Tsivanidis, 2023). Henderson et al. (2021) highlight how institutional redevelopment costs drive the persistence of central slums.

from (Rojas Ampuero, 2022), but not nearer to, city centers (Camacho et al., 2022).[11]

These contributions have implications for rethinking housing policy in developing countries. Distortions in housing markets like those faced in Ethiopia (such as weak property rights and regulatory failures) are widespread across many contexts, making it likely that unmet demand for better housing exists elsewhere (Collier and Venables, 2014; Brueckner and Lall, 2015). However, government interventions to address these gaps do not automatically succeed. The relative success of Ethiopia's program—both in terms of meeting demand and improving outcomes for residents—contrasts with evidence from some other contexts and is plausibly linked to three factors. First, the scale and density of the new neighbourhoods likely fostered employment opportunities, facilitated dense social networks, and supported private transport connections. I provide evidence supporting these mechanisms. These results contrast with Barnhardt et al. (2017), where recipients struggled to recover from network loss, possibly due to the smaller scale of the Indian program or its specific focus on self-employed women. Second, the program's flexibility, allowing households to rent out homes, likely prevented suboptimal moves for those who may otherwise have been negatively affected. Third, the housing was built in less remote locations than in some other contexts, such as Brazil (Belchior et al., 2023), and was supported by strong transport connections to the city center, which mitigated relocation costs. I begin the paper, in Section 2.1, with a discussion of how Ethiopia's housing markets and policies compare to those in other developing-country contexts.

2 Context and data

2.1 Context

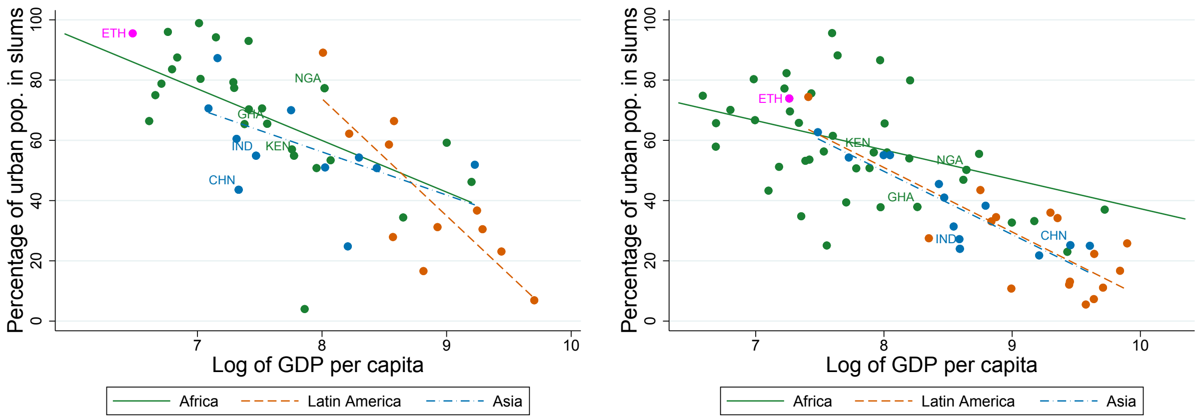
Figure 1 shows the cross-country relationship between GDP per capita and the share of urban households living in slums. Ethiopia is by no means an outlier in terms of the share of households living in slums relative to GDP per capita. More than 60% of the urban population lives in slums in many African countries. In Africa, the relationship between GDP and slums is remarkably weak. Appendix A1 presents novel evidence at the household-level on housing conditions and wealth in six large African cities, including Addis Ababa. These results show that housing quality, measured by durable construction materials and access to basic services, is remarkably inelastic to household wealth, and therefore suggest that the persistence of slums cannot be explained by low incomes alone. Instead, relatively weak preferences for improved housing or supply constraints seem to play a role.

Ethiopia's tenure system, centered on government ownership of all urban land, is one likely constraint on housing supply. All land is made available through leasehold agreements, and no private ownership of land is permitted (Prunier and Ficquet, 2015). In Addis Ababa, many households (approximately 26% of households in my sample) rent informally on government-owned land at nominal fees of about 1% of the estimated market rent (this is known as "kebele" housing). Another 66% of my sample rent from private (slum) landlords who do own the land but rent out houses informally at market-

[11] A recent study emulates my design, without a baseline, to study the effects of the Ethiopian housing program on educational outcomes (Agness and Getahun, 2024).

Figure 1: **GDP per capita and slums across developing countries**

(a) GDP and slums in 1990. (b) GDP and slums in 2014.



Data comes from UN-HABITAT, Madison World Tables, and the World Bank. Calculations my own.

determined rates.[12]

While Ethiopia's particular tenure system is somewhat unique, these dynamics– low tenure security, limited investment, and reliance on informal arrangements– are common across developing countries. Slums in other countries are often built on government- or tribally-owned land, facing similar de facto tenure arrangements to slum households in Ethiopia.

Other constraints, beyond tenure systems, are critical to understanding slum persistence and the limited supply of affordable housing. Indeed, an increasing share of Addis Ababa's land has been made available to the market via large-scale auctions of undeveloped state land, yet very little of that has been converted into affordable housing by the private sector. Brueckner and Lall (2015) point to restrictive zoning regulations that constrain urban housing markets across the developing world, including density limits, height restrictions, and minimum plot sizes. Inefficiencies in the construction sector, including the high cost of building materials and limited access to housing finance, further restrict formal housing supply (Collier and Venables, 2014). Additionally, inadequate infrastructure, such as roads and utilities, may hinder private investment and contribute to the slow improvement of slums (Michaels et al., 2017).

Ethiopia's condominium housing program:

Ethiopia Integrated Housing and Development Program (IHDP) follows a similar model to other large-scale housing programs in developing countries. Table A1 shows a partial list of recent large scale housing policies across the world. The key modality is the construction of new brick and mortar houses, usually– but not always – on the edge or outside of cities that are then sold or given away to eligible households. This is the modality of programmes in South Africa and Brazil, which have built at least 3 and 4 million houses, respectively.

The Ethiopian government outsources the construction of new formal housing apart-

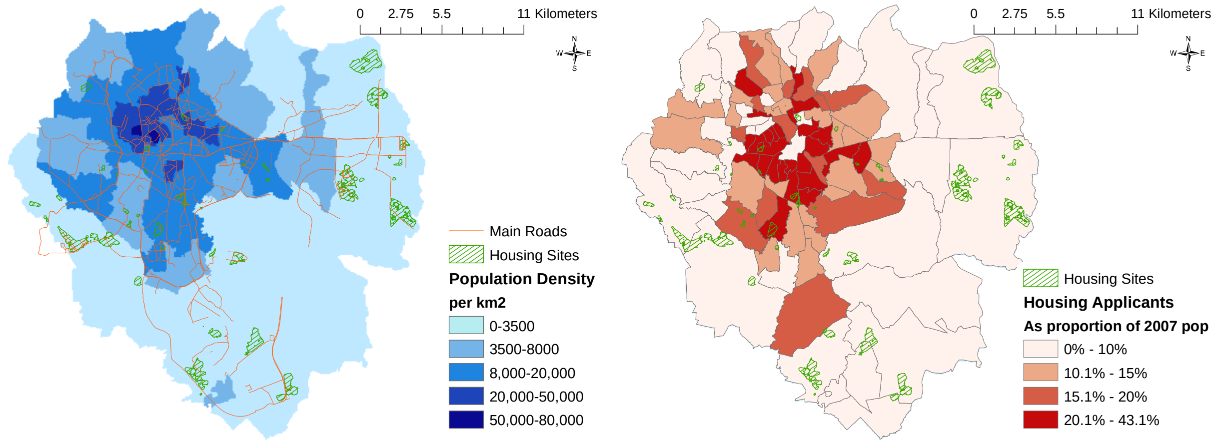
[12] A small proportion of households in my sample owns because they are technically excluded from government programs due to ownership restrictions.

ments to private firms, focusing on peripheral land to minimize costs. The largest site houses over 60,000 residents in 500 blocks, located predominantly over 15 kilometers from the city center, as shown in Figure 2. The most remote site in the south of the city is 20 to 25 kilometres away by road. These developments came with essential infrastructure like roads, sewers, and water.

Figure 2: **Addis Ababa population and housing sites**

(a) Housing sites are located on the very outskirts.

(b) Applicants mostly live in the city centre



Housing units, housed in 5-storey walk-ups with 20-30 units each, are pictured in Figure A3 in the appendix. Equipped with basic utilities and facilities, households personalize their spaces and collaboratively maintain public areas. The program's scale ensures high population densities similar to slums. Ground-floor commercial units are sold at market rates. Unit sizes vary from studio apartments ($32m^2$) to 1-, 2-, or 3-bedroom options (51, 75, or $100m^2$), with the majority (approximately 70%) being 1- or 2-bedroom. These are very large homes by the city's standards. Using cadastral surveys collected by the city government, I find that the size of city-centre informal housing units, many of which are occupied by multiple households, varies from $15m^2$ to $45m^2$.

Sales prices are subsidized, with the average household paying around $10,000, implying a subsidy of 50% on the total development cost (see Section 4). Winning households must make a 20% down-payment and sign a mortgage, payable over 15 years at 9.5% per annum through the Commercial Bank of Ethiopia. Surprisingly, after 8 years, most households have completely paid off these mortgages. While renting out units is allowed, resale is restricted for five years.

Housing lotteries: The state allocates new housing through a computerized lottery from a pool of wait-listed applicants. Eligibility for the wait list requires only that the applicant not own property and have resided in Addis Ababa for six months. Applicants must save monthly in a dedicated account for the down-payment if they win. The savings requirement was $318 (on average, across housing types) about three times the average monthly mortgage repayment. Prior to the 10th round lottery, the wait list was updated and consolidated by the government, with households that were no longer eligible or interested being removed from the list. Similarly households that had not met the savings threshold at the lottery's time were excluded. I acquired the list of households that was entered into the 10th round lottery from the housing administration.

The 10th round lottery, the focus of this paper, awarded 34,000 apartments in 2015, the largest allocation to date. This lottery marked a significant expansion in state-built housing, primarily on the city's outskirts. Over 700,000 households were registered, while 130,000 early registrants were entered into this particular lottery.[13] Winners were assigned to apartments completely at random, with 97% allocated to ten main sites (Table A2). Winners (or their renting tenants) began occupying the houses from the 10th lottery in early 2016. There were a number of lotteries after the 10th round, for which households that did not win the 10th round (and therefore include my control group) were eligible (see Table 1).

2.2 Data

Table 1 provides an overview of the data collection relative to the key events in the program. The result of this section describes each component of the data collection in more detail.

Table 1: Timeline of Events for Research Study

Date	**Event**
April 2015	Round 10 lottery results announced
May 2015	Baseline survey
August 2016	Homes are occupied (average)
2016	Round 11 lottery results announced
December 2018	Supplementary condominium market survey I
January 2018	First endline survey
July 2019	Supplementary condominium market survey II
2018	Round 12 lottery results announced
2020	Round 13 lottery results announced
2022	Round 14 lottery results announced
January 2024	Second Endline Survey

2.2.1 Main representative panel

My primary sample comes from government administrative records of households that had applied and were eligible for the housing scheme.[14] I match this pool of applicants to the list of winners of the March 2015 lottery. Fewer than 30% of households in the pool of eligible applicants received a house in the lottery of 2015. Therefore, to maximize power,

[13]The lottery gives additional weight female applicants and government employees. 30% of beneficiaries were randomly selected from female applicants, 20% from public employees, and the rest from the remaining pool. My results are unchanged if I re-weight the results to be representative of the applicant pool.

[14]These lists came from the Ministry of Urban Development and Housing of the Government of Ethiopia.

I drew my sample immediately after the lottery was run, allowing me to oversample from the pool of households who won the lottery so that my sample is split equally between winners and losers. In addition, the government conditioned winning probabilities on household characteristics in the administrative data. In particular, female applicants and applicants employed in the public sector were prioritized. To ensure each household in the study had the same ex ante odds of winning the lottery, I divided the treatment and control households into strata with identical administrative characteristics. I then draw my sample from those strata equally across winners and losers of the lottery.

The baseline was conducted in May 2015. The only available information by which to contact applicants was a single phone number in the administrative data.[15] It was impossible to track households when their numbers had become dormant or been disconnected. In total, 82% of listed households were reached. Inactive phone numbers account almost all (75%) of the non-response in the construction of the baseline sample. Importantly, whether a household had an inactive phone number was not affected by whether a household had won the lottery. This is unsurprising, as the phone numbers had been updated *before* the lottery was conducted. Lottery winners were no more likely to respond than non-winners. In total, the survey team reached 783 lottery winners and 781 non-winners, with a total baseline sample size of 1564.

The first endline survey was conducted from December to 2017 to February 2018, at which time households that moved into the units have lived in the housing for roughly 18 months, on average.[16] The second endline was conducted from November 2023 to January 2024, more than 8 years after the 10th round lottery and nearly 7 years after the homes were occupied. Qualitative interviews were also conducted with a small sample of households early in 2018.

Attrition: The survey team were able to contact 91.18% of the sample at the first endline. Tables A7 and A8 shows the determinants of attrition. Attrition is uncorrelated with winning the lottery, and relatively few covariates predict attrition.[17] At the second endline, I am able to interview 87.6% of households.

Sample balance: I find clear evidence that the housing lottery is fair. I conduct balance tests, shown in Table A3. The results are similar with and without conditioning on the administrative outcomes on which randomization was conditioned. I conduct a joint F-test of the predictive power of fourteen main survey outcomes, in addition to administrative outcomes. I fail to reject that the coefficients of the effect on winning the lottery of my list of covariates are jointly equal to zero. Table A5 shows that baseline covariates are broadly balanced across randomly assigned sites.

[15] In very few cases administrative data on household addresses as also useful, but without a consistent address system in use in Addis Ababa, the house numbers provided by the administration were not usable for tracking.

[16] I track only the sample of households found at the baseline survey, having been convinced that the winning and losing samples are comparable since the lottery is fair and that non-response at the baseline was not affected by winning the lottery.

[17] For the first endline, the joint F-test on the effect of a large set covariates on attrition is not significant. To address concerns about differing attrition patterns between treatment and control groups, I interact treatment with baseline covariates and conduct a joint F-test. The results show no evidence of differential attrition predictors in the treatment group (p=0.859).

Who applies for the program? Government administrative records suggest that over 700,000 individuals registered for the housing scheme as a whole. Projections from the 2007 Census forward to 2015 suggest that there are a little over a million households in the city as a whole. I estimate that between 50% and 70% of households in the city have applied for the program. The sheer size of the pool of applicants from which I draw my sample mitigates concerns that my results apply only to a highly selected group of households. Panel B of Figure 2 shows where the applicant households come from: they are overwhelmingly drawn from the city center of the city, where slums and government-owned slums, in particular, are located.

Applicants live in very poor housing conditions and are overwhelmingly poor. I estimate that only 2.6% of lottery applicants in my sample live in a home that matches the basic construction quality of government-provided units. Eligibility criteria for the program screen out the wealthiest households: only households who do not own a home can apply. Table A4 compares my sample of applicants to representative data from the Household Consumption and Expenditure Survey (HCES) conducted in 2011.[18] While households in my sample are slightly more likely to have durable housing materials (notably, hard floors), their homes are considerably more over-crowded, and have similar levels of access to private toilets and improved water. A similar proportion live in slums, according to the standard UN definition. Figure A4 shows that the distribution of household expenditure per adult equivalent is comparable, but to the left of that in representative data: applicants are not overwhelmingly wealthy.[19]

2.2.2 Supplementary survey data from central winners

Since almost all of my representative sample won housing far from the city center, I am underpowered to test the effects of winning a house closer to the city center in that sample. I draw an additional sample specifically from those sites closer to the city center, which is used only for the estimation of heterogeneous treatment effects. For the first endline, this includes 99 additional households randomly sampled from these more central sites, while for the second endline, I include another 126 households to improve the precision of my estimates for this group.

2.2.3 Condominium market-rent survey data

I conduct a separate survey of the housing rental market in the Condominiums in late 2017 and mid-2019. The survey targets a random sample of housing blocks built for the lottery I study, and I attempted to collect data for all units within each selected block. These surveys gathered information from both renters and owners, capturing the gross rent paid by renters to owners. This survey was critical because a high proportion of households live in owner-occupied units, resulting in relatively few rental observations in my evaluation sample.

I observe the basic demographic profile of the renting households, their assessment of the home amenities, and the rent that they pay monthly to live there. I use these data to

[18] Conducted by the Ethiopian Statistical Agency (CSA/ESS).

[19] Winners who rent out their units almost always do so to a household that is wealthier than them.

estimate the value of condominium housing and perform hedonic regressions of condominium housing value to impute housing consumption for owner-occupiers. Observing this rental market over two periods also allows me to plot the trajectory of housing values after the period of my main endline survey.[20]

2.2.4 Secondary data

Administrative and cost data: The Addis Ababa Housing Development Administration Agency provided detailed cost data for the housing built for the 10th round lotteries in 2015. This dataset came from the project accounts directly, and provided a breakdown of the different types of costs in the delivery of housing, including construction, administrative, compensation (for farmers living on the land) and estimated land costs. For my analysis, I assume constant construction and other costs across different sites, but weight the costs for different sizes of housing units according to the total floor space per unit. A key parameter that comes from these data is the estimate of 3821 Birr (or $137.55 in 2015) per square meter of constructed floor space.

I acquired building shapefiles for all planned condominium housing sites in the city. I use these shapfiles to extract key location data for each housing block, including distance from the city, distance from the boundary of housing site, distance from roads and the size and layout of the block. All of these variables are used in hedonic regressions of housing value in condominiums units.

Land auction data: To estimate the cost to the government of delivering housing I need to estimate the value of the land at the time that it was constructed. This is challenging in a setting where all land is officially owned by the government, including the land used for the construction of the condominiums. The governments' own estimates of the value of the land are unreliable (and also do not vary across sites, which is crucial for my analysis). I leverage data that comes from auctions run by The Addis Ababa City Administration since 2012. These were second-price auctions for plots of undeveloped land zoned for specific purposes, run from 2012 to 2016. The data includes the first- and second- prices offered, the location of the plots, date of auction and the zoning category. I use this to estimate the value of land on which condominiums were built, by matching auction price data from the years in which projects broke ground based on the woreda (administrative district) in which the housing was built.

3 Empirical strategy

I estimate the intent-to-treat (ITT) effect of winning government housing through a lottery. Due to the 97% take-up rate, this estimator is very close to the average treatment effect of subsidized home-ownership. Equation 1 estimates the intent-to-treat effect β_1 of winning the lottery (T_i^{10}) on outcome y_i. I control for a set of household baseline

[20] I collect data on 7,593 housing units in 2017 to estimate differences in rents by a granular set of housing characteristics. A smaller sample of 2,329 in 2019 are used to estimate differences changes in those home values over time, by housing site and unit size. I did not collect this market data in 2023/24, but used the observed rental income data of owner-renters to impute increases in rental values from 2017-2019 to 2023.

characteristics x_{i0} in all specifications, as well the baseline outcome of interest $y_{i,pre}$ in all regressions.[21] For each wave of endline data I estimate:

$$y_i = \beta_0 + \beta_1 \mathtt{T}_i^{10} + \beta_2 \mathtt{T}_i^{later} + \alpha y_{i,pre} + \delta x_{i,pre} + \mu_i. \tag{1}$$

I control for a vector of dummies indicating whether a household won each lottery after the 10th round ($\mathtt{T}_i^{later}$), since these households may have been in the process of moving into their houses at the time of by endline data collection, and therefore their outcomes may have been confounded.[22] In appendix tables, I test for the effect of winning any early lottery by the time of the second endline and show that the results are similar to those for the 10th round alone.

3.1 Multiple hypothesis testing

To account for multiple hypothesis testing, I control the False Discovery Rate (FDR) at $\alpha = 0.05$ using the adaptive method of Benjamini et al. (2006). Specifically, this correction is performed over all of the main outcomes presented in the paper at the household level (see, specifically, Tables A23 and A24 in Section A4.7), Similarly, this correction is performed separately for each table presented at the individual level. For each set of hypotheses tested at the household level, the same FDR correction is applied separately for each endline (time period). Following Anderson (2008), I report the minimum q-value at which each hypothesis can be rejected.

3.2 Estimating differential effects by movers and non-movers

To isolate the effect of moving into government housing from simply winning a lottery, I need to account for unobservable differences between households that move and those that do not. Using data from the second endline and lotteries conducted after the first endline, I use winners of lotteries 12 and 13, who had not won at the first endline but had made their moving decisions by the second, to define a counterfactual for households who had moved into their units at the time of the first endline.

Specifically, I define $\mathtt{M}_i^{10,12,13}$ as a dummy equal to one if a household had moved into their unit: at the first endline for 10th-round winners, and at the second endline for 12th and 13th-round winners. Similarly, $\mathtt{S}_i^{10,12,13}$ indicates that a winning household did not move, defined analogously. Both dummies equal zero for non-lottery winners and for winners of rounds 11 and 14. I cannot use round 11 winners as they had already won by the first endline, nor round 14 winners who had not yet had the opportunity to move

[21] I include in x_{i0} all variables from the administrative data used by the government to stratify the lottery: the gender of the applicant, whether the household head works for the government, type of housing unit applied for (studio, 1-, 2- or 3- bedrooms).

[22] This control varies over time. At the time of the first endline, only lottery 11 had occurred, so I include a dummy for having won that lottery. By the second endline, rounds 12, 13 and 14 had occurred, and I control for all of those, as well as all strata of the administrative variables on which randomization was predicated, because the differential probability of winning across strata varies from lottery to lottery as the length of the waiting list in each category changes. The main results are robust to not including these controls.

by the second endline. Dummies for winning these and 12th and 13th-round lotteries are included in the control vector $\texttt{T}_i^{later}$. I then estimate:

$$y_i = \beta_0 + \beta_1 \texttt{T}_i^{10}\texttt{M}_i^{10,12,13} + \beta_2 \texttt{T}_i^{10}\texttt{S}_i^{10,12,13} + \beta_3 \texttt{M}_i^{10,12,13} + \beta_4 \texttt{T}_i^{later} + \alpha y_{i,pre} + \delta x_{i,pre} + \mu_i. \tag{2}$$

Here, β_1 and β_2 identify the causal effects of winning the 10th lottery for households that move and do not move, respectively, assuming that the factors driving the decision to move are consistent across lottery rounds.[23] The difference, $\beta_1 - \beta_2$, captures the effect of moving into condominiums for lottery winners, under the assumption that the effect of winning (independent of moving) is the same for movers and non-movers. These assumptions are reasonable: later lottery housing was built in similar locations to the 10th round, and moving decisions were measured 2-3 years after households had the opportunity to move in, and overall moving rates are statistically similar across lottery rounds.[24] The key test of this assumption is provided in Table A21, where a joint test fails to reject that observable drivers of occupation for 10th-round winners are the same as those for later rounds.[25]

I will estimate equation 2 for endline 1, but cannot replicate this strategy for endline 2 as I can longer identify a group who haven't moved by then, but that I know will in the future.[26] Therefore, the paper will say less about the separate effects for movers at endline 2. As a more *descriptive* exercise comparing movers to non-movers, I can estimate the following equation:

$$y_i = \beta_0 + \beta_1 \texttt{T}_i^{10}\texttt{M}_i^{10} + \beta_2 \texttt{T}_i^{10}\texttt{S}_i^{10} + \beta_3 \texttt{T}_i^{later} + \alpha y_{i,pre} + \delta x_{i,pre}^{ml} + \mu_i. \tag{3}$$

where now $\texttt{M}_i^{10}$ and $\texttt{S}_i^{10}$ are defined only for households who moved after winning in the 10th round. I include a vector of controls for winning any later lotteries $\texttt{T}_i^{later}$. Instead, I follow Belloni et al. (2014) by using a first-stage lasso regression to select baseline variables that predict the decision to move in and include those as controls in $x_{i,0}^{ml}$. While the main estimates (β_1 and β_2) from equation 3 should be treated with some caution, when I estimate equation 3 on the first endline data the results are similar to those from equation 2, suggesting that controlling for observables is an effective way to control for selection bias in this setting.

3.3 Heterogeneous effects by site location

I want to separately estimate the effects of winning government housing in different sites at varying distances from the city centre. My main specification uses data representative of the average 10th round lottery winner. 95% of these winning households received

[23]This method parallels Franklin et al. (2024), which separates the effects of public works on eligible and ineligible households by using eligibility status from later data rounds to define the control group.

[24]See Table A6 for occupation rates by lottery at both endlines.

[25]Using data on 10th and later lottery winners, I regress moving decisions (3 years post-winning) on baseline covariates and their interactions, then test the joint significance of these interactions.

[26]Estimating equation 2 on the second endline would yield the effect of having won housing slightly earlier for movers and non-movers, respectively.

housing on the very outskirts of the city, and so the main results are reasonably interpreted as the effects of housing very far away. I use my additional data on households randomly sampled from those that won housing in more central city sites, specifically, 0 and 4 kilometres, and between 6 and 12 kilometres from the city centre by road. Adding these additional households to the sample, I estimate differential treatment effects by the randomly assigned distance of the housing unit from the centre, following Equation 1.

$$y_i = \beta_0 + \beta_1 \mathtt{T}_i^{\{0,4\}} + \beta_2 \mathtt{T}_i^{\{6,12\}} + \beta_3 \mathtt{T}_i^{\{15,20\}} + \beta_4 \mathtt{T}_i^{\{20,25\}} + \alpha y_{i,pre} + \gamma \mathtt{T}_i^{later} + \delta x_{i,0} + \mu_i. \tag{4}$$

$\mathtt{T}_i^{\{d_1,d_2\}}$ indicates that a household won a house in a site where d_1 (d_2) is minimum (maximum) distance of that site from the center *by road*. In Table A5 I show that baseline covariates are broadly balanced across randomly assigned sites.

3.4 Measuring housing consumption

Measuring housing consumption is challenging: for private renters, this is given by their monthly rent, but my data includes two groups of households for whom I do not observe rents directly. Some households (22% of the baseline sample) live in "kebele housing," a type of government-owned, slum-quality housing rented at nominal amounts, which do not reflect market value. Similarly, condominium owner-occupiers pay no rent but repay government-set mortgages that do not reflect actual housing values. I estimate hedonic models to impute housing consumption for all households and decompose it into physical and location components. I estimate two separate models: one for the low-quality housing market in Addis Ababa, where there is overlap in the quality and location of kebele and privately-rented stock, and another for the condominium market using data on rents paid by tenants (outlined in Section 2.2.3). For each housing type $k \in c, n$, I estimate an equation with the standard hedonic form:

$$\ln(r^k) = \alpha^k + \eta^k L^k + \lambda^k P^k + \epsilon^k, \tag{5}$$

where r^k is the monthly rent for housing type k, L^k represents location characteristics (e.g., travel time, distance from CBD), and P^k denotes physical housing attributes (e.g., size, materials).[27]

I then impute total housing consumption as $\hat{r}^n$ for non-condominium households and $\hat{r}^c$ for condominium owners. Since I observe only the total rent paid, not the cost of housing per unit of area or quality, I decompose housing consumption into location and physical quality components, using a which evaluates, sequentially, the marginal contribution of location and distance using the additively separable properties of Equation 5. Appendix Section A2 describes this approach in detail. For condominium housing, which predominantly occupies the outskirts with higher physical quality and minimal overlap in location distribution, I impute the rent as if these units were located at the average central location of the private market, and subtract the location value of those

[27] Table A22 shows the results of the hedonic model for condominium houses in my sample.

locations to back out the physical value for condominiums. Condominiums on the outskirts exhibit physical-values as high as the best houses in the non-condominium sample, but with considerably lower location values.

4 Demand for government housing

In this section, I proceed in two steps. First, I estimate the price of government housing, and use a simple return-on-investment framework to compare that price to the upfront cost of producing the housing. Second, I assess the magnitude of the demand for housing by looking at the occupation decisions of randomly selected lottery winners, who can choose to rent out and thus face a price directly related to the market rate estimated in the first step. I then provide evidence that these occupation decisions reveal a preference for higher quality housing further away that was not available before the government built it.

4.1 Estimating the market returns government housing

A central measure of the welfare implications *for the occupants* of government-built housing is how the marginal occupant's willingness to pay (WTP) compares to the total costs of production. By contrast, the subsidized price at which the state sells units is not relevant. Two counterfactual pricing scenarios illustrate this point:

1. Full Subsidy: If the state gives away the homes for free, the relevant consideration is the marginal value of public funds (MVPF) for an in-kind transfer, which is the ratio of WTP to cost (Finkelstein and Hendren, 2020). In other words, do households value the in-kind transfer more than the cost of delivering it?

2. Market Pricing: if the state acted as a private developer, selling or renting units at market rates, then the key consideration would be the financial rate of return: would the government profit from building these units?

In both scenarios, the relevant calculation is the same: the ratio of WTP (revealed by market prices) to the total cost of production to the state. My monthly rent data reveals WTP, but I must compare these rents to the full, upfront costs borne by the government, some years before the housing went on the market. To that end, I use a straightforward internal rate of return (IRR) analysis to test whether, viewed as an investment, renting out these properties at market rates would have been financially worthwhile for the state.[28]

4.1.1 Data sources

The costs and revenues associated with the housing project are derived from various data sources. Appendix A3 provides a very detailed account of how each of these values were

[28] For now, I assume there are no fiscal externalities resulting from state production of housing, an assumption I return to in my analysis of the treatment effects of government housing on labour supply and social outcomes.

calculated and the assumptions underlying those calculations. Construction costs are estimated using government data, including land auction prices and total construction budgets, divided by housing floor space to determine per unit costs. I also estimate the cost per unit of the infrastructure (roads, water, and electricity) from government estimates. Land costs are adjusted for location, with central sites having higher values. Given that there are likely some economies of scale in the production of housing, these are a lower bound estimate of the marginal cost.[29] Investments and upkeep costs are derived from housing survey data and include expenses for finishing and maintaining the units in both endlines. Rents are estimated from data on rents reported by *tenants* and owners in rental market surveys from 2017, 2019, and 2023, deflated to 2017 values. I account for rental market frictions by calculating brokerage fees paid on rental units. Finally, home value estimates for 2024 are based on sale data from the second endline, using a model to predict values and estimate a rent-to-value ratio for imputation.

4.1.2 Value stream calculations

Table 2 summarizes the data used for these calculations, for each housing site location, and on average. Panel A describes the different housing sites, Panel B presents the total construction costs, Panel C the cash flows resulting to owners of housing, and in Panel D I estimate IRR rates of return to the development of the housing.[30] Throughout, I use conservative assumptions to give lower bound on the returns to government housing.

Equipped with the full stream of incomes and costs for each period (all deflated to 2017 USD), including the initial costs of construction, upkeep costs, and rental frictions, I calculate the Internal Rates of Return (IRR) to government housing. These returns are calculated from the perspective of a hypothetical government developer, who had developed and rented out or sold the units at their market rate. These estimates are undiscounted and I do not adjust for implied opportunity costs of capital.

I calculate these as rates of return from the point at which development began, in 2013, until the period of the second endline, 2024, making a number of different assumptions about the asset is priced in the final period. (i) For my preferred specification I use the estimated sale value in 2024, (ii) in case my sale value estimates are inaccurate, I do not assume that the unit is sold but rather than the revenue and income streams remain as they are in 2024 in perpetuity. (iii) I assume that the housing unit is sold at the total deflated cost of *constructing* the housing unit in 2013. (iv) In my very lower-bound scenario, I assume that the housing is sold after 11 years at the cost of *land* on which it was built at 2013 real prices adjusted very conservatively by 3% growth per year.

The calculations are shown in Panel D. The estimated rates of return are positive on average for all methods except my lower-bound scenario. This hides substantial heterogeneity. For the most central sites, IRRs are negative if they were housing were to be sold at current market values or priced based on current rents. This suggests that

[29] There is a view that economies of scale are limited and that these average costs are likely to be fairly close to the marginal costs. See Eriksen and Orlando (2022) or discussion here.

[30] Table A10 shows the breakdown by housing unit size. For all calculations, I separately estimate costs and values at the location-unit type level (for example, 1-bedroom households in the Site 16km from the city centre) and then aggregate up to the site, type or aggregate level by using the true share of units in each type across the entire project, as opposed to just in my evaluation sample.

Table 2: Estimated internal rates of return, all types by site (2017 USD)

	All sites	Group 1	Group 2	Group 3	Group 4
Panel A: Site Descriptions					
Distance (driving)		0-4km	6-12km	15-20km	20-25km
Population density (2007)		19974.69	2119.82	1138.94	218.80
Winners 10th round	32020	928	3,862	17,287	9,943
Share of all winners	100.00%	2.90%	12.06%	53.99%	31.05%
Subsidised sale price	10,376	10,376	10,376	10,376	10,376
Panel B: Government construction costs					
Land cost per unit	9,659.8	68,692.4	16,839.0	7,163.3	5,702.1
Construction cost per unit	12,719.1	12,719.1	12,719.1	12,719.1	12,719.1
Infrastructure cost per unit	1,279.9	1,279.9	1,279.9	1,279.9	1,279.9
Panel C: Owners costs and earnings					
Total cost per unit	22,378.9	81,411.5	29,558.1	19,882.4	18,421.2
Initial investment	815.9	815.9	815.9	815.9	815.9
Initial maintenance	93.5	93.5	93.5	93.5	93.5
Final maintenance	83.8	83.8	83.8	83.8	83.8
Rent 2017	1,098.8	2,643.5	1,399.4	1,121.5	798.5
Rent 2019	1,299.9	2,637.4	1,394.5	1,294.7	1,147.5
Rent 2024	1,314.7	2,622.4	1,382.1	1,320.7	1,156.1
Sale Price Est	27,037.6	53,929.0	28,423.7	27,160.6	23,775.4
Panel D: IRR Calculations					
Sale at est. value	0.0527	-0.0072	0.0293	0.0659	0.0592
Sale est. value (with infrastructure costs)	0.0467	-0.0088	0.0249	0.0590	0.0519
No sale	0.0500	-0.0067	0.0284	0.0624	0.0562
Sale at cost	0.0348	0.0215	0.0288	0.0388	0.0363
Sale at land value	-0.0141	0.0108	-0.0068	-0.0168	-0.0280

Note: See text in Section 4.1.1 for details of calculations. All costs, prices and revenues are deflated or inflated to 2017 Ethiopian Birr and then converted to USD at the average exchange rate in 2017. Flows are presented in annual terms throughout. For example, households spent an average of 93.5 USD per year on maintenance in 2017.

building government housing is a misallocation of this valuable land. If the units were sold at the original cost of the land, the estimated returns would be more favourable. By contrast, building housing on more remote land significantly uplifts land values in those areas. IRRs are positive at current market values for the other groups of sites. For sites built right on the edge of current extent of the site, the average IRR is 6.59%, and for sites built even further away the return is slightly lower at 5.92%.

On average, the calculated IRR for government housing is 5.27%. This estimate does not include the costs of infrastructure. When I include these, returns are slightly smaller but similar. The WTP at the current margin, is higher than the costs of supplying it, if not by very much. The demand curve appears to sit above the supply curve, at the single point that I observe them: with 200,000 units built. While I make no claims that investment in government housing is the best use of government funds in a marginal value of public funds sense (Finkelstein and Hendren, 2020), these positive returns suggest that we can at least rule out strongly distortionary effects of the state's intervention in the supply of housing.

These estimates are likely a very lower-bound guide to the welfare effects of government housing for the broader population: my approach only estimates the valuation of government housing for the marginal consumer, after 200,000 units have been delivered. In theory, if the (presumably-downward) slope of the demand curve was known, we could recover the total consumer surplus for the government's intervention.

4.2 Demand for government housing among lottery winners

Plausibly, the observed occupants of government housing are those households with higher-than-average valuations of improved housing. Here, I turn to housing choices among the *representative* sample of lottery applicants, who are the intended beneficiaries of the program, and drawn from a large population (over 700,000 households applied), than just the highly-selected marginal consumer.

Lottery winners can chose to rent out their units and thus face a price directly tied to the market rate if they move in. However, this reveals a slightly separate willingness to pay than the market price that renters pay in Table 2. First, owners pay an implicitly lower price because they don't have to pay brokers or other costs of renting that might be baked into market rents. To account for this, I include these rental market frictions on the cost side of my IRR calculations in Table 2. Second, there may be some particular amenity value of living in one's own home, relative to a rental. In this sense, I identify demand for *owner-occupied* housing at the market price.

Table 3 describes the proportion of lottery winners who moved into their homes across the four different groups of housing sites, and at each time period. Column 1 represents the average occupation rates for the representative sample of lottery winners.[31]

I find that approximately 52% of households move into their units when they have the chance, and this proportion remains remarkably stable over eight years. In the first endline (2018), some units were still not available for occupation due to delays in handing them over to owners or delays in renovations.[32] In total, 46% of winners lived in their units, rising to 52% of those whose homes were available for occupation. Selling the units was very rare at this point, as it was officially illegal.

By the second endline, the rate of occupation remains almost identical, at 52%. The occupiers are not always the same people. In all, 67% of households lived in their units at some point over the last 8 years. By 2024, selling the units had been legal for approximately 3 years, and 20% of units had been sold. These were mostly units that were rented out in 2018.

4.3 Revealed preferences for improved housing

These results are consistent with the lottery providing access to higher quality formal housing that was not previously accessible to winners before they moved. Households with a higher revealed preference for formal housing over location move, while households who value their original location more do not. An alternative explanation is that households who won the lottery experience increases in permanent income due to the

[31] Note that the number of observations in Columns 2-5 do not add up exactly to the number in Column 1, because Columns 2 and 3 contain oversampled households from the more central sites that are not included in the representative sample.

[32] These delays were particularly prevalent in Group 4 — a site about a 25 km drive from the center — which was the last to be constructed, and fully 17% of units were not occupied in 2018.

Table 3: Occupation rates and condominium status by site

	(1) **Representative Sample**	(2) **0-4 km**	(3) **6-12 km**	(4) **15-20 km**	(5) **20-25 km**
Panel A: First Endline (2018)					
Lives in condominium	0.46	0.32	0.40	0.48	0.42
In process of moving in	0.04	0.00	0.00	0.03	0.06
Rented out	0.39	0.69	0.48	0.39	0.37
Sold	0.02	0.01	0.00	0.02	0.03
Unoccupied or not bought	0.11	0.00	0.04	0.09	0.17
Lives in condominium (cond. on available)	0.52	0.32	0.42	0.53	0.51
Ever moved in (cond. on available)	0.55	0.35	0.44	0.56	0.55
Observations	715	108	50	423	233
Panel B: Second Endline (2024)					
Lives in condominium	0.51	0.42	0.41	0.51	0.52
In process of moving in	0.01	0.01	0.00	0.01	0.00
Rented out	0.32	0.44	0.35	0.30	0.34
Sold	0.15	0.15	0.12	0.15	0.16
Unoccupied or not bought	0.03	0.01	0.05	0.03	0.02
Lives in condominium (cond. on available)	0.52	0.41	0.42	0.52	0.52
Ever moved in (cond. on available)	0.67	0.52	0.51	0.67	0.68
Observations	676	162	114	402	223

wealth effects from winning the lotteries, which induce changes in housing consumption – higher quality housing, at more distance locations – consistent with higher purchasing power. In this section, I present a number of pieces of evidence that suggest that it is preferences, not income effects, that explains why households move.

Fact 1a: Lottery winners trade housing quality for location 1-for-1 in market-value terms

To understand the trade-offs facing households who win government housing, I study the effects of winning the lottery and of moving into condominiums on household consumption, at both endlines. Table 4 shows that winning housing dramatically increases the quality of housing by 0.68 standard deviations while it increases household distance from the city center by almost 100%, after three years. The results are remarkably similar six years later, suggesting that the control group are not catching up in housing quality. Table A11 provides detail on the subcomponents of the housing index and the effects of winning the lottery on each.

My estimates of the market value of housing consumption (using hedonic regressions outlined in 3.4) are unaffected by winning the lottery, suggesting that the market value of slum housing in the centre is similar to a condominium further away, at least at the time of the first endline. This implies a budget-neutral trade of location for better housing quality. Six years later the effect on the market value of housing consumption is larger, reflecting the fact that market rents in condominiums grew faster than other forms of housing (as discussed in Section 4). Predictably, moving further away increases

Table 4: Effects of winning the lottery and moving house on consumption, housing, and location

	2018 Endline			2024 Endline			
Outcome	N (1)	Control mean (2)	ITT Lottery (3)	N (4)	Control mean (5)	ITT Lottery (6)	Diff pval (7)
Housing quality index	1,426	0.000	0.680*** [0.053]	1,370	0.056	0.672*** [0.088]	0.907
Distance from city centre	1,426	5.403	4.381*** [0.261]	1,370	6.441	4.274*** [0.290]	0.790
Housing consumption	1,426	77.828	2.545 [1.824]	1,370	90.319	20.752*** [3.994]	0.000
Transport expenditure	1,426	12.262	3.086*** [0.761]	1,370	14.440	2.637 [1.908]	0.849
All other consumption	1,426	142.199	3.874 [4.834]	1,370	137.497	7.885 [8.717]	0.437
Non-housing Asset index	1,352	0.064	-0.068 [0.055]	1,370	-0.039	0.024 [0.028]	0.261

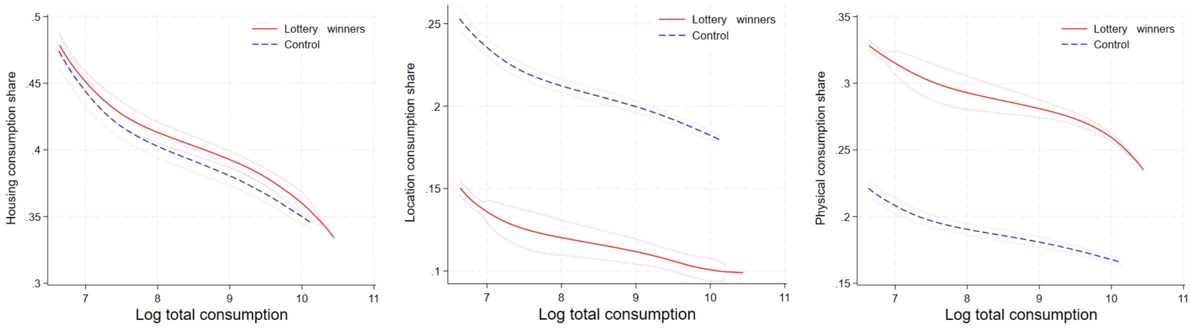
Note: Each row represents a regression of the named outcome on whether the household won the lottery using the ANCOVA specification in Equation 1. I show the results separately for the 2018 and 2024 endlines (one regression for each endline, per outcome). "ITT Lottery" identifies the parameter of interest, with the relevant SE of the estimate shown in square brackets below. Column 7 provides the p-value for a test of equality of the coefficient between the 2018 and 2024 endlines. This is estimated using a saturated regression combining both endlines and including interactions between all covariates and an "endline" dummy. "All other consumption" is the aggregate of a full consumption module *less* transport and housing consumption. All monetary values are given as monthly 2017 USD.

expenditure on transport by the equivalent of $3 a month, although note that this a much smaller increase implied by the distance of the moves that households make. This is plausibly because the cost (and we will see, speed) of travel through the outskirts are much lower than travelling through the more congested central areas of the city.

Fact 1b: Lottery winners do not increase non-housing consumption If income effects were driving improved housing conditions among lottery winners, theory would predict that other forms of consumption to increase together with housing quality. Instead, winning the lotteries does not affect non-housing consumption and household asset ownership, even eight years later. The coefficient on consumption is positive and equivalent to an increase of 3% of total consumption but is not significant. Including measures of housing implies that total household consumption increases by 11%, 8 years after winning the lottery, but was not changed in the short-run.

Fact 2: Changes in housing consumption are consistent with shifts in, rather than movements along, Engel curves. Facts 1a and 1b suggests that winning access to housing expanded households choice sets allowing them to trade location for better housing, rather than consuming more overall. I formalise this intuition by estimating housing Engel curves. Figure 3 shows non-parametric regressions of housing consumption shares $\hat{r}^k/y$ on $\ln(y)$, where $\hat{r}^k$ is imputed housing consumption for a household living in housing type k using my hedonic model in Section 3.4, and y is total household consumption (which includes all other measured household expenditures plus $\hat{r}^k$).[33] In Appendix Table A15 I estimate these functions parametrically also controlling for household covariates and baseline housing consumption shares.

Figure 3: Engel curves for housing consumption



A) Total housing share   B) Location share   C) Physical share

I find that, in the control group, housing shares fall with total consumption, including consumption shares of both location and physical quality. This suggests a pure wealth shock should reduce housing expenditure shares. On the contrary, I find a small insignificant increase in housing shares at the endline among lottery winners, and equal but opposite shifts in the shares spent on consumption on location (downwards) and on physical quality (upwards) of approximately 8 percent points (or 45%), respectively. In other words the results are consistent with shifts in housing Engel curves, rather than moves along them. Shifts in these Engel curves are mostly parallel. The results are similar when I put measures of total household income including rent income on the right hand side (Figure A5). Finally, I run this Engel curve analysis separately for households that move (compared to households that will move in the control group) and non-movers, in Figures A6 and A7. The results confirm that the shifts in Engel curves are driven entirely by households that move, with no discernible difference for households who experienced the wealth shock but did not move.

Fact 3: Revealed preference (using baseline data) for housing quality relative to location, predicts who moves in. Wealth and income do not.

I hypothesize that baseline housing choices among private renters reflects preferences for housing quality and location, and these revealed preferences should predict whether households move. On the other hand, wealth effects may be driving the decision. But would an increase in wealth cause households to move further from, rather than closer to, the centre? In standard models of location choice with iceberg commuting costs, the effect of wealth on location is ambiguous (Gaigné et al., 2022). Generally, richer households live closer to the city centre because they face a higher opportunity cost of commuting, but if neighbourhood amenities *improve* with distance from the city at a sufficiently rapid rate relative to commuting costs, richer households will live further from the city center. If this is the case, we should find that wealthier households are more likely to move to government housing.

[33] The results are similar when I use log household income instead of consumption (see Figure A5).

Table A16 examines how baseline income, wealth, housing quality, and location predict moving into units among private renters, controlling for additional predictors selected via lasso regression (Table A20).[34] The results indicate that preferences for housing quality over location, rather than income or wealth, drive the decision to move. Households with higher baseline housing consumption are more likely to move, with physical quality positively predicting and location consumption negatively predicting moving in (based on hedonic decomposition in Section 3.4). Income and wealth have no effect.

Social networks do not predict moving in, but membership in community groups (*iddirs*) decreases the likelihood of moving. *Iddirs*, traditionally mutual aid associations, now serve broader functions in urban Ethiopia. This suggests a stronger pull of communities than general social networks. This result persists after controlling for potential confounders and is consistently selected by lasso regressions.

Fact 4: Winning housing doesn't increase household income in the short run. Another piece of evidence comes from changes to household income and liquidity. Winning households receive a significant wealth transfer through a condominium, but this asset is illiquid and financed by mortgages with high repayment rates(Table A14). Initially, net housing income is negatively affected because mortgage repayments exceed rental income and savings from occupying the unit. Winners have lower cash savings and higher debt from mortgages and loans taken to make down payments. By year 8, 60% have paid off mortgages, and 20% have sold their units, often while incurring other debts, possibly informal loans. This suggests winners are not cash-rich and why they do not increase consumption, including housing in market value terms.

Fact 5: Non-movers do not change their consumption patterns.
If the wealth effects of winning the housing asset were driving the results in Table 4 we would expect to see changes in housing consumption for non-winners too. Instead I find changes in housing consumption are by households that move into the condominiums that they won, and non-moving households exhibit housing and non-housing consumption indistinguishable from the control group. Table A34 shows the results for mover households and non-mover households separately, using Specification 2.[35] This lack of effects is likely to due to the lack of change in cash income documented in Fact 4.[36]

Fact 6: Lottery winners invest significantly in additional housing amenities which they consume if they move in.
Lottery winners improved their housing by adding amenities like tiling, showers, and internal doors, investing roughly $2,000 USD (10% of construction costs) more than the

[34] Table A16 focuses on private renters to isolate baseline housing preferences, as households in government-owned slum housing had limited choices at baseline. Replications with all households (Appendix, Table A17) show similar patterns, though baseline housing effects are attenuated. Results are also robust in the second endline (Table A19), where physical housing quality continues to predict moving in.

[35] The results are similar when I use Equation 3, which controls for the observables determining the occupation decision to address selection on observables, suggesting that selection on unobservables is not a significant concern. I use Equation 3 to estimate the effects of moving versus staying for the second endline and also find very similar results: changes in location, housing quality, and consumption are driven by households that move (see Table A39).

[36] Note that because different households attrit from each endline, the union of the two endlines required to estimate Equation 2 yields a smaller sample size than in other specifications.

control group (Table A12). These upgrades, detailed in Figure A8, are rarely found in informal homes, and were not provided by the state in the new condominiums (they were also not included in my estimates of housing quality in Table 4). Winners also consume these amenities: investments are larger for those who move into their units (Table A12). Table A13 shows that 8 years later, households who moved into their own condominiums have significantly improved housing conditions in an index only including these additional amenities not provided by the state.[37]

This investment plausibly stems from greater tenure security and/or lower costs of upgrading formal structures. For instance, plastering and painting a wood and mud house is costlier and harder to maintain, and installing a proper shower is nearly impossible without formal water connections. By providing formal homes, the state unleashes household demand for these amenities.

5 The impacts of winning and moving to housing

5.1 Labour market effects

I find no overall effect of winning the housing lottery on labour market aggregates, both in the short and longer run. I show this both at the individual level in Table 5, and at the aggregate household aggregate level in Table A27.[38] The coefficients on earnings are small but positive. I can rule out large losses in earnings or job quality due to winning the housing lottery, including in the long run.[39]

The individual-level results, with two endlines, help to explain how households were able to adjust to living so much further from the city centre without hurting their labour market outcomes. After 3 years, I see that treated individuals are more likely to have switched their type of work (either from or to wage or self employment) and are more likely to work in a location that is close to one of the main new housing sites, but are still less likely to work close to home. This suggests that some households have been able to change their place of work to suit their new residence, others just commute further. Average commuting times and costs are significantly higher. After 8 years, there is almost no effect on any individual labour market outcomes, including type of place of work, or mode of transport. Even total commuting costs are no higher on average, although commuting times are still 17% longer. The results suggest that households are able to adjust their employment habits – while also enduring slightly longer commutes– in the long run. They are no less likely to report working very close to home or even to walk to work after 8 years, suggesting that there are job opportunities in the new neighbourhoods where housing was built.[40] This is confirmed qualitatively by the active labour markets that developed in condominium sites, with restaurants and services opening up in the commercial spaces reserved on the ground floor of condominium blocks. I find no effect on job quality in the long run.

[37]I collected detailed data on the consumption of these amenities in the second endline, but do not have this detail for all households in the first endline.

[38]I show sharpened q-values Benjamini et al. (2006) to account for multiple hypothesis testing.

[39]The household-level results fail to reject equality of coefficients between the two endlines for those main aggregates.

[40]Very few lottery applicants have their own cars.

Table 5: Effects of winning the lottery on individual labour market outcomes

			ITT Estimate Lottery		
Outcome	N	Control mean	Coeff	Std. Err.	q-value
	(1)	(2)	(3)	(4)	(5)
Panel A: First Endline (2018)					
Did any work in the last 7 days	3,711	0.627	-0.021	0.015	0.379
Wage-employed work in the last 7 days	3,711	0.446	-0.007	0.016	0.794
Self-employed work in the last 7 days	3,711	0.119	-0.006	0.011	0.794
Individual monthly earnings (USD)	3,711	83.424	1.075	3.355	0.815
Individual hours worked in the last 7 days	3,711	29.677	-0.999	0.777	0.379
Permanent work	3,711	0.294	0.014	0.013	0.515
White collar-work	3,711	0.195	0.026**	0.012	0.123
Permament white-collar work	3,711	0.323	0.019	0.014	0.379
Switched between self/wage employment	1,631	0.098	0.034*	0.018	0.161
Switched occupations (40 main occupations)	1,507	0.491	0.005	0.027	0.856
Works in areas near housing sites	3,711	0.066	0.043***	0.011	0.001
Works close to home	3,711	0.047	-0.026***	0.008	0.004
Works in own home	2,249	0.058	0.003	0.010	0.815
Commute time (cond)	2,249	61.491	18.376***	2.872	0.001
Commute cost (cond)	2,317	9.239	3.894***	0.817	0.001
Factory job	3,711	0.009	-0.002	0.004	0.794
Construction job	3,711	0.079	0.005	0.010	0.794
Panel B: Second Endline (2024)					
Did any work in the last 7 days	3,493	0.438	-0.025	0.026	0.796
Wage-employed work in the last 7 days	3,493	0.343	-0.046*	0.026	0.664
Self-employed work in the last 7 days	3,493	0.094	0.020	0.018	0.721
Total earnings in the last month	3,493	61.961	0.894	5.547	0.929
Individual hours worked in the last 7 days	3,493	20.570	-1.030	1.350	0.840
Permanent work	3,493	0.257	-0.039	0.024	0.664
White-collar work	3,493	0.162	-0.005	0.018	0.929
Permament white-collar work	3,493	0.265	-0.037	0.025	0.664
Switched between self/wage employment	1,220	0.280	0.057	0.049	0.721
Switched occupations	775	0.552	-0.036	0.061	0.840
Works in areas near housing sites	3,493	0.048	0.009	0.012	0.840
Works close to home	3,493	0.049	-0.015	0.013	0.721
Works in own home	3,493	0.009	0.000	0.006	0.929
Commute time (cond)	978	42.491	6.888*	4.094	0.664
Commute cost (cond)	1,735	5.722	-1.037	1.789	0.840
Takes a minibus to work	3,493	0.066	-0.005	0.016	0.929
Walks to work	3,493	0.051	-0.008	0.014	0.840
Factory job	3,493	0.004	0.001	0.006	0.929
Construction job	3,493	0.020	-0.003	0.007	0.840

Note: Each row represents a regression of the named outcome on whether the household won the lottery using the ANCOVA specification in Equation 1. All regressions control for baseline covariates and for whether individuals live in households that won later lotteries (rounds 11 through 14). I show the results separately for the 2018 and 2024 endlines in Panel A and Panel, respectively. Column 5 shows an sharpened q-value to control the false discovery rate.

Heterogeneity by gender and seniority within households: It is likely that heads of households (usually men) make the decision to move their families. While heads may be selected based on their ability to adjust appropriately to the change in location, women or younger members of their families may not. Women, in particular, might find it harder to adjust to losing access to local work in the city centre. I find no evidence for this when looking at heterogeneous treatment effects by gender at each endline in Tables A28 and A29, and by seniority (household heads relative to other household members) in Tables A30 and A31. I fail to reject that the coefficient estimates are different between men and women, for example, and no coefficient suggests large negative effects for women. The standard errors of these heterogeneous estimates are similar to those for all individuals because errors are clustered at the household level.

Movers versus stayers: In Tables A35 and A36 I break down these results by households who moved into the condominiums that they won and those that did not, at endline 1, using specification 2.[41] I find no evidence that aggregate outcomes differ across households that move and those that did not, suggesting that there is a no separate effect of either moving to a new neighbourhood or of winning the lottery itself on important outcomes.[42] The reasons for a lack of direct effects are likely due to the short-term financial consequences of winning housing discussed in Section 4.3. The short-term adjustments that individuals made in their job choices, commuting times, and locations *are* all driven by households that moved.

Commuting and transport: The relatively small effects on commuting times are partly related to the transport technology from the outskirts to the centre. Lottery winners that move live 160% further from the city centre. Commuting costs (conditional on working) are higher by 113%, but their actual commuting times increased by less than 60% (Table A36). This partly reflects congestion patterns: the large roads built to the government housing are largely uncongested while travelling through the periphery of the city, but commuters usually hit heavy traffic closer in. This makes average travel speeds significantly faster from the outskirts; the increase in travel time and cost is proportionately smaller than the increase in Euclidean distance.

5.2 Social networks, community and neighbourhood amenities

Table 6 presents the effects of housing lotteries on various quality-of-life outcomes for urban residents. Most housing sites were built on the city's outskirts, areas with little to no existing population before construction began. Therefore, the quality of these new neighbourhoods is determined almost entirely by the new residents who moved in.

Social networks and conflict: Consistent with other studies on programs relocating households, winning housing lotteries reduces the total size of social networks (measured by the number of people the respondent talks to more than once a week) by roughly 30%,

[41] Here the control group for households that move is the subgroup of non-winning households that will win a lottery after the first endline and will move into that condominium when they win.

[42] I find very similar results at the second endline (and again for the first endline) when I use my more correlational approach where I control for all baseline variables that predict whether households move into their condominiums, to control for selection on observables. These results are in Tables A40 and A41.

driven by a loss of *local* neighbourhood networks. This suggests that moving households lost friends that they used to interact with in old neighbourhoods, but were also able to make some new friends locally. The first endline shows ambiguous effects of these net losses: respondents are less likely to turn to neighbors for advice and more likely to say they lacked friends to help them. However, they are also less likely to have arguments or conflicts with neighbors. Overall satisfaction with social lives is unaffected.

Households reported that life informal settlements involved considerable levels of conflict around the shared use of resources like toilets, cooking areas and other communal spaces. In the data, I find that households not only reduce their overall social interactions but reduce their levels of economic interactions even within their remaining social network. That is, they reduce the number of other people they interact with on an economic basis by more than they reduce their total network size. In qualitative interviews households also report a value for the privacy that they enjoy in formal housing.

Eight years later, lottery winners still talk to fewer people overall, but arguments and conflicts with neighbors remain persistently lower. They are *less* likely to feel lonely or lack friendships.[43] The effects on satisfaction with social life are now positive; though not quite significant in the ITT they are significantly higher for households that moved into their units (see Table A43). These results suggest that households that moved experienced a long-term loss in their support networks but now benefit from less conflictual relationships with their neighbors. Qualitative interviews confirm that living in formal condominiums reduces conflicts over shared resources (such as toilets, cooking areas, and other communal spaces) common in informal settlements. Residents also appreciated the privacy of formal housing and were relieved to lessen the social obligations that came with slum living.

Community: The effects of condominiums on community inclusion are strongly positive. Lottery winners, especially movers, are significantly more likely to join an *iddir* (community support group) and participate in community meetings, with movers often taking on leadership roles. These effects persist after 8 years. One of the strongest predictors of whether households moved was their original membership in an *iddir*; those not part of an *iddir* were more likely to move. Qualitative interviews conducted with households confirm what these results suggest: winners without prior *iddir* membership moved to new areas and formed new *iddirs* with other movers. If *iddir* membership in the old communities was somewhat exclusive, moving to a new neighbourhood provided an opportunity to form more inclusive community associations.[44]

[43]These results from a smaller sample size because the outcome is missing for households who requested to respond to a shorter version of the questionnaire due time constraints on their side.

[44]Many households that moved reported that they were not in local risk-sharing groups in their old neighbourhoods because they were excluded from those groups. Moving to new neighbourhoods allowed them to more freely associate with their neighbours and set up risk-sharing groups on their own terms.

Table 6: Social and neighbourhood outcomes

Outcome	2018 Endline N	2018 Endline Control mean	2018 Endline ITT Coef	2018 Endline ITT SE	2024 Endline N	2024 Endline Control mean	2024 Endline ITT Coef	2024 Endline ITT SE	Diff pval
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Subjective wellbeing (ladder)	1,426	4.282	-0.056	0.141	1,370	4.231	0.488***	0.156	0.087
Social networks outcomes									
Total number of social ties	1,414	11.369	-2.271***	0.446	1,358	6.194	-1.098*	0.626	0.087
Social ties in local neighbourhood	1,425	6.551	-2.596***	0.649	1,370	3.456	-0.536*	0.321	0.015
Can turn to neighbours for advice	1,426	1.795	-0.197**	0.090	1,370	2.656	-0.054	0.056	0.298
Felt lonely	1,375	1.522	-0.072	0.050	876	2.021	-0.386***	0.120	0.003
Needed help and couldn't find with friends	1,375	1.652	0.195***	0.060	876	2.137	-0.456***	0.121	0.000
Satisfied with social life in neighbourhood (1/0)	1,426	0.806	0.005	0.020					
Satisfied with neighbours	1,426	3.296	-0.094**	0.038					
Satisfied with social life in general					1,370	3.237	0.075	0.066	
Satisfied with social life in neighbourhood					1,370	3.169	0.107	0.069	
Community outcomes									
Beliefs: neighbours' contribution to pub. goods	1,311	-0.020	0.072	0.057	876	0.072	-0.050	0.117	0.330
Arguments with neighbours	1,426	0.411	-0.124***	0.044	876	2.337	-0.231***	0.055	0.246
Household is a member of at least one iddir	1,426	0.546	0.124***	0.025	1,370	0.669	0.085**	0.039	0.489
Community meetings participation	1,426	0.369	0.108***	0.028	1,370	2.619	0.235***	0.081	0.083
Respondent has leadership role in community	1,426	0.036	0.013	0.011	1,370	0.006	-0.002	0.007	0.450
Public goods outcomes									
Index of public goods	1,426	-0.004	-0.223***	0.056	1,370	0.000	-0.114	0.086	0.246
Clinic/hospital quality	1,426	3.244	-0.148***	0.035	1,370	2.969	0.036	0.045	0.002
Primary school quality	1,426	3.061	-0.057*	0.030	1,370	2.944	-0.017	0.053	0.453
Public space quality					1,370	2.962	0.093*	0.048	
Amenities outcomes									
Index of neighbourhood amenities	1,358	0.015	-0.234***	0.060	1,370	-0.000	0.194**	0.086	0.000
Neighbourhood has *less* smell of drains or sewerage	1,374	-0.007	0.104*	0.058	1,370	-0.000	0.331***	0.088	0.034
Neighbourhood has working streetlights	1,426	0.395	-0.132***	0.026	1,370	0.206	-0.005	0.033	0.006
Less debris/rubble lying around neighbourhood	1,422	2.688	-0.286***	0.044	1,370	2.544	0.071	0.060	0.000
Condition of piping and sewerage system	1,362	-0.011	-0.037	0.061	1,370	0.000	0.167*	0.087	0.068
Feels safe at night	1,370	5.720	0.028	0.039	1,370	5.475	0.216**	0.085	0.025
Overall neighbourhood rating					1,370	5.356	0.408**	0.183	
Proud of neighbourhood					1,370	3.675	0.240***	0.088	
Preference to stay	1,426	2.764	-0.641***	0.079	1,370	3.481	0.267**	0.109	0.000

Note: Each row represents a regression of the named outcome on whether the household won the lottery using the ANCOVA specification in Equation 1. All regressions control for baseline covariates and for whether households won later lotteries (rounds 11 through 14).I show the results separately for the 2018 and 2024 endlines (one regression for each endline, per outcome). "ITT Lottery" identifies the parameter of interest, with the relevant SE of the estimate shown in square brackets below. Column 7 provides the p-value for a test of equality of the coefficient between the 2018 and 2024 endlines. This is estimated using a saturated regression combining both endlines and including interactions between all covariates and an "endline" dummy.

Amenities, public goods, and crime: The effects of condominiums on access to public services and local amenities exhibit a reversal of fortune. In the short-run, lottery winners report significantly worse public goods (like schools and medical clinics). Eight years later, this effect has dissipated. Initially, after 2 years, lottery winners report lower scores on an index of neighbourhood quality (including drains, sewerage, rubble, and debris). However, after 8 years, this reverses: now lottery winners live in significantly better neighbourhoods and feel safer (from crime) at night. After eight years, winners report higher satisfaction and pride with their neighbourhoods, and a stronger preference for continuing to living there. All of these results are driven by households that moved into their units, with negligible effects on those that didn't move (Table A43). These results plausibly correspond to improvements in neighbourhood quality in condominium sites over time, as residents moved into their neighbourhoods and the state improved access to public facilities that were initially not present. Overall subjective well-being (measured on a "ladder" from 1 to 10) is not affected in the short run, but 0.5SDs higher after 8 years.[45] These conclusions survive multiple-hypothesis testing corrections when I apply corrections across all main outcomes at the household level (see Tables A23 and A24) or specifically just across the outcomes in Table 6 (see Tables A25 and A26).

5.3 Education outcomes

Moving to government housing in new neighbourhoods could plausibly have affected respondents schooling outcomes through a number of channels. First, access to good quality schools have been worse for households that moved to condominium sites. The results suggest that this was true in the short run, but the difference dissipates eight years later. Second, formal housing might make studying easier, by providing a well lit, smoke free, and quieter environment, and improved the health of young people living there.[46] Third, social interactions may have been different, depending on the composition of the new neighbourhoods and the way in which new housing might shape those interactions– for example, if crime is lower in formal housing, as Table 6 suggests that is in the long run, this could be correlated with a social environment that encourages higher attainment in school and less delinquency. Fourth, if winning a house increased household wealth, this could have resulted in increases in schooling expenditures (Kumar, 2021). Finally, moving house could cause disruptions to learning.

In Table 7 I report the results of individual regressions on education outcomes, including household controls and individual age and gender fixed effects.[47] These outcomes are reported by the head of household, including aspirations for that child's future education. The results show no evidence of affects – after eight years– of winning the housing lotteries on enrolment, attainment or final grades (from standardized high school test

[45]The effects are bigger for households that move, though the difference relative to non-movers is not significant, in my correlation exercise using Equation 3.

[46]I collected detailed self-reported health outcomes in my first endline and found no evidence of significant changes in these outcomes due to winning the lottery. See Table A32 and A33 for adults and children, respectively.

[47]I did not collect detailed data on children's schooling outcomes in the first endline data. These educational outcomes are plausibly only affected after more than a year or two of living in government housing.

scores.) Households regressions show no changes in household expenditure on schooling and health outcomes for households that have been living in their homes from eight years. I look at how the effects differ by children in households that move and that do not move in A44 and find no evidence of heterogeneity between these two groups.

I do find evidence that moving housing can disrupt education in the short-run. In Table A45 I report the effects of winning the 13th round (who moved in in just the previous year) and 14th round (who were still in process of moving) lotteries relative to having never won a lottery. I find evidence of lower enrolment rates, possibly because of moving home disrupts schooling. The evidence from the 10th round suggests that these disruptive effects are short-lived.

Table 7: Children and young adult education outcomes at Endline 2

Outcome	N	Control mean	ITT Estimate Lottery Coeff	Std. Err.	Sharpened q-value
	(1)	(2)	(3)	(4)	(5)
Enrolled (all < 30)	1,898	0.643	-0.029	0.024	0.613
Enrolled (all < 18)	1,025	0.963	-0.014	0.018	0.689
Enrolled (primary age, < 15)	675	0.988	-0.015	0.014	0.613
Enrolled in highschool or higher (all $15-19$)	476	0.618	0.041	0.074	0.689
Enrolled in tertiary (all $19-24$)	498	0.238	-0.068	0.070	0.613
Enrolled in University (all $19-24$)	498	0.193	-0.119*	0.064	0.613
Completed highschool (all > 18)	665	0.722	0.031	0.056	0.689
Completed degree (all > 24)	257	0.591	-0.011	0.093	0.902
Completed or enrolled in highschool (all > 14)	1,141	0.767	-0.014	0.039	0.782
Grade in most recent year of school (all < 19)	733	79.591	1.523	1.458	0.613
Days absent from school in last 30 (all < 18)	993	0.867	-0.227	0.180	0.613
Aspires to tertiary education (all < 18)	1,025	0.969	0.010	0.015	0.689
Confidently aspires to tertiary education (all < 18)	1,025	0.891	0.049	0.031	0.613

Note: Each row represents a regression of the named outcome on whether the household won the lottery using the ANCOVA specification in Equation 1. I show the results for the 2024 endline for which I have detailed education data. "ITT Lottery" identifies the parameter of interest, with the relevant SE of the estimate shown in column 4. Column 5 shows sharpened q-values to correct for multiple hypothesis testing.

5.4 Heterogeneity by location of condominium sites

Next I look at heterogeneous effects of winning the lottery by the location of randomly assigned housing site. For the estimation of heterogeneous effects I use my sample of central sites described in 2.2.2 to increase the sample size for more central locations.[48] I use the identification strategy outlined in Section 3.3. Recall that households assigned to sites in the city centre paid the exact same price as those who won on the periphery, including the size of their down-payments and monthly mortgage repayments but won an asset considerably more valuable and costly to build. Despite relatively smaller samples sizes at central locations, I am able to find evidence of significantly heterogeneity in treatment effects across randomly allocated sites.

[48]Only about 2% of households in the lottery won a house in the most central sites, and relatively few won in the "intermediate" distance (6-12km).

Table 8: Heterogeneity of treatment effects by randomly assigned site of condominium

Outcome	N	CM	Differential effects by km from City Centre 0-4	6-12	15-20	20-25	pval
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: First Endline (2018)							
Housing quality index	1,525	-0.05	0.34***	0.48***	0.70***	0.57***	0.004
			(0.10)	(0.14)	(0.06)	(0.07)	
Distance from city centre	1,525	5.40	0.90	3.37***	4.31***	4.84***	0.000
			(0.55)	(0.77)	(0.32)	(0.39)	
All other consumption	1,525	142.20	3.60	9.91	10.48*	-8.61	0.053
			(9.71)	(13.18)	(5.52)	(6.68)	
Household labour market index	1,525	0.02	-0.17*	-0.02	0.02	-0.11	0.177
			(0.10)	(0.14)	(0.06)	(0.07)	
Earnings per working age adult	1,525	85.44	-27.53***	-5.54	5.27	-4.65	0.001
			(7.96)	(11.04)	(4.65)	(5.63)	
Total number of social ties	1,525	11.37	-3.27***	-1.39	-2.38***	-2.17***	0.484
			(0.83)	(1.15)	(0.48)	(0.58)	
Satisfied with social life in neigh.	1,525	0.81	0.02	-0.00	0.03	0.01	0.839
			(0.04)	(0.06)	(0.02)	(0.03)	
Panel B: Second Endline (2024)							
Housing quality index	1,597	0.29	0.62***	0.63***	0.66***	0.66***	0.978
			(0.11)	(0.13)	(0.09)	(0.10)	
Distance from city centre	1,597	6.07	0.96*	2.68***	3.87***	6.01***	0.000
			(0.50)	(0.57)	(0.41)	(0.45)	
All other consumption	1,597	143.20	33.89***	34.28***	9.29	7.37	0.022
			(11.79)	(13.26)	(9.31)	(10.27)	
Household labour market index	1,597	-0.02	-0.17	-0.07	0.04	-0.12	0.086
			(0.11)	(0.13)	(0.09)	(0.10)	
Earnings per working age adult	1,597	69.43	-14.97*	12.23	7.74	4.92	0.004
			(8.13)	(9.31)	(6.64)	(7.33)	
Total number of social ties	1,597	4.99	-3.38***	-1.08	-2.53***	1.65***	0.000
			(0.64)	(0.74)	(0.53)	(0.58)	
Satisfied with social life in neigh.	1,597	3.23	0.01	0.03	0.12	0.10	0.259
			(0.09)	(0.09)	(0.07)	(0.08)	

Note: Each row represents a regression of the named outcome on which housing site the household was assigned to, with non-lottery winners as the omitted category, as in specification 4. I show the results separately for the 2018 and 2024 endline data (one regression for each endline, per outcome) in Panels A and B, respectively. Columns 3 to 6 show the ITT effect of winning a government house in the distance band indicated in the column header. Column 7 provides the p-value for a joint test of equality of the four site-specific coefficients in Columns 3 to 6. "All other consumption" is the aggregate of a full consumption module *less* transport and housing consumption. All monetary values are given as monthly 2017 USD.

Table 8 presents the ITT effects of being assigned to each group of sites after 2 (Panel A) and 8 years (Panel B). I present a selected set of outcomes to summarise the key outcomes. As expected, households who win housing in more remote sites live significantly further from the city than those who win in closer sites.[49]

The results show some clear evidence of differential treatment effects by distance of the randomly assigned site. Three striking results arise for households assigned to closest locations (between 0 and 4 kilometers from the city centre). First, the positive impacts on the housing quality index are muted for this group in the first endline are strongly attenuated, driven by the fact that these households are significantly less likely to move into their units. This difference has disappeared after 8 years, possibly reflecting the fact that difference in occupation rates have narrowed by that point.[50] Second, non-housing consumption is not significantly affected for any site-distance in the 2018 endline. However, by 2024, households who won housing in central locations exhibit increased non-housing consumption, likely due to the income effects of winning these more valuable housing units. Winners of homes further from the city centre do not experience these consumption affects. Third, I find that winning a central house depresses labour market outcomes both 2 and 8 years after the lottery. Households who win houses in the city centre have a standardized labour market index 0.33 standard deviations lower after 2 years and earn early 20% less 8 years later. There are no such effects on total earnings for housing further from the city centre, even though those sites are significantly further away from job opportunities in the city centre.[51]

Households that win units closest to the centre experience the largest reduction in the size of their social networks after 8 years, while those winning houses furthest away actually experience increases in their network size. I am not well powered to test for differences in outcomes between those that moved and those that don't for these smaller central sites, but these results at least contradict the view that moving households to more remote areas will hurt social networks relative to closer locations. Overall satisfaction with social networks is not correlated with the randomly assigned site.

6 Conclusion

This paper examines the case for state intervention in the supply of housing. First, my market analysis compares the willingness to pay of households to the costs of producing government housing. I find that the market value of the housing implied by the marginal consumer's WTP slightly exceeds the costs of producing it. This identifies demand for the program for the marginal renter of the housing. The second section uses winners of the lottery to test for how broad this demand for housing is. I find that half of lottery winners forgo this market rental income to live in their units, and argue that this is

[49]Note that the dependent variable is the Euclidean distance of the household from the city, while sites are classified by the travel distance by road.

[50]It is also possible that households who won housing in central sites have used the income from renting out these very valuable units to upgrade their non-condominium housing.

[51]However, I do find that households who win further away see reductions in labour supply at the extensive margin, suggesting that these household optimise labour supply within the household, for example by the main breadwinner earning more, while other household members working less, leaving total earnings unaffected.

driven by household preferences rather than the income effects of the lotteries.

After considering the demand for housing, I turn to the intent-to-treat effects. These tell us that the assumptions behind revealed preference were not obviously violated: households did not experience measurable losses to their well-being that they might not have anticipated, including on earnings, employment, well-being, and various social outcomes. It also rules out important externalities of the program, which may affect the case for government housing directly if these imply fiscal externalities (for example by reducing taxation from formal employment). If anything, by creating neighborhoods with improved amenities and social outcomes, the program may be generating important positive externalities. Similarly, the improvement in living standards may eventually translate into important health and human capital benefits in the longer run, which may also generate such social gains. There may be other positive externalities of building so much new housing: for example, it could have lower equilibrium housing prices throughout the city, lowered density and congestion in slums in the centre, or allowed more households to move from rural areas to the city by providing more housing. Since identifying these effects is beyond the scope of this paper, my results remain a lower bound on the overall effects of the program.

My results raise the question of how the state was able to supply housing at a price below what consumers are willing to pay. Although the margins are small, my results suggest that a government selling this housing at market price would be making a small profit at the margin, even with over 200,000 units built. Yet the supply of such housing prior to the program was, and remains, almost non-existent. If the state's supply curve does indeed lie below the private sector curve, why? One obvious answer is that this is due to regulation of the government's making. Land markets in Ethiopia are highly regulated and the ability to buy and sell land is limited, as it is in many developing countries (Brueckner and Lall, 2015). This could compound existing market failures arising from land assembly problems that would make it impossible for a private developer to acquire a site large enough to build at sufficient scale (Brooks and Lutz, 2016). The state may also have other advantages due to its scale and financial position. My results suggest that the scale of government housing, built on new sites on the edge of the city, might be important to its success: the density of the sites allows for employment and regular transport links to pop up there.

My paper tells us something about where government housing should be built. Conventional wisdom, pointing to the potential dislocating effects of moving households further from the center, has often advocated for building closer to the center. By conducting my analysis separately for multiple locations across the city, I show that the costs of building on valuable land in the center are extremely high. While this is reflected in higher rents, the implied returns are lower than for other sites, and it also means that fewer of the intended beneficiaries actually move into their housing in the short run. Moreover, the large wealth effects due to these desirable locations appear to reduce labor supply for winners of these central homes. While governments may have other reasons for building in central locations, it is not clear that this is efficient from the perspective of the intended beneficiaries alone.

References

Agness, Daniel and Tigabu Getahun, "Housing and Human Capital: Condominiums in Ethiopia."," 2024.

Alzúa, María Laura, Julián Amendolaggine, Guillermo Cruces, and Catrihel Greppi, "Housing subsidies, labor supply and household welfare. experimental evidence from argentina," 2016.

Ampuero, Fernanda Catalina Rojas, "Sent away: The long-term effects of slum clearance on children and families." PhD dissertation, UCLA 2022.

Andersen, Asbjørn G, Simon Franklin, Tigabu Getahun, Andreas Kotsadam, Vincent Somville, and Espen Villanger, "Does wealth reduce support for redistribution? Evidence from an Ethiopian housing lottery," *Journal of Public Economics*, 2023, *224*, 104939.

Anderson, Michael L, "Multiple inference and gender differences in the effects of early intervention: A reevaluation of the Abecedarian, Perry Preschool, and Early Training Projects," *Journal of the American statistical Association*, 2008, *103* (484).

Apgar, William C, "Which housing policy is best?," 1990.

Armentano, Vincent, Craig McIntosh, Felipe Monestier, Rafael Piñeiro-Rodríguez, Fernando Rosenblatt, and Guadalupe Tuñón, "Movin'on up? The impacts of a large-scale housing lottery in Uruguay," *Journal of Public Economics*, 2024, *235*, 105138.

Banerjee, Abhijit, Rema Hanna, Benjamin A Olken, and Diana Sverdlin Lisker, "Social protection in the developing world," 2024.

Barnhardt, Sharon, Erica Field, and Rohini Pande, "Moving to opportunity or isolation? network effects of a randomized housing lottery in urban india," *American Economic Journal: Applied Economics*, 2017, *9* (1), 1–32.

Belchior, Carlos, Gustavo Gonzaga, and Gabriel Ulyssea, "Unpacking neighborhood effects: Experimental evidence from a large-scale housing program in Brazil," 2023.

Belloni, Alexandre, Victor Chernozhukov, and Christian Hansen, "High-dimensional methods and inference on structural and treatment effects," *Journal of Economic Perspectives*, 2014, *28* (2), 29–50.

Benjamini, Yoav, Abba M Krieger, and Daniel Yekutieli, "Adaptive Linear Step-up Procedures that Control the False Discovery Rate," *Biometrika*, 2006, *93* (3), 491–507.

Brooks, Leah and Byron Lutz, "From today's city to tomorrow's city: An empirical investigation of urban land assembly," *American Economic Journal: Economic Policy*, 2016, *8* (3), 69–105.

Brueckner, Jan K and Somik V Lall, "Cities in developing countries: fueled by rural–urban migration, lacking in tenure security, and short of affordable housing," *Handbook of regional and urban economics*, 2015, *5*, 1399–1455.

Camacho, Adriana, Valentina Duque, Michael Gilraine, and Fabio Sanchez, "The Effects of Public Housing on Children: Evidence from Colombia," 2022.

Chetty, Raj and Nathaniel Hendren, "The impacts of neighborhoods on intergenerational mobility I: Childhood exposure effects," *The Quarterly Journal of Economics*, 2018, *133* (3), 1107–1162.

_ , _ , and Lawrence F Katz, "The effects of exposure to better neighborhoods on children: New evidence from the moving to opportunity experiment," *American Economic Review*, 2016, *106* (4), 855–902.

Chyn, Eric, "Moved to opportunity: The long-run effects of public housing demolition on children," *American Economic Review*, 2018, *108* (10), 3028–3056.

Collier, Paul and Anthony J Venables, "Housing and urbanization in Africa: unleashing a formal market process," Technical Report, The World Bank 2014.

Collin, Matthew, Justin Sandefur, Andrew Zeitlin et al., "Falling off the map: The impact of formalizing (some) informal settlements in Tanzania," *Centre for the Study of African Economies Working Paper, University of Oxford*, 2015.

Collinson, Robert, Ingrid Gould Ellen, and Jens Ludwig, "Low-income housing policy," Technical Report, National Bureau of Economic Research 2015.

Currie, Janet and Aaron Yelowitz, "Are public housing projects good for kids?," *Journal of public economics*, 2000, *75* (1), 99–124.

Devoto, Florencia, Esther Duflo, Pascaline Dupas, William Parienté, and Vincent Pons, "Happiness on tap: piped water adoption in urban Morocco," *American Economic Journal: Economic Policy*, 2012, *4* (4), 68–99.

Dijk, Winnie Van, "The socio-economic consequences of housing assistance," *University of Chicago Kenneth C. Griffin Department of Economics job market paper, 0–46 i–xi*, 2019, *36.*

Eriksen, Michael D and Anthony W Orlando, "Returns to scale in residential construction: The marginal impact of building height," *Real Estate Economics*, 2022, *50* (2), 534–564.

Finkelstein, Amy and Nathaniel Hendren, "Welfare analysis meets causal inference," *Journal of Economic Perspectives*, 2020, *34* (4), 146–167.

Franklin, Simon, "The demand for government housing: Evidence from lotteries for 200,000 homes in Ethiopia," *Work. Pap., London Sch. Econ., London*, 2019.

_ , "Enabled to work: The impact of government housing on slum dwellers in South Africa," *Journal of Urban Economics*, 2020, *118*, 103265.

_ , Clement Imbert, Girum Abebe, and Carolina Mejia-Mantilla, "Urban public works in spatial equilibrium: Experimental evidence from Ethiopia," *American Economic Review*, 2024, *114* (5), 1382–1414.

Gaigné, Carl, Hans RA Koster, Fabien Moizeau, and Jacques-François Thisse, "Who lives where in the city? Amenities, commuting and income sorting," *Journal of Urban Economics*, 2022, *128*, 103394.

Galiani, Sebastian and Ernesto Schargrodsky, "Property rights for the poor: Effects of land titling," *Journal of Public Economics*, 2010, *94* (9-10), 700–729.

Gechter, Michael and Nick Tsivanidis, "Spatial spillovers from high-rise developments: Evidence from the Mumbai Mills," *Unpublished manuscript*, 2023.

Glaeser, Edward, *Triumph of the City*, Pan, 2011.

Glaeser, Edward L, "A world of cities: The causes and consequences of urbanization in poorer countries," *Journal of the European Economic Association*, 2014, *12* (5), 1154–1199.

_ , Joseph Gyourko, and Raven Saks, "Why is Manhattan so expensive? Regulation and the rise in housing prices," *The Journal of Law and Economics*, 2005, *48* (2), 331–369.

Glaeser, Edward Ludwig and Joseph E Gyourko, *Rethinking federal housing policy: How to make housing plentiful and affordable*, Aei Pr, 2008.

Gollin, Douglas, Remi Jedwab, and Dietrich Vollrath, "Urbanization with and without Industrialization," *Journal of Economic Growth*, 2016, *21* (1), 35–70.

Harari, Mariaflavia and Maisy Wong, "Slum Upgrading and Long-Run Urban Development: Evidence from Indonesia," *mimeo*, 2018.

Henderson, J Vernon, Tanner Regan, and Anthony J Venables, "Building the city: from slums to a modern metropolis," *The Review of Economic Studies*, 2021, *88* (3), 1157–1192.

Jacob, Brian A and Jens Ludwig, "The effects of housing assistance on labor supply: Evidence from a voucher lottery," *American Economic Review*, 2012, *102* (1), 272–304.

Kumar, Tanu, "The housing quality, income, and human capital effects of subsidized homes in urban India," *Journal of Development Economics*, 2021, *153*, 102738.

Lee, Kenneth, Edward Miguel, and Catherine Wolfram, "Experimental evidence on the economics of rural electrification," *Journal of Political Economy*, 2020, *128* (4), 1523–1565.

Marx, Benjamin, Thomas Stoker, and Tavneet Suri, "The economics of slums in the developing world," *Journal of Economic Perspectives*, 2013, *27* (4), 187–210.

McIntosh, Craig, Gonzalo Villaran, and Bruce Wydick, "Microfinance and home improvement: using retrospective panel data to measure program effects on fundamental events," *World Development*, 2011, *39* (6), 922–937.

_ , Tito Alegría, Gerardo Ordóñez, and René Zenteno, "The Neighborhood Impacts of Local Infrastructure Investment: Evidence from Urban Mexico," *American Economic Journal: Applied Economics*, 2017.

Michaels, Guy, Dzhamilya Nigmatulina, Ferdinand Rauch, Tanner Regan, Neeraj Baruah, and Amanda Dahlstrand, "Planning ahead for better neighborhoods: Long-run evidence from tanzania," *Journal of Political Economy*, 2021, *129* (7), 2112–2156.

_ , _ , _ , _ , _ , and Amanda Dahlstrand-Rudin, "Planning Ahead for Better Neighborhoods: Long Run Evidence from Tanzania," 2017.

Ommeren, Jos N Van, Arno J Van der Vlist et al., "Households' willingness to pay for public housing," *Journal of Urban Economics*, 2016, *92* (C), 91–105.

Picarelli, Nathalie, "There is no free house," *Journal of Urban Economics*, 2019, *111*, 35–52.

Prunier, Gérard and Eloi Ficquet, *Understanding contemporary Ethiopia: Monarchy, revolution and the legacy of Meles Zenawi*, Oxford University Press, 2015.

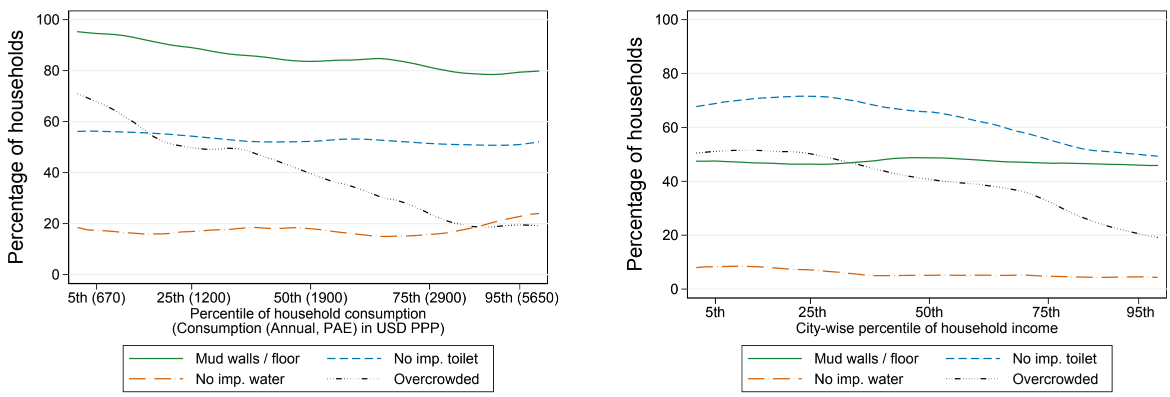
Appendix: For Online Publication

A1 Slums, housing consumption and wealth in Africa

This section presents two pieces of correlational evidence consistent with the view that constraints on housing supply are trapping urban households in Africa in slums. I show that as households get richer in Addis Ababa and other large African cities, their housing quality does not improve as much as one would expect if housing were a normal good. Households seem to be able to afford more space in slum-like housing, but not to move up to formal housing (the type built by large government programs). Similarly, I show that the relationship between GDP per capita and the share of the urban population living in slums is considerably weaker in Africa than in Asia and Latin America: countries in Africa have gotten richer without seeing commensurate improvements in housing quality.

Figure A1: **Household wealth and slums**

(a) Consumption & slums in Addis Ababa (b) Income & slums in African primate cities



Housing quality relative to total expenditure in Addis Ababa

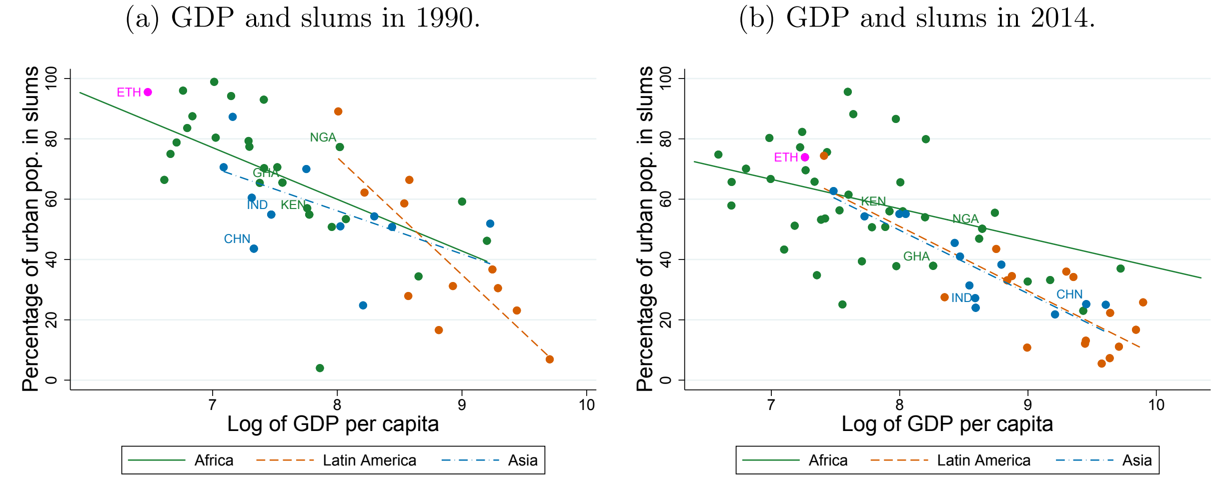
In Addis Ababa, slum housing is not only a problem of the very poor. Using representative household data, I plot four main deprivations of informal housing against household expenditure for Addis Ababa, and against household income for the primate cities of ten other African countries, in Panels A and B of Figure A1, respectively.[52] Even relatively wealthy households rarely live in homes with improved walls and floors, or improved sanitation and private improved water. By contrast, overcrowding declines rapidly with household wealth. Households seem to be able to move up to larger slum housing as they get richer, but not to make large fixed investments in home upgrades when they live in slums.

Cross-country correlations:

[52] For Addis, I use the 2011 Household Consumption and Expenditure Survey, which is a large representative survey used for national poverty assessments. For other cities, including Kampala, Blantyre, Dar-es-Salaam, and Accra, I use the most recent LSMS data. In each case, I normalize my outcome by the per adult equivalent household size.

If slums will eventually go away with economic development, Africa is lagging behind the rest of the world. Rapid urbanization in Africa has meant that both the absolute number and the proportion of people living in slums have grown over time. This lack of progress on housing is perhaps symptomatic of the phenomenon of urbanization without industrialization said to be taking place in Africa (Gollin et al., 2016; Glaeser, 2014).

Figure A2: **GDP per capita and slums across developing countries**



Data comes from UN-HABITAT, Madison World Tables, and the World Bank. Calculations my own.

I relate GDP per capita to the proportion of urban households in slums in 1990 (Figure A2). The strong correlation suggests that slums would go away if Africa managed to generate sufficient growth. Indeed, the proportion of urban households living in slums in Africa has fallen from roughly 70% to 60% between 1990 and 2014. However, the rate of progress has not been as fast as one would expect given the economic growth experienced over this period. The relationship between development and slum prevalence in 2014 is considerably weaker in Africa than it is in the rest of the developing world (Panel B of Figure A1): economic growth over the period 2005 to 2014 is not significantly correlated with changes in the urban population living in slums. Furthermore, rapid urbanization has meant that both the absolute number and the proportion of people living in slums have grown over time.

A2 Decomposition of housing value into physical and location components

Housing consumption imputations

To impute housing consumption for all households, including those residing in "kebele housing" and condominium owners, I estimate separate hedonic regression models for non-condominium (n) and condominium (c) housing. The hedonic model for non-condominium units is specified as:

$$\ln(r^n) = \alpha^n + \eta^n L^n + \lambda^n P^n + \epsilon^n, \tag{A1}$$

where r^n represents the log monthly rent for non-condominium housing, L^n encompasses location characteristics (e.g., travel time, distance from CBD), and P^n includes physical housing attributes (e.g., size, materials). Similarly, for condominiums, the model is:

$$\ln(r^c) = \alpha^c + \eta^c L^c + \lambda^c P^c + \epsilon^c. \tag{A2}$$

Using the estimated coefficients from Equation (A2), I predict the total housing consumption for condominium and non-condominiums households, respectively:

$$\hat{r}^c = \exp\left(\hat{\alpha}^c + \hat{\eta}^c L^c + \hat{\lambda}^c P^c\right). \tag{A3}$$

$$\hat{r}^n = \exp\left(\hat{\alpha}^n + \hat{\eta}^n L^n + \hat{\lambda}^n P^n\right). \tag{A4}$$

To decompose housing consumption into location (l) and physical quality (p) components, I adopt a Shapley-inspired decomposition approach. This method evaluates the marginal contributions of location and physical quality by considering two distinct sequences of attribution and averaging these contributions to ensure a fair allocation.

Decomposition for non-condominiums:
I start by performing the decomposition for each non-condominium unit.

First, I perform a decomposition based on the location of the unit relative to the worst location in the non-condominium sample L^{max}, so that location value is zero at that most distance location.

$$\hat{l}^{A,n} = \exp\left(\hat{\alpha}^n + \hat{\eta}^n L^n\right) - \exp\left(\hat{\alpha}^n + \hat{\eta}^n L^{max}\right), \tag{A5}$$

$$\hat{p}^{A,n} = \hat{r}^n - \hat{l}^{A,n}. \tag{A6}$$

Second, I perform the decomposition emphasising the physical quality, comparing the unit to the worst possible housing unit, ie. one with $P = 0$.

$$\hat{p}^{B,n} = \exp\left(\hat{\lambda}^n P^n\right) - 1, \tag{A7}$$

$$\hat{l}^{B,n} = \hat{r}^n - \hat{p}^{B,n}. \tag{A8}$$

The final location and physical quality components are then obtained by averaging these contributions:

$$\hat{l}^n = \frac{1}{2}\left(\hat{l}^{A,n} + \hat{l}^{B,n}\right), \tag{A9}$$

$$\hat{p}^n = \frac{1}{2}\left(\hat{p}^{A,n} + \hat{p}^{B,n}\right). \tag{A10}$$

This ensures that the sum of the location and physical quality components equals the total predicted rent:

$$\hat{l}^n + \hat{p}^n = \hat{r}^n. \tag{A11}$$

Decomposition for condominiums Next, I turn to a decomposition for condominium housing. Because of the lack of common support in the locations of condominiums and non-condominiums, I perform a decomposition for condominiums benchmarked against non-condominiums. First, in order to insure that I predict the rent for condominiums had they been built at the average location of non-condominium units, using the non-condominium model parameters:

$$\hat{r}^{c*} = \exp\left(\hat{\alpha}^n + \hat{\eta}^n \overline{L^n} + \hat{\lambda}^n P^c\right). \tag{A12}$$

Here, $\overline{L}^n$ denotes the average location characteristics of non-condominium housing. This counterfactual prediction facilitates the decomposition of condominium rent into location and physical components. I calculate the physical component for condominiums as the their value had they been built at the average location of non-condominiums less the average location value of non-condominiums:

$$\hat{p}^c = \hat{r}^{c*} - \overline{\hat{l}^n}, \tag{A13}$$

and the location component is the residual of the total rent less the physical component:

$$\hat{l}^c = \hat{r}^c - \hat{p}^c. \tag{A14}$$

A3 Detailed Cost and Revenue Calculations

Construction costs: Land values are estimated using the data on land auctions from the time that the housing is developed. I estimate a regression model of land value using the auction price paid and a set of location and time variables, and then predict the market land value of the land used to develop the condominiums. As a result of differences in land values by location, the implied land costs are significantly higher in the central sites relative to those further away. I have land cost estimates provided to me by the government. For peripheral sites, these estimates are reasonable, albeit lower, compared to my auction data, but for centrally located sites, they are radical under-estimates.

For construction costs, I estimate the per square metre construction costs of the housing by using government data on the total construction budget divided by the total amount of housing floor space delivered by the project. This allows me to estimate construction costs by type, which I assume to be the same across sites. I assume that construction costs per unit are directly proportional to unit floor space. Cost estimation by unit size is more complicated. Since I have land and construction values as totals, I infer the per unit cost of construction based on the relative floor space of the different housing types. On average, land costs constitute just less than half of the costs of delivering each housing unit. This varies by location, with land costs making up more than 80

Houses are sold to lottery winners at (mortgaged) prices well below the price of construction, especially for very valuable centrally-located units, where lottery winners pay the same price as far less valuable houses much further away. Houses more than 25 km from the city center are sold at 55% of total delivery cost.

Investments and upkeep: Households spend considerable amounts of money improving their units prior to being rented out. These improvements are reflected in the market value of these units. The units are sold mostly unfinished: concrete blocks with doors, plumbing and windows, but without tiles, kitchens, and bathroom amenities. I estimate the average cost of these final development costs, borne by owners. I use my primary survey data from 2017 and 2023 to estimate the costs of initially "finishing" the condominium units. I then also estimate monthly upkeep and maintenance costs from my data, interpolating between 2017 and 2023 to account for possible changes in the costs of upkeep over time. I assume that these investment and maintenance costs differ with the size of the condominium units but are constant at different locations.

Rent estimates: Using rich rental market survey data, I estimate the average rent income values for 2017, 2019, and 2023.[53] To deflate 2023 housing values to 2017, I deflate by the increase in rents in non-condominium housing elsewhere in the city.[54] I then interpolate between these three time periods to determine the rent income flow for each time period since the housing was made available. As shown in Panel C, rents increase in real terms throughout the study period. Most of the increase, especially from 2017 to 2019, is driven by units in Group 4: this was a site that was relatively empty in 2017, and increased in population density quickly between 2017 and 2019. It is plausible that units became more valuable in that area as more households moved in.

Rental frictions: Renting out a housing unit involves costs that an owner-occupy does not have to pay. Although owner-occupiers do not pay these costs, an appropriate estimate of the return on investment for a developer renting out the unit should include those costs. Mortgage brokers in find a clients to rent out the units, screen them on behalf of the owners, and manage the recollection of monthly rent. They charge a fee to the owners I report the rent estimates amount above gross, including any payments that go to mortgage brokers. To estimate these costs, I use inteviews that I conducated with mortgage brokers in 2018. Brokers reported that the charged a fee of 10% of the first payment to the owner, and nothing after that. They varied on whether they charged 10% of 1, 2, or 3 months of rent. To be conservative, I assume that all brokers charged 10% on 3 months of rent. I also assume that, conservatively, that tenancy agreements lasted just 1 year each (although the data suggests that they tend to be considerably longer) such that these brokerage fees recur on an annual basis. In other words, brokerage frictions are 2.5% of gross rent annually.

Home value estimates: For some calculations, I use an estimate of the market value of homes in 2024 for IRR calculations. Here, I use relatively sparse data on respondents who have sold their units at the time of that survey in the last few years. I use a model of the predicted home values over the last few years, including a time trend and housing type fixed effects. I then use predicted sale values by type, aggregate up, and estimate an average rent-to-value ratio in 2024, which I find to be 20.5, which is not inconsistent

[53] For 2017 and 2019, I have enough granular data to do this for each site and pair. For 2023, my data is not granular enough, and I instead estimate a site-specific rate of (deflated) rent growth and apply that to all unit types.

[54] Deflating nominal income values from 2023 to 2017 prices is challenging due to the high inflation environment over those years, with the true rate of inflation over that period being disputed. This makes results using CPI deflators highly sensitive to the source of inflation data.

with the real estate literature. I then use that ratio to impute home values for each site and type.

A4 Additional tables and figures

A4.1 Material related to Section 2

Figure A3: Government housing in a new site 25kms from the centre. (photograph by Charlie Rosser)

Table A1: Government housing programs providing fully formal housing units for free or subsidies rates for the urban poor/slum dwellers in low and middle income countries.

Country	Policy	Scale (Units)
Ethiopia	IHDP	200,000 units so far
		947,376 registered
Angola	Meu Sonho, Minha Casa	1 million
Kenya	The Big Four Agenda	1 million by 2022
South Africa	RDP	4 million (est.) complete
Egypt	Social housing	1 million by 2020
Nigeria	Affordable housing program	1 million annually (aim)
Brazil	Minha Casa, Minha Vida	4.2 million
Mexico	Infonavit	4.3 million
Chile	MINVU	100,000 per year
Columbia		50,000 per year
rental programs:		
Algeria		3.8 million

This is an inexhaustive list based on my own research and reading of government reports.

Table A2: Housing sites and number of units awarded

Site	Number of Units	Distance (km)	Average rent
Yeka Abado	12501	19	92
Tulu Dimtu	12272	25	66
Yeka ayat	2865	17	95
Gelan	1272	18	*
Genet Menafesha	1212	15	85
Summit	750	15	*
Basha Wolde Chilot	535	2	170
Karakore	495	14	88
Lideta Redevelopmnt	393	3	170
Mekanisa Kotari	352	6	*
Jemo		10	105
Total (main 10 sites)	32647		
Total (all sites)	33585		

A4.2 Material related to Section 3

Table A3: Balance- treatment and control

Outcome	N	Control Mean	Std Dev.	Coeff	p (F-test)
Scheme contributions (pre-lottery, 1000s ETB)	1564	11.23	11.26	-0.17	0.77
Female registered	1564	0.46	0.50	-0.01	0.76
Public employee registered	1564	0.33	0.47	0.03	0.17
Applied for 1-Bedroom	1564	0.12	0.32	-0.00	0.92
Applied for 2-Bedroom	1564	0.56	0.50	-0.01	0.57
Applied for 3-Bedroom	1564	0.31	0.46	0.02	0.46
Household size	1564	3.52	1.93	-0.15	0.13
Number female members	1564	1.90	1.32	-0.04	0.59
Number of small children (<6)	1564	0.33	0.58	0.00	0.99
Number of children 6-18	1564	0.83	1.00	-0.07	0.15
Age of household head	1563	43.25	11.20	-0.38	0.51
Female household head	1563	0.36	0.48	-0.00	0.86
HH head migrant (born out of Addis)	1564	0.70	0.46	0.01	0.72
Years living in current home	1564	14.90	23.41	0.60	0.62
Tenure: lives free or owns home	1564	0.19	0.39	0.01	0.67
Tenure: rents government owned home	1564	0.26	0.44	0.02	0.31
Housing quality index	1564	0.00	3.53	-0.08	0.64
Lives in slum (UN-Habitat)	1564	0.73	0.44	0.02	0.26
Housing assets index	1564	0.00	0.99	-0.04	0.46
Preference to stay in neighbhourhood	1562	2.81	1.47	-0.05	0.47
Member of an iddir	1564	0.49	0.50	0.01	0.61
Household has been victim of crime in last year	1564	0.12	0.33	-0.01	0.52
Number of close social ties (hh head)	1551	7.69	7.72	-0.54	0.17
Head finished highschool	1564	0.24	0.43	0.03	0.22
Head completed tertiary education	1564	0.34	0.47	-0.02	0.32
Head ethnicity: amhara	1564	0.49	0.50	0.02	0.51
Head religion: orthodox	1564	0.80	0.40	0.01	0.73
Head is married	1564	0.50	0.50	-0.00	0.88
Working members (per WA adult)	1552	0.72	0.32	-0.01	0.45
Hours worked in last 7 days(per WA adult)	1552	32.92	19.51	-0.93	0.35
Earnings per working age adult (ETB, monthly)	1564	4223.71	3907.72	-221.76	0.26
Total consumption (pae, monthly USD 1000s)	1564	1485.41	1107.83	-72.91	0.19

Joint F-test of predictive power: all above predictors on treatment status

Predictor variables	F-stat	p-value
All variables above	0.84	0.71
All variables above, partial F-rest on survey outcomes	0.93	0.58
Regression with survey outcomes only	0.80	0.78

Table A4: How does the sample compare to the Addis Ababa population?

Outcome	Sample Means Housing Sample (2015)	 HCES (2011)
Household size given	3.52	3.98
HH member under 18	1.16	0.67
Female headed HH	0.36	0.40
Monthly consumption (per adult equivalent, 2015 ETB)	1,502.83	1,363.58
Growth adjusted consumption (2011-2015, 8% p.a.)	1,502.83	1,855.14
Household below urban poverty line as defined in 2011	0.22	0.22
Total number of working age adults in HH	2.47	2.88
Self employed members (per WA adult)	0.16	0.20
Wage employed members (per WA adult)	0.55	0.44
Household head age	43.25	43.88
Household head marital status	0.50	0.52
People per room	3.18	2.16
Floors made of hard/solid material	0.74	0.59
Cemented walls	0.24	0.15
Roof is mode of corrugated iron sheet	0.87	0.92
HH has a private toilet	0.26	0.29
Access to improved sanitation facility	0.57	0.47
Tenure: lives free or owns home	0.19	0.38
Tenure: rents government owned home	0.26	0.31
Tenure: rents on private market	0.55	0.31
Total number of rooms in household	2.01	2.29
HH has access to an improved water source	0.90	0.82
HH owns a mobile/wireless phone	0.85	0.83
HH owns a commercial vehicle/car	0.09	0.02
Housing deprivations (UN definition, max=4)	1.23	1.30
Slum housing (UN definition using only floors)	0.73	0.70
Slum housing (UN definition with inadequate walls and floors)	0.87	0.89
Head education - highschool only	0.24	0.12
Head education - degree or diploma	0.34	0.29
N	1,564	3,741

Table A5: Balance- by randomly assigned location relative to control

Outcome	N	CM	Differential effects by km from City Centre 0-4	6-12	16-2	25-30	pval
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Household size	1,564	3.60	0.12	-0.16	-0.21	-0.13	0.753
			(0.31)	(0.28)	(0.12)	(0.15)	
Number female members	1,564	1.91	0.14	0.04	-0.02	-0.12	0.545
			(0.19)	(0.20)	(0.08)	(0.09)	
Number of small children (<6)	1,564	0.33	0.03	0.07	0.02	-0.03	0.592
			(0.10)	(0.11)	(0.04)	(0.04)	
Number of children 6-18	1,564	0.90	0.15	-0.03	-0.13**	-0.13	0.475
			(0.19)	(0.16)	(0.06)	(0.07)	
Age of household head	1,563	43.27	-0.62	-1.27	-0.18	-0.16	0.955
			(1.74)	(2.10)	(0.70)	(0.81)	
Female household head	1,563	0.34	0.02	0.10	-0.00	-0.00	0.554
			(0.06)	(0.07)	(0.02)	(0.02)	
HH head migrant (born out of Addis)	1,564	0.70	-0.02	-0.03	0.01	0.02	0.927
			(0.08)	(0.08)	(0.03)	(0.03)	
Years living in current home	1,564	14.10	4.09	1.29	0.68	0.96	0.937
			(5.31)	(4.78)	(1.42)	(1.69)	
Tenure: lives free or owns home	1,564	0.18	-0.03	-0.06	0.01	0.02	0.625
			(0.06)	(0.06)	(0.02)	(0.03)	
Tenure: rents government owned home	1,564	0.24	0.04	-0.04	0.03	0.04	0.752
			(0.08)	(0.07)	(0.03)	(0.03)	
Housing quality index	1,564	-0.04	-0.55	-0.22	0.13	-0.16	0.469
			(0.53)	(0.53)	(0.22)	(0.25)	
Lives in slum (UN-Habitat)	1,564	0.73	0.09	-0.02	0.01	0.01	0.701
			(0.07)	(0.08)	(0.03)	(0.03)	
Housing assets index	1,564	-0.01	-0.11	-0.06	-0.00	-0.00	0.902
			(0.17)	(0.15)	(0.06)	(0.08)	
Preference to stay in neighbhourhood	1,562	2.85	0.14	0.15	-0.06	-0.15	0.521
			(0.26)	(0.25)	(0.09)	(0.11)	
Member of an iddir	1,564	0.48	-0.02	0.07	0.00	0.03	0.780
			(0.09)	(0.09)	(0.03)	(0.04)	
Household has been victim of crime in last year	1,564	0.13	0.02	0.06	-0.03	0.00	0.338
			(0.06)	(0.07)	(0.02)	(0.02)	
Number of close social ties (hh head)	1,551	8.07	-1.67*	-1.82**	-0.28	-1.05*	0.190
			(0.90)	(0.90)	(0.50)	(0.53)	
Head finished highschool	1,564	0.24	0.10	-0.04	0.01	0.01	0.654
			(0.08)	(0.07)	(0.03)	(0.03)	
Head completed tertiary education	1,564	0.34	-0.08	-0.09	-0.02	-0.03	0.728
			(0.07)	(0.08)	(0.03)	(0.03)	
Head ethnicity: amhara	1,564	0.47	0.05	0.12	0.04	-0.03	0.180
			(0.09)	(0.09)	(0.03)	(0.04)	
Head religion: orthodox	1,564	0.78	-0.03	0.08	0.03	-0.01	0.441
			(0.08)	(0.06)	(0.02)	(0.03)	
Head is married	1,564	0.52	-0.06	-0.02	-0.00	-0.03	0.825
			(0.08)	(0.09)	(0.03)	(0.04)	
Working members (per WA adult)	1,552	0.73	0.01	0.08	-0.00	-0.04	0.153
			(0.04)	(0.06)	(0.02)	(0.02)	
Hours worked in last 7 days(per WA adult)	1,552	33.26	1.16	0.97	-1.02	-1.38	0.856
			(3.44)	(3.95)	(1.23)	(1.43)	
Earnings per working age adult (ETB, monthly)	1,564	4,253.35	685.66	-842.07***	-76.68	-248.20	0.076
			(938.89)	(304.58)	(236.38)	(275.22)	
Total consumption (pae, monthly USD 1000s)	1,564	1,496.89	-118.17	-155.58	-43.59	-40.52	0.931
			(246.97)	(191.79)	(65.38)	(80.79)	

Figure A4: Kernel density: household consumption among housing applicants and representative data from the Ethiopian household consumption and expenditure survey (HCES) from 2011 and HCES from 2016

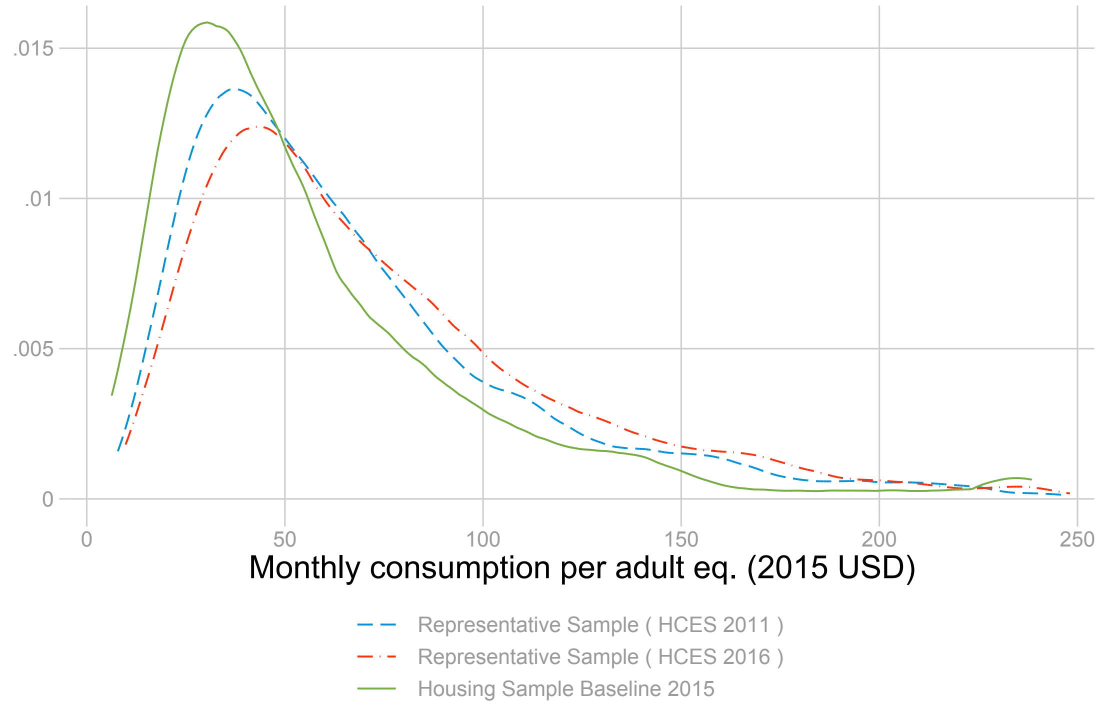


Table A6: The different lottery rounds and occupancy shares at each endline

Lottery	Year homes available	Moved by 2018	Moved in 2024
10	2016	0.4112	0.5104
11	2017	0.1729	0.4662
12	2020	0	0.5000
13	2022	0	0.4343
14	2023	0	0.1681

Table A7: Predictors of attrition (first endline)

	Attrition and non-response			
	Only Treatment		All Covariates	
Dependent Variable: No-response or refused	Coeff	Std. error	Coeff	Std. error
	(1)	(2)	(3)	(4)
Won Housing Lottery	-0.016	0.012	-0.005	0.016
Household size			-0.006	0.007
Number female members			0.007	0.009
Any children in household			-0.032	0.018*
Age of household head			0.001	0.001
Female household head			-0.013	0.016
HH head migrant (born out of Addis)			0.006	0.017
Won 11th Round Condominium			-0.010	0.025
Years living in current home			-0.000	0.000
Tenure: lives free or owns home			0.000	0.000
Tenure: rents government owned home			-0.032	0.022
Tenure: rents on private market			-0.020	0.023
Housing quality index			0.001	0.002
Lives in slum (UN-Habitat)			0.002	0.019
Housing assets index			-0.005	0.008
Housing assets index			-0.005	0.008
Number of close social ties (hh head)			-0.000	0.001
Head finished highschool			0.033	0.020
Head completed tertiary education			-0.009	0.019
Head ethnicity: amhara			-0.023	0.015
Head religion: orthodox			-0.010	0.020
Working members (per WA adult)			-0.013	0.024
Earnings per working age adult (ETB, monthly)			0.000	0.000*
Total consumption (pae, monthly USD 1000s)			0.000	0.000
P-value of F-test	0.1919		0.2432	
N	2,275		1,539	

Note: This table estimates the effect of winning the housing lottery and other baseline covariates on the probability of not responding to or refusing participation in the endline survey.

Table A8: Predictors of attrition (second endline)

Dependent Variable: No-response or refused	Only Treatment Coeff (1)	Std. error (2)	All Covariates Coeff (3)	Std. error (4)
Won Housing Lottery	0.026	0.017	0.020	0.018
Household size			0.001	0.009
Number female members			-0.005	0.011
Any children in the household			-0.028	0.020
Age of household head			-0.001	0.001
Female household head			0.026	0.020
HH head migrant (born out of Addis)			-0.034	0.021
Won 11th Round Condominium			-0.031	0.027
Years living in current home			0.000	0.000
Tenure: lives free or owns home			0.000	0.000
Tenure: rents government owned home			-0.035	0.029
Tenure: rents on private market			-0.052	0.026**
Housing quality index			0.006	0.003*
Lives in slum (UN-Habitat)			0.001	0.023
Housing assets index			-0.003	0.010
Housing assets index			-0.003	0.010
Number of close social ties (hh head)			-0.000	0.001
Head finished highschool			-0.050	0.021**
Head completed tertiary education			-0.033	0.023
Head ethnicity: amhara			0.010	0.018
Head religion: orthodox			-0.017	0.022
Working members (per WA adult)			0.021	0.028
Earnings per working age adult (ETB, monthly)			0.000	0.000
Total consumption (pae, monthly USD 1000s)			0.000	0.000
P-value of F-test	0.1252		0.0631	
N	1,566		1,539	

Note: This table estimates the effect of winning the housing lottery and other baseline covariates on the probability of not responding to or refusing participation in the endline survey.

Table A9: Effects of the lottery on household composition

Outcome	Control mean (1)	ITT Estimate Lottery N (2)	Coeff (3)	Std. Err. (4)	Adj q-value (5)
Current household size	3.886	1,426	-0.062	0.075	0.964
Current number of working age adults	3.052	1,426	-0.041	0.051	0.964
Number of newly joined members (incl. births)	0.650	1,426	-0.003	0.058	0.964
Number of newly joined adult members	0.401	1,426	-0.013	0.043	0.964
Original members who left the household	0.529	1,426	0.052	0.051	0.964
Original members who remained in household	3.132	1,426	-0.007	0.057	0.964

Note: This table shows the ITT results of winning the 10th round lottery on endline household composition. The results presented are estimated using specification 1.

A4.3 Material related to Section 4:IRRS

Table A10: Estimated internal rates of return, all sites by type

	All sites - studio	All sites - 1 bed	All sites - 2 bed	All sites - 3 bed	All sites and types
Land cost per unit	5,355	8,460.9	12,429	16,547	9,659.8
Construction cost per unit	7,051	11,140.5	16,365	21,788	12,719.1
Infrastructure cost per unit	710	1,121.0	1,647	2,192	1,279.9
Total cost per unit	12,406	19,601.4	28,794	38,335	22,378.9
Initial investment	274	624.5	1,188	1,799	815.9
Initial maintenance	22	76.2	160	160	93.5
Final maintenance	51	74.5	99	148	83.8
Rent 2017	721	987.6	1,359	1,696	1,098.8
Rent 2019	923	1,209.5	1,549	1,833	1,299.9
Rent 2024	854	1,179.2	1,626	2,053	1,314.7
Sale Price Est	21,356	24,514.2	26,343	47,903	27,037.6
Sale at est. value	0.0919	0.0583	0.0284	0.0472	0.0527
Sale est. value (with infrasturcture costs)	0.0854	0.0522	0.0226	0.0415	0.0467
No sale	0.0817	0.0577	0.0403	0.0260	0.0500
Sale at cost	0.0482	0.0378	0.0309	0.0266	0.0348
Sale at land value	0.0056	-0.0096	-0.0198	-0.0263	-0.0141

Note: See text in Section 4.1.1 for details of calculations. All costs, prices and revenues are deflated or inflated to 2017 Ethiopian Birr and then converted to USD at the average exchange rate in 2017. Flows are presented in annual terms throughout. For example, households spent an average of 93.5 USD per year on maintenance in 2017. This table shows figures for different housing types (number of bedrooms) aggregated across housing sites.

A4.4 Material related to Section 4: Effects of lotteries on consumption and housing

Table A11: Effects of winning the lottery and moving house housing - subcomponents

	2018 Endline			2024 Endline			
Outcome	N (1)	Control mean (2)	ITT Lottery (3)	N (4)	Control mean (5)	ITT Lottery (6)	Diff pval (7)
Housing quality index	1,426	0.000	0.680*** [0.053]	1,370	0.056	0.672*** [0.088]	0.907
Formal wall	1,426	0.288	0.315*** [0.025]	1,370	0.350	0.229*** [0.042]	0.088
Formal floor	1,426	0.780	0.092*** [0.020]	1,370	0.838	0.075** [0.030]	0.777
Private formal water source	1,426	0.406	0.214*** [0.026]	1,370	0.756	0.045 [0.038]	0.000
Improved toilet (shared $<$ 5 others)	1,426	0.218	0.326*** [0.025]	1,370	0.381	0.247*** [0.043]	0.133
Cooks with electricity	1,426	0.769	0.056*** [0.020]	1,370	0.856	0.057* [0.030]	0.892
Cooks indoors	1,426	0.846	0.040** [0.017]	1,370	0.531	0.032* [0.019]	0.608
Number of people per room	1,426	3.970	-0.422*** [0.116]	1,370	4.481	-0.516*** [0.198]	0.825

Note: Each row represents a regression of the named outcome on whether the household won the lottery using the ANCOVA specification in Equation 1. I show the results separately for the 2018 and 2024 endlines (one regression for each endline, per outcome). "ITT Lottery" identifies the parameter of interest, with the relevant SE of the estimate shown in square brackets below. Column 7 provides the p-value for a test of equality of the coefficient between the 2018 and 2024 endlines. This is estimated using a saturated regression combining both endlines and interactions between all covariates and an "endline" dummy.

Table A12: Effect on total housing investment, other assets and liabilities (Endline 1) .

Outcome	N (1)	Control mean (2)	ITT Lottery (3)	By Moving Decision Moved (4)	Stayed (5)	Equality pval (6)
Complementary housing investment	1,426	90.62	1,562.22*** (75.34)	1,802.51*** (116.17)	1,377.48*** (84.67)	0.00
Household durable purchases	1,426	50.67	121.71*** (23.77)	270.28*** (46.22)	7.48 (14.86)	0.00
Total savings	1,426	69.82	-40.96*** (3.71)	-44.97*** (4.42)	-37.88*** (4.14)	0.09
Total remaining mortgages	1,426	253.33	4,129.34*** (148.93)	4,507.28*** (203.90)	3,838.78*** (186.88)	0.01
Total loans (excluding mortgages)	1,426	120.06	269.34*** (54.58)	232.09*** (68.62)	297.99*** (68.66)	0.43

Note: This table estimates the effect of winning the housing lottery on housing investment and household finances. Column (3) shows the *intent-to-treat* estimate of winning the lottery on household. Row (1) shows the effect on all household investment in housing upgrades over the 24 months before the endline, covering the period of time in which lottery winners would have been investing in their new condominiums.

Table A13: Effects of winning the lottery and moving house on complementary housing amenities not provided in government housing. Endline 2

Outcome	N	Control mean	ITT Lottery	By Moving Decision: Moved	Stayed	Equality pval
	(1)	(2)	(3)	(4)	(5)	(6)
Housing amenities index	876	-0.11	0.49***	0.74***	0.14	0.00
			(0.13)	(0.13)	(0.14)	
Tiling or installed carpet in the living room	876	0.70	0.16***	0.24***	0.06	0.00
			(0.05)	(0.05)	(0.06)	
Tiling in the bathroom	876	0.35	0.35***	0.60***	-0.00	0.00
			(0.05)	(0.05)	(0.05)	
Tiling the kitchen	876	0.37	0.34***	0.57***	0.03	0.00
			(0.05)	(0.05)	(0.05)	
A shower	876	0.46	0.38***	0.65***	-0.00	0.00
			(0.05)	(0.05)	(0.06)	
Glass windows that open and close.	876	0.69	0.25***	0.41***	0.01	0.00
			(0.06)	(0.05)	(0.06)	
Kitchen sink built in.	876	0.41	0.41***	0.69***	0.01	0.00
			(0.05)	(0.05)	(0.05)	
Electric sockets built into the wall.	876	0.80	0.16***	0.26***	0.03	0.00
			(0.05)	(0.05)	(0.06)	
Plastered and painted walls inside	876	0.16	-0.03	-0.06	-0.00	0.10
			(0.04)	(0.04)	(0.05)	
Painted walls outside	876	0.57	0.22***	0.30***	0.10*	0.00
			(0.06)	(0.06)	(0.06)	

Note: This table shows the ITT estimates of winning the housing lottery side-by-side with heterogeneous effects for households that move into their units and those that stay (do not move). ITT results in Column 3 come from one regression, the decomposition in Columns 4-6 come from a separate regression, which uses Equation 3 to look at outcomes for mover and non-movers from the 10th round while controlling for a rich set of baseline covariates that predict whether households move in or not. Column 6 presents the p-value for a test of equality between the results in Column 4 and Column 5.

Table A14: Effects of winning the lottery on household finances and income

Outcome	N (1)	2018 Endline Control mean (2)	2018 Endline ITT Lottery (3)	N (4)	2024 Endline Control mean (5)	2024 Endline ITT Lottery (6)	Diff pval (7)
Rent payments	1,426	48.250	-20.844***	1,370	40.153	-7.358	0.028
			[2.658]			[4.916]	
Mortgage repayments	1,426	3.450	76.678***				
			[2.486]				
Rent income	1,426	2.936	32.937***	1,370	4.926	36.567***	0.462
			[2.031]			[3.202]	
Net housing cash	1,426	-49.131	-20.473***				
			[2.934]				
Income from earnings	1,426	222.405	3.940	1,370	145.838	16.980	0.411
			[10.062]			[12.414]	
Income from other sources	1,426	180.112	6.575	1,370	15.029	1.398	1.000
			[29.595]			[2.822]	
Total income	1,426	352.203	-7.424	1,370	165.793	54.791***	0.133
			[30.062]			[12.587]	
Total savings	1,426	1,815.279	-1,081.458***	1,370	588.210	-102.150	0.000
			[96.647]			[95.422]	
Remaining mortgage debt	1,426	253.329	4,118.617***	1,370	142.308	-117.484*	0.000
			[146.143]			[65.872]	
Remaining other debt	1,426	120.055	264.456***	1,370	62.790	206.776***	0.569
			[54.090]			[61.431]	

Note: Each row represents a regression of the named outcome on whether the household won the lottery using the ANCOVA specification in Equation 1. I show the results separately for the 2018 and 2024 endlines (one regression for each endline, per outcome). "ITT Lottery" identifies the parameter of interest, with the relevant SE of the estimate shown in square brackets below. Column 7 provides the p-value for a test of equality of the coefficient between the 2018 and 2024 endlines. This is estimated using a saturated regression combining both endlines and interactions between all covariates and an "endline" dummy. **Net housing income** is a calculated monthly as: rental income - mortgage repayment - rent paid. Rental income includes possible rents from condominiums if they are rented out. I do not calculate this in the second endline as most households have paid off their mortgages.

A4.5 Material related to Section 4: Engel Curves

Table A15: Engel curves: effects on housing consumption shares

	(1)	(2)	(3)	(4)	(5)	(6)
	Housing shares of consumption					
	All	Location	Physical	All	Location	Physical
Won Housing Lottery	0.010	-0.088***	0.099***	0.143	-0.278***	0.422***
	(0.006)	(0.006)	(0.006)	(0.102)	(0.098)	(0.102)
Log Total Consumption	-0.185***	-0.096***	-0.089***	-0.178***	-0.106***	-0.072***
	(0.007)	(0.007)	(0.007)	(0.009)	(0.009)	(0.009)
Won * Log(Tcons)				-0.016	0.022*	-0.038***
				(0.012)	(0.012)	(0.012)
Baseline housing share	0.190***	0.114***	0.076***	0.190***	0.113***	0.077***
	(0.027)	(0.026)	(0.027)	(0.027)	(0.026)	(0.027)
Observations	1,426	1,426	1,426	1,426	1,426	1,426
R-squared	0.417	0.267	0.269	0.417	0.269	0.274
Control mean	0.4031	0.1956	0.2075	0.4031	0.1956	0.2075

Note: This table estimates Engel curves for housing consumption shares. The dependent variable "All" is the share of total imputed housing consumption using an hedonic model. "Location" and "Physical" are the decomposed version of housing consumption into location and physical quality using the same model. I regress these consumption shares on the log of total consumption (all other consumption plus imputed housing consumption) and whether the household won the housing lottery.

Figure A5: Engel curves in household income (i) Total housing share (ii) Housing location (iii) Housing quality

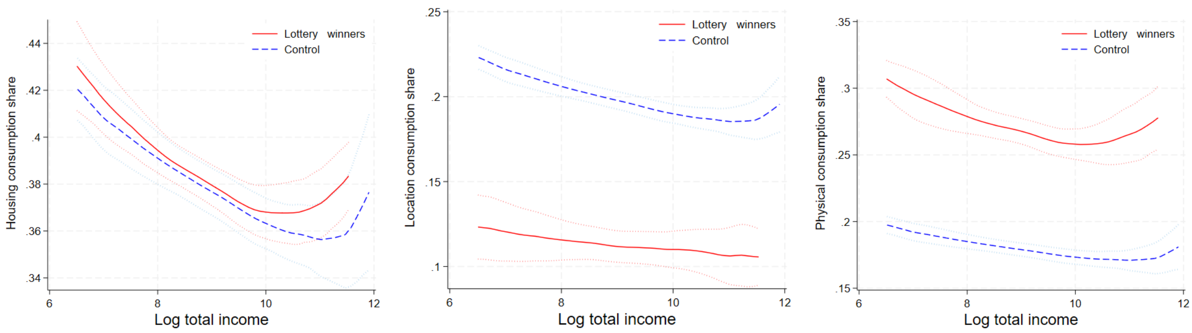


Figure A6: Engel curves using household consumption – MOVERS only (i) Total housing share (ii) Housing location (iii) Housing quality

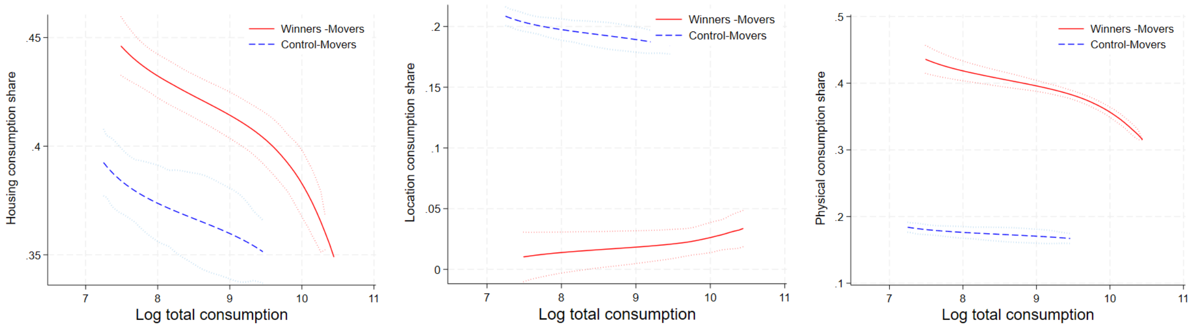
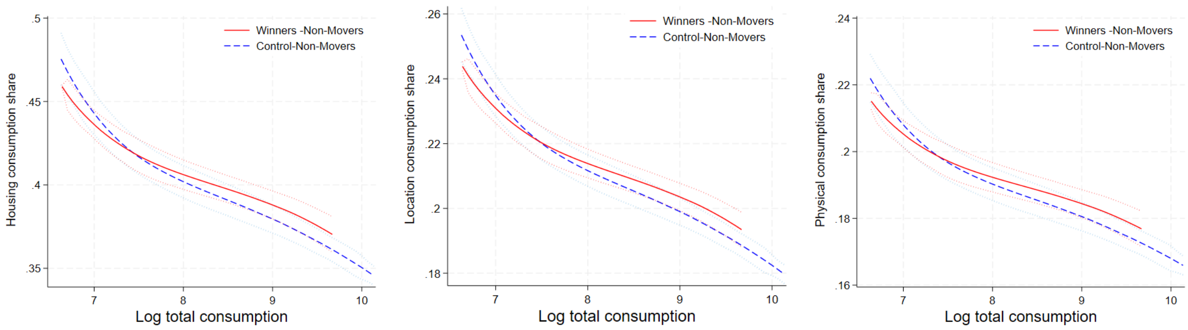


Figure A7: Engel curves using household consumption – NON-MOVERS only (i) Total housing share (ii) Housing location (iii) Housing quality



A4.6 Material related to Section 4: Predictors of moving in

Table A16: Baseline predictors of housing occupation for private renters (Endline 1)

	(1)	(2)	(3)	(4)	(5)
	Dep Variable: Lottery winner lives in their condominium.				
Household income	0.000904	-0.00669	-0.0263	-0.0110	-0.0241
	(0.0292)	(0.0309)	(0.0325)	(0.0311)	(0.0323)
Wealth (index)	0.0348	0.0252	0.0180	0.0306	0.0182
	(0.0380)	(0.0395)	(0.0394)	(0.0381)	(0.0392)
Social ties	-0.0254	-0.0269	-0.0283	-0.0243	-0.0269
	(0.0248)	(0.0252)	(0.0253)	(0.0251)	(0.0252)
Community group	-0.0433*	-0.0359	-0.0310	-0.0388	-0.0341
	(0.0243)	(0.0275)	(0.0278)	(0.0248)	(0.0276)
Travel time to centre	0.0580***	0.0521**			
	(0.0208)	(0.0215)			
Physical housing quality	0.0174**	0.0181**			
	(0.00735)	(0.00775)			
Total housing consumption			0.0994***		
			(0.0341)		
Housing consumption (location)				-0.0450*	-0.0425*
				(0.0238)	(0.0239)
Housing consumption (physical)				0.0934***	0.0998***
				(0.0331)	(0.0340)
Observations	420	420	420	420	420
R-squared	0.0600	0.0790	0.0670	0.0620	0.0790
Lasso controls	No	Yes	Yes	No	Yes
Condo Site FE	Yes	Yes	Yes	Yes	Yes

Note: Each column shows the results for a regression, for condominium owners, of whether the live in the condominium that they own, on a set of baseline covariates. All right hand side variables are normalised to have mean zero and standard deviation one to make them easier to interpret. Social ties is a measure of the total number of other people that they household head speaks to on a regular basis. Housing consumption variables (included location and physical, respectively) are imputed for baseline housing choices, using the method outlined in Section 3.4. In some specifications I control for additional predictors of whether the household moves in, selected from the non-zero parameters in a separate lasso regression.

Table A17: Determinants of housing occupation all households at endline 1

	(1)	(2)	(3)	(4)	(5)
	Dep Variable: Lottery winner lives in their condominium.				
Household income	-0.00904	-0.0187	-0.0240	-0.0106	-0.0239
	(0.0193)	(0.0206)	(0.0210)	(0.0200)	(0.0211)
Wealth (index)	-0.00769	-0.00490	-0.00794	-0.00909	-0.00794
	(0.0221)	(0.0228)	(0.0230)	(0.0226)	(0.0231)
Social ties	0.00528	0.00615	0.00631	0.00391	0.00631
	(0.0167)	(0.0167)	(0.0168)	(0.0169)	(0.0168)
Community group	-0.0481***	-0.0242	-0.0254	-0.0513***	-0.0254
	(0.0170)	(0.0196)	(0.0197)	(0.0172)	(0.0197)
Travel time to centre	0.0530***	0.0412**			
	(0.0164)	(0.0167)			
Physical housing qual	0.00731	0.00818			
	(0.00547)	(0.00570)			
Total housing cons.			0.0316		
			(0.0220)		
Housing cons.-location				-0.00703	0.00286
				(0.0171)	(0.0176)
Housing cons.- physical				0.0263	0.0316
				(0.0216)	(0.0220)
Observations	775	775	775	775	775
R-squared	0.0320	0.0540	0.0460	0.0220	0.0460
Lasso controls	No	Yes	Yes	No	Yes
Condo Site FE	Yes	Yes	Yes	Yes	Yes

Note: Each column shows the results for a regression, for condominium owners, of whether the live in the condominium that they own, on a set of baseline covariates. All right hand side variables are normalised to have mean zero and standard deviation one to make them easier to interpret. Social ties is a measure of the total number of other people that they household head speaks to on a regular basis. Housing consumption variables (included location and physical, respectively) are imputed for baseline housing choices, using the method outlined in Section 3.4. In some specifications I control for additional predictors of whether the household moves in, selected from the non-zero parameters in a separate lasso regression.

Table A18: Determinants of housing occupation all households at endline 2

	(1)	(2)	(3)	(4)	(5)
	incondo	incondo	incondo	incondo	incondo
Household income	-0.029	-0.034	-0.034	-0.035	-0.027
	(0.0213)	(0.0242)	(0.0244)	(0.0245)	(0.0218)
Wealth (index)	0.009	-0.001	-0.001	-0.002	0.008
	(0.0239)	(0.0239)	(0.0241)	(0.0242)	(0.0242)
Social ties	-0.005	-0.001	-0.001	-0.001	-0.006
	(0.0184)	(0.0184)	(0.0185)	(0.0185)	(0.0185)
Community group	-0.018	-0.0508**	-0.0537**	-0.0537**	-0.021
	(0.0189)	(0.0209)	(0.0209)	(0.0209)	(0.0189)
Travel time to centre	0.022	0.023			
	(0.0178)	(0.0178)			
Index of physical housing quality	0.0116*	0.007			
	(0.00620)	(0.00632)			
Housing consumption total			0.015		
			(0.0242)		
Housing location cons				0.015	0.015
				(0.0190)	(0.0190)
Housing physical cons				0.015	0.028
				(0.0243)	(0.0238)
Observations	669.000	669.000	669.000	669.000	669.000
R-squared	0.025	0.051	0.047	0.047	0.019

Note: Each column shows the results for a regression, for condominium owners, of whether the live in the condominium that they own, on a set of baseline covariates. All right hand side variables are normalised to have mean zero and standard deviation one to make them easier to interpret. Social ties is a measure of the total number of other people that they household head speaks to on a regular basis. Housing consumption variables (included location and physical, respectively) are imputed for baseline housing choices, using the method outlined in Section 3.4. In some specifications I control for additional predictors of whether the household moves in, selected from the non-zero parameters in a separate lasso regression.

Table A19: Determinants of housing occupation private renters at endline 2

	(1)	(2)	(3)	(4)	(5)
	Dep Variable: Lottery winner lives in their condominium.				
Household income	-0.019	-0.042	-0.058	-0.060	-0.042
	(0.0314)	(0.0364)	(0.0371)	(0.0372)	(0.0329)
Wealth (index)	-0.013	-0.022	-0.019	-0.019	-0.008
	(0.0403)	(0.0402)	(0.0397)	(0.0397)	(0.0397)
Social ties	-0.042	-0.043	-0.043	-0.043	-0.042
	(0.0267)	(0.0267)	(0.0266)	(0.0266)	(0.0266)
Community group	-0.024	-0.0492*	-0.043	-0.042	-0.013
	(0.0259)	(0.0287)	(0.0288)	(0.0288)	(0.0259)
Travel time to centre	-0.014	-0.012			
	(0.0218)	(0.0218)			
Index of physical housing quality	0.0283***	0.0225***			
	(0.00809)	(0.00835)			
Housing consumption total			0.114***		
			(0.0360)		
Housing location cons				0.029	0.021
				(0.0255)	(0.0255)
Housing physical cons				0.114***	0.140***
				(0.0362)	(0.0353)
Observations	372.000	372.000	372.000	372.000	372.000
R-squared	0.066	0.098	0.105	0.106	0.075

Note: Each column shows the results for a regression, for condominium owners, of whether the live in the condominium that they own, on a set of baseline covariates. All right hand side variables are normalised to have mean zero and standard deviation one to make them easier to interpret. Social ties is a measure of the total number of other people that they household head speaks to on a regular basis. Housing consumption variables (included location and physical, respectively) are imputed for baseline housing choices, using the method outlined in Section 3.4. In some specifications I control for additional predictors of whether the household moves in, selected from the non-zero parameters in a separate lasso regression.

Table A20: Lasso estimates of the predictors of moving in (first endline)

	(1) incondo	(2) incondo	(3) incondo
Member of an iddir	-0.0171	-0.0219	
Time to city centre	0.0247	0.0389	
Head ethnicity: amhara	0.0119	0.0218	0.0169
Head completed tertiary education	0.00196		0.00943
Tenure: rents on private market	0.0109	0.0946	0.0276
Household size		-0.000722	-0.00237
Tenure: rents government owned home		0.0878	
Moved in last 5 years			0.00494
Preference to stay in neighbhourhood			-0.000634
b_index_class			-0.00186
Observations	783	783	783

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Table shows the non-zero coefficients selected from a lasso regression of whether a household lives in the condominium they own, on a wide range of baseline covariates. Column (1) presents the results from a lasso regression using a simple cross-validation procedure. Column 2 applies an adaptive CV procedure. Column 3 uses adaptive CV, but excludes from the model the variables that I use in my main model. It is the covariates selected from column (3) that I use as controls in my main model (eg. Table A17).

Table A21: Test for differential drivers of moving in between 10th and later lotteries

	(1) In condo	(2) In condo
10th round	-0.0433	
	(0.0340)	
*Interactions: 10th round*covariate:*		
Household income		-0.0380
		(0.0388)
Wealth (index)		0.00474
		(0.0428)
Social ties		-0.0294
		(0.0327)
Community group		0.00655
		(0.0363)
Travel time to centre		0.0847**
		(0.0350)
Physical housing qual		-0.00712
		(0.0113)
Condo won: 1-bed		-0.0805
		(0.0616)
Condo won: 2-bed		-0.0825
		(0.0800)
Condo won: 3-bed		0.254
		(0.520)
Head ethnicity: amhara		0.0145
		(0.0333)
Moved in last 5 years		0.00319
		(0.0366)
Preference to stay in neighbhourhood		-0.0484
		(0.0336)
Head completed tertiary education		0.0329
		(0.0341)
Household size		0.00835
		(0.0384)
Class identification index		-0.0791**
		(0.0384)
Tenure: rents on private market		0.0648
		(0.0753)
Observations	1,067	1,055
R-squared	0.002	0.050
F-stat		1.143
P-val		0.310

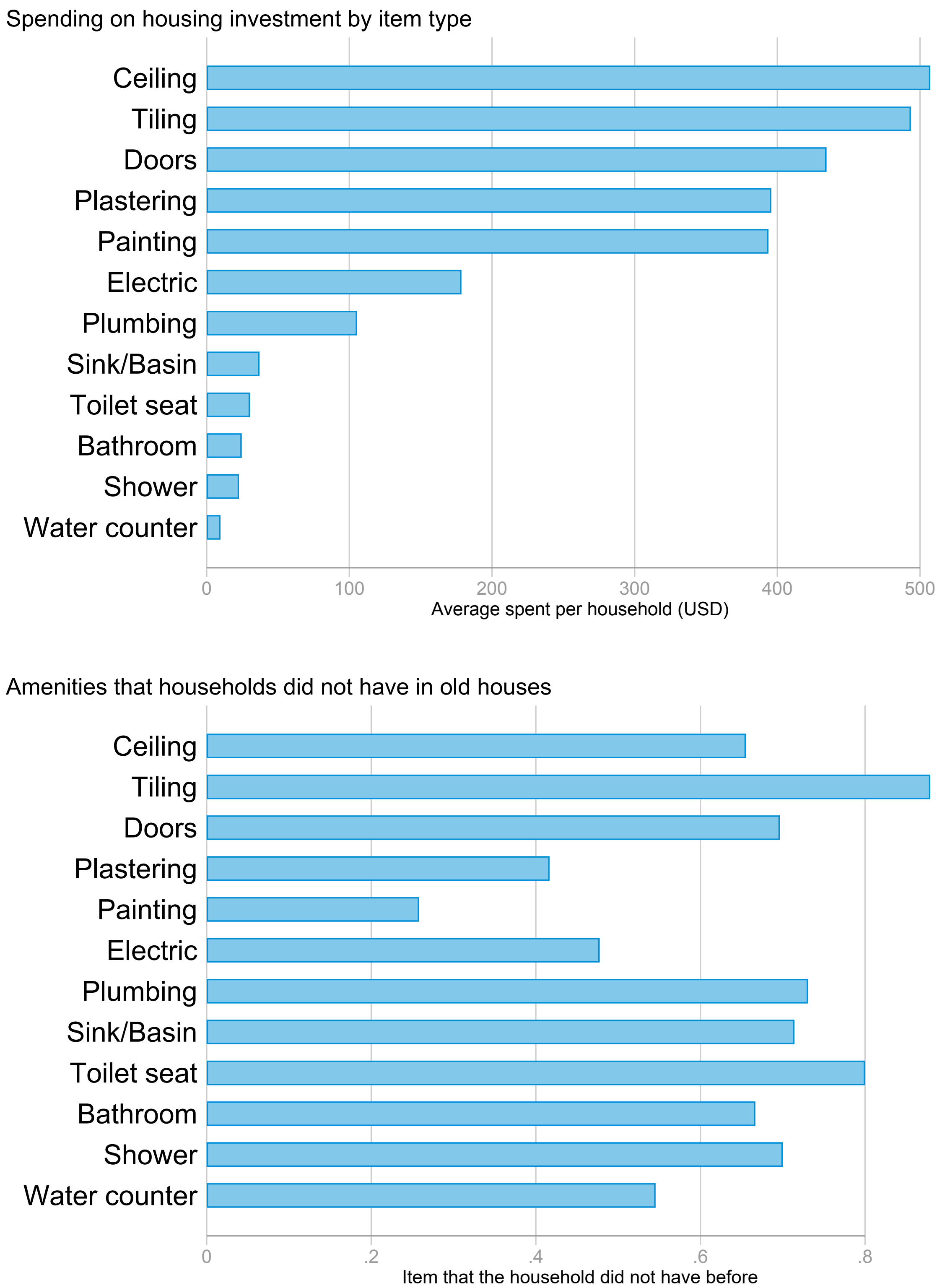
Note: This table tests for differences in the correlates of moving into condominiums between the 10th round and later lottery rounds. Column 1 shows that 10th round lottery winners are not significantly more or less likely to move into their units relative to later winners, at the same time (2-3 years) after they won them. Column 2 tests for the effects of interactions between winning the 10th round lottery and the probability that a household moves into its condominium, controlling for all (non-interacted) variables (coefficients not shown).

Table A22: Predicted apartment rent using apartment location and amenities (in USD pm)

Outcome: rent	Coefficent	(SE)
Floor (level)	-1.878***	(0.381)
Studio	-59.45***	(1.739)
1- Bed	-34.71***	(1.490)
3- Bed	33.78***	(2.740)
Site FE 1	-40.02***	(1.565)
Site FE 2	-28.77***	(1.896)
Site FE 4	-46.03***	(2.545)
Site FE 5	-26.60***	(3.077)
Block has communal slaughter area	4.039***	(1.236)
Block has shop space	2.462*	(1.317)
Distance from roads	-6.591***	(0.107)
Basic quality of finishing (baseline index)	1.442**	(0.637)
Observations	1,406	
R-squared	0.851	

Note: This table shows results of the hedonic regression of predicted condominium rent using the unit characteristics, including the floor number, access to amenities and distance of roads. I also measure the quality of the finishing of the block at baseline using direct observation by data collectors.

Figure A8: **Detail on amenity upgrades made to condominium houses**



A4.7 Multiple hypothesis corrections at the household level

Table A23: Summary of main estimated coefficient estimates at the household level with FDR-adjusted q-values (Endline 1).

Outcome	N (1)	Control mean (2)	ITT Estimate Lottery Coeff (3)	Std. Err. (4)	Sharpened q-value (5)
Housing quality index	1,426	0.000	0.658***	0.052	0.001
Distance from city centre	1,426	5.470	4.384***	0.287	0.001
Housing consumption	1,426	78.639	2.632	1.816	0.269
Transport expenditure	1,426	12.831	3.114***	0.776	0.001
Consumption (no housing & transport)	1,426	143.432	4.349	4.937	0.437
Non-housing Asset index	1,352	0.081	-0.068	0.055	0.270
Household labour market index	1,426	0.000	-0.041	0.051	0.448
Earnings per working age adult	1,426	86.286	0.729	4.006	0.856
Total employed per working age adult	1,415	0.656	-0.022	0.016	0.269
Hours worked per working age adult	1,415	28.845	-1.161	0.861	0.269
Total number of social ties	1,414	11.409	-2.247***	0.439	0.001
Arguments with neighbours	1,426	0.408	-0.124***	0.044	0.010
Beliefs: neighbours' contribution to pub. goods	1,311	0.000	0.072	0.056	0.269
Index of public goods	1,426	-0.000	-0.222***	0.056	0.001
Index of neighbourhood amenities	1,358	0.000	-0.234***	0.061	0.001

Note: Column (3) shows the *intent-to-treat* estimate of winning the lottery on household. Column (5) shows report the minimum q-value at which each hypothesis is rejected, using the method of Benjamini et al. (2006) to control the false discovery rate at $\alpha = 0.05$.

Table A24: Summary of main estimated coefficient estimates at the household level with FDR-adjusted q-values (Endline 2).

Outcome	N (1)	Control mean (2)	ITT Estimate Lottery Coeff (3)	Std. Err. (4)	Sharpened q-value (5)
Housing quality index	1,370	0.366	0.650***	0.089	0.001
Distance from city centre	1,370	6.039	4.326***	0.392	0.001
Housing consumption	1,370	106.741	20.549***	4.557	0.001
Transport expenditure	1,370	14.664	2.591	1.768	0.307
Consumption (no housing & transport)	1,370	144.249	9.402	8.846	0.466
Non-housing Asset index	1,370	-0.015	0.025	0.024	0.466
Household labour market index	1,370	-0.028	-0.039	0.086	0.655
Earnings per working age adult	1,370	70.637	4.581	6.319	0.541
Total employed per working age adult	1,359	0.498	-0.027	0.033	0.522
Hours worked per working age adult	1,359	23.571	-1.430	1.704	0.522
Total number of social ties	1,358	4.920	-1.191**	0.533	0.065
Arguments with neighbours	838	2.282	-0.239***	0.053	0.001
Beliefs: neighbours' contribution to pub. goods (index)	803	0.022	-0.056	0.124	0.655
Index of public goods	1,370	0.016	-0.101	0.076	0.342
Index of neighbourhood amenities	1,370	0.009	0.193**	0.083	0.060

Note: Column (3) shows the *intent-to-treat* estimate of winning the lottery on household. Column (5) shows report the minimum q-value at which each hypothesis is rejected, using the method of Benjamini et al. (2006) to control the false discovery rate at $\alpha = 0.05$.

Table A25: Household-level social and amenity outcomes with FDR-adjusted q-values (Endline 1).

Outcome	N	Control mean	ITT Estimate Lottery Coeff	Std. Err.	Sharpened q-value
	(1)	(2)	(3)	(4)	(5)
Subjective wellbeing (ladder)	1,426	4.156	-0.048	0.224	0.830
Total number of social ties	1,414	11.409	-2.247***	0.439	0.001
Social ties in local neighbourhood	1,425	6.327	-2.588***	0.589	0.001
Can turn to neighbours for advice	1,426	1.827	-0.199**	0.091	0.048
Felt lonely	1,375	1.532	-0.072	0.052	0.226
Needed help and couldn't find with friends	1,375	1.642	0.195***	0.061	0.003
Satisfied with social life in neighbourhood (1/0)	1,426	0.807	0.008	0.022	0.757
Satisfied with neighbours	1,426	3.318	-0.094**	0.037	0.019
Beliefs: neighbours' contribution to pub. goods	1,311	0.000	0.072	0.056	0.252
Arguments with neighbours	1,426	0.408	-0.124***	0.044	0.009
Household is a member of at least one iddir	1,426	0.541	0.124***	0.024	0.001
Community meetings participation	1,426	0.367	0.109***	0.028	0.001
Respondent has leadership role in community	1,426	0.038	0.013	0.012	0.334
Index of public goods	1,426	-0.000	-0.222***	0.056	0.001
Clinic/hospital quality	1,426	3.245	-0.148***	0.035	0.001
Primary school quality	1,426	3.063	-0.057*	0.029	0.084
Index of neighbourhood amenities	1,358	0.000	-0.234***	0.061	0.001
Neighbourhood has *less* smell of drains or sewerage	1,374	0.000	0.104*	0.058	0.104
Neighbourhood has working streetlights	1,426	0.394	-0.131***	0.026	0.001
Less debris/rubble lying around neighhbourhood	1,422	2.637	-0.287***	0.047	0.001
Condition of piping and sewerage system	1,362	-0.000	-0.037	0.060	0.588
Feels safe at night	1,370	5.750	0.028	0.037	0.516
Preference to stay	1,426	3.309	0.643***	0.078	0.001

Note: Column (3) shows the *intent-to-treat* estimate of winning the lottery on household. Column (5) shows report the minimum q-value at which each hypothesis is rejected, using the method of Benjamini et al. (2006) to control the false discovery rate at $\alpha = 0.05$.

Table A26: Household-level social and amenity outcomes with FDR-adjusted q-values (Endline 2).

Outcome	N	Control mean	ITT Estimate Lottery Coeff	Std. Err.	Sharpened q-value
	(1)	(2)	(3)	(4)	(5)
Subjective wellbeing (ladder)	1,365	4.527	0.507***	0.150	0.004
Total number of social ties	1,358	4.920	-1.191**	0.533	0.061
Social ties in local neighbourhood	1,370	2.734	-0.533	0.348	0.194
Can turn to neighbours for advice	1,298	2.662	-0.032	0.060	0.671
Felt lonely	876	1.689	-0.391***	0.109	0.003
Needed help and couldn't find with friends	876	1.785	-0.459***	0.110	0.001
Satisfied with social life in general	1,370	3.315	0.075	0.059	0.274
Satisfied with social life in neighbourhood	1,370	3.241	0.113*	0.061	0.105
Beliefs: neighbours' contribution to pub. goods (index)	803	0.022	-0.056	0.124	0.710
Arguments with neighbours	838	2.282	-0.239***	0.053	0.001
Household is a member of at least one iddir	1,370	0.685	0.081**	0.038	0.068
Community meetings participation	1,370	2.638	0.233***	0.083	0.020
Respondent has leadership role in community	1,370	0.017	-0.003	0.010	0.752
Index of public goods	1,370	0.016	-0.101	0.076	0.264
Clinic/hospital quality	1,370	2.973	0.031	0.044	0.607
Primary school quality	1,370	2.897	-0.030	0.053	0.671
Public space quality	1,370	2.971	0.092**	0.042	0.061
Index of neighbourhood amenities	1,370	0.009	0.193**	0.083	0.052
Neighbourhood has *less* smell of drains or sewerage	1,370	0.014	0.327***	0.089	0.003
Neighbourhood has working street lights	1,370	0.257	-0.002	0.035	0.963
Less debris/rubble lying around neighbourhood	1,370	2.457	0.065	0.060	0.371
Condition of piping and sewerage system	1,370	-0.004	0.169*	0.090	0.104
Feels safe at night	1,370	5.549	0.217***	0.079	0.021
Overall neighbourhood rating	1,370	5.375	0.389**	0.186	0.068
Proud of neighbourhood	1,370	3.790	0.241***	0.081	0.013
Preference to stay	1,370	3.592	0.260**	0.106	0.042

Note: Column (3) shows the *intent-to-treat* estimate of winning the lottery on household. Column (5) shows report the minimum q-value at which each hypothesis is rejected, using the method of Benjamini et al. (2006) to control the false discovery rate at $\alpha = 0.05$.

A4.8 Labour market outcomes [Section 5.1]

Table A27: Effects of winning the lottery on labour supply (comparing endlines 1 and 2)

	2018 Endline			2024 Endline			
Outcome	N (1)	Control mean (2)	ITT Lottery (3)	N (4)	Control mean (5)	ITT Lottery (6)	Diff pval (7)
Household labour market index	1,426	0.000	-0.042 [0.050]	1,370	-0.021	-0.037 [0.088]	0.931
Earnings per working age adult	1,426	85.436	0.632 [4.022]	1,370	67.472	4.309 [6.320]	0.727
Total employed per working age adult	1,415	0.670	-0.022 [0.016]	1,359	0.522	-0.024 [0.032]	0.780
Hours worked per working age adult	1,415	29.403	-1.167 [0.860]	1,359	25.145	-1.387 [1.730]	0.756

Note: Each row represents a regression of the named outcome on whether the household won the lottery using the ANCOVA specification in Equation 1. I show the results separately for the 2018 and 2024 endlines (one regression for each endline, per outcome). "ITT Lottery" identifies the parameter of interest, with the relevant SE of the estimate shown in square brackets below. Column 7 provides the p-value for a test of equality of the coefficient between the 2018 and 2024 endlines. This is estimated using a saturated regression combining both endlines and including interactions between all covariates and an "endline" dummy.

Table A28: Individual labor by gender First endline

Outcome	Control mean (1)	ITT Lottery (2)	By Gender Female (3)	Male (4)	Equality pval (5)
Did any work in the last 7 days	0.633	-0.019	-0.029	-0.020	0.75
		(0.015)	(0.022)	(0.020)	
Wage-employed work in the last 7 days	0.445	-0.005	-0.004	-0.022	0.56
		(0.016)	(0.022)	(0.024)	
Self-employed work in the last 7 days	0.121	-0.005	-0.018	0.012	0.16
		(0.011)	(0.013)	(0.018)	
Individual monthly earnings (USD)	82.075	1.624	2.996	1.082	0.78
		(3.516)	(3.886)	(6.006)	
Individual hours worked in the last 7 days	29.817	-0.946	-1.552	-1.012	0.72
		(0.791)	(1.129)	(1.109)	
Permanent work	0.291	0.016	0.009	0.015	0.83
		(0.013)	(0.019)	(0.022)	
White collar-work	0.186	0.030**	0.038**	0.020	0.44
		(0.012)	(0.017)	(0.019)	
Permanent white-collar work	0.321	0.019	0.020	0.018	0.93
		(0.015)	(0.020)	(0.022)	
Switched between self/wage employment	0.102	0.032*	0.013	0.044*	0.28
		(0.018)	(0.021)	(0.024)	
Switched occupations (40 main occupations)	0.479	0.002	0.005	-0.000	0.93
		(0.027)	(0.042)	(0.035)	
Works in areas near housing sites	0.070	0.042***	0.055***	0.027*	0.13
		(0.011)	(0.013)	(0.016)	
Works close to home	0.051	-0.027***	-0.023***	-0.031***	0.52
		(0.008)	(0.008)	(0.011)	
Works in own home	0.058	0.002	-0.003	0.007	0.58
		(0.010)	(0.018)	(0.007)	
Commute time (cond)	60.295	18.768***	18.443***	19.060***	0.89
		(2.903)	(3.580)	(3.805)	
Commute cost (cond)	8.788	3.961***	3.823***	4.086***	0.85
		(0.823)	(0.871)	(1.245)	
Factory job	0.011	-0.002	-0.002	-0.002	0.93
		(0.004)	(0.005)	(0.004)	
Construction job	0.078	0.002	0.001	0.004	0.88
		(0.010)	(0.008)	(0.018)	

Note: Each row represents a regression of the named outcome on whether the household won the lottery using the ANCOVA specification in Equation 1. Column shows the main effect for all individuals. Columns 3-5 compares the treatment effects for household members with different characteristics. Column (3) shows the effect for females, Column (4) the effects for males. Column (5) shows the test for equality of the coefficients between females and males.

Table A29: Individual labor by gender - Second endline

		ITT	By Gender		
	Control	Lottery	Female	Male	Equality
Outcome	mean (1)	(2)	(3)	(4)	pval (5)
Did any work in the last 7 days	0.433	-0.003 (0.017)	-0.001 (0.022)	-0.005 (0.023)	0.88
Wage-employed work in the last 7 days	0.338	-0.015 (0.016)	-0.021 (0.021)	-0.006 (0.024)	0.62
Self-employed work in the last 7 days	0.094	0.013 (0.010)	0.020* (0.012)	0.000 (0.017)	0.34
Total earnings in the last month	58.813	-1.440 (3.794)	-0.863 (3.949)	-2.195 (6.719)	0.86
Individual hours worked in the last 7 days	20.550	0.080 (0.836)	-0.233 (1.074)	0.227 (1.241)	0.77
Permanent work	0.250	-0.007 (0.015)	-0.012 (0.019)	-0.001 (0.022)	0.69
White-collar work	0.153	0.007 (0.012)	0.016 (0.017)	-0.008 (0.017)	0.28
Permanent white-collar work	0.259	-0.004 (0.015)	-0.007 (0.020)	-0.001 (0.022)	0.81
Switched between self/wage employment	0.273	0.009 (0.028)	0.034 (0.040)	-0.009 (0.035)	0.38
Switched occupations	0.520	-0.038 (0.037)	-0.051 (0.056)	-0.028 (0.050)	0.76
Works in areas near housing sites	0.045	0.012 (0.008)	0.019* (0.010)	0.004 (0.012)	0.36
Works close to home	0.048	-0.008 (0.008)	-0.000 (0.010)	-0.018* (0.011)	0.19
Works in own home	0.010	0.002 (0.003)	0.005 (0.005)	-0.002 (0.004)	0.26
Commute time (cond)	40.995	8.963*** (2.560)	7.125** (3.035)	10.822*** (3.583)	0.38
Commute cost (cond)	5.836	1.482** (0.732)	1.669* (0.995)	1.305 (0.954)	0.78
Takes a minibus to work	0.070	-0.009 (0.010)	-0.010 (0.011)	-0.007 (0.014)	0.86
Walks to work	0.052	0.001 (0.008)	0.010 (0.011)	-0.011 (0.012)	0.16
Factory job	0.005	0.005* (0.003)	0.005 (0.004)	0.006 (0.004)	0.93
Construction job	0.019	-0.008* (0.004)	-0.004 (0.004)	-0.013 (0.008)	0.31

Note: Each row represents a regression of the named outcome on whether the household won the lottery using the ANCOVA specification in Equation 1. Column shows the main effect for all individuals. Columns 3-5 compares the treatment effects for household members with different characteristics. Column (3) shows the effect for females, Column (4) the effects for males. Column (5) shows the test for equality of the coefficients between females and males.

Table A30: Individual labor by seniority - First endline

Outcome	Control mean (1)	ITT Lottery (2)	By HH Member Head (3)	Not Head (4)	Equality pval (5)
Did any work in the last 7 days	0.633	-0.019	-0.020	-0.031	0.66
		(0.015)	(0.017)	(0.024)	
Wage-employed work in the last 7 days	0.445	-0.005	-0.015	-0.008	0.80
		(0.016)	(0.021)	(0.024)	
Self-employed work in the last 7 days	0.121	-0.005	0.009	-0.021	0.08
		(0.011)	(0.015)	(0.013)	
Individual monthly earnings (USD)	82.075	1.624	5.478	-2.405	0.19
		(3.516)	(4.611)	(4.844)	
Individual hours worked in the last 7 days	29.817	-0.946	-0.966	-1.761	0.56
		(0.791)	(0.945)	(1.209)	
Permanent work	0.291	0.016	0.028	-0.010	0.15
		(0.013)	(0.019)	(0.020)	
White collar-work	0.186	0.030**	0.032*	0.027	0.83
		(0.012)	(0.017)	(0.020)	
Permament white-collar work	0.321	0.019	0.031	0.004	0.33
		(0.015)	(0.020)	(0.021)	
Switched between self/wage employment	0.102	0.032*	0.039**	0.002	0.27
		(0.018)	(0.019)	(0.033)	
Switched occupations (40 main occupations)	0.479	0.002	0.010	-0.031	0.43
		(0.027)	(0.029)	(0.049)	
Works in areas near housing sites	0.070	0.042***	0.050***	0.033**	0.32
		(0.011)	(0.014)	(0.014)	
Works close to home	0.051	-0.027***	-0.029***	-0.024***	0.60
		(0.008)	(0.010)	(0.008)	
Works in own home	0.058	0.002	-0.004	0.015	0.31
		(0.010)	(0.010)	(0.018)	
Commute time (cond)	60.295	18.768***	20.689***	14.745***	0.20
		(2.903)	(3.205)	(4.352)	
Commute cost (cond)	8.788	3.961***	4.469***	2.880**	0.21
		(0.823)	(0.910)	(1.194)	
Factory job	0.011	-0.002	-0.004	0.001	0.41
		(0.004)	(0.005)	(0.005)	
Construction job	0.078	0.002	0.002	0.002	0.98
		(0.010)	(0.012)	(0.013)	

Note: Each row represents a regression of the named outcome on whether the household won the lottery using the ANCOVA specification in Equation 1. Column shows the main effect for all individuals. Columns 3-5 compares the treatment effects for household members with different characteristics. Column (3) shows the effect for heads of households, Column (4) the effects for all other members. Column (5) shows the test for equality of the coefficients between heads and other members.

Table A31: Individual labor by seniority - Second endline

		ITT	By HH Member		
	Control	Lottery	Head	Not Head	Equality
Outcome	mean (1)	(2)	(3)	(4)	pval (5)
Did any work in the last 7 days	0.433	-0.003	-0.003	-0.003	1.00
		(0.017)	(0.021)	(0.022)	
Wage-employed work in the last 7 days	0.338	-0.015	-0.022	-0.004	0.52
		(0.016)	(0.021)	(0.022)	
Self-employed work in the last 7 days	0.094	0.013	0.019	0.001	0.30
		(0.010)	(0.014)	(0.012)	
Total earnings in the last month	58.813	-1.440	-0.420	-2.725	0.71
		(3.794)	(5.382)	(4.179)	
Individual hours worked in the last 7 days	20.550	0.080	-0.238	0.224	0.74
		(0.836)	(1.069)	(1.123)	
Permanent work	0.250	-0.007	0.001	-0.017	0.46
		(0.015)	(0.020)	(0.019)	
White-collar work	0.153	0.007	0.008	0.003	0.83
		(0.012)	(0.017)	(0.017)	
Permament white-collar work	0.259	-0.004	0.003	-0.013	0.52
		(0.015)	(0.020)	(0.019)	
Switched between self/wage employment	0.273	0.009	0.008	0.016	0.90
		(0.028)	(0.029)	(0.064)	
Switched occupations	0.520	-0.038	-0.032	-0.066	0.68
		(0.037)	(0.039)	(0.079)	
Works in areas near housing sites	0.045	0.012	0.024**	-0.002	0.03
		(0.008)	(0.011)	(0.009)	
Works close to home	0.048	-0.008	-0.008	-0.008	0.96
		(0.008)	(0.011)	(0.009)	
Works in own home	0.010	0.002	0.004	-0.000	0.47
		(0.003)	(0.004)	(0.005)	
Commute time (cond)	40.995	8.963***	8.431***	10.120***	0.69
		(2.560)	(3.113)	(3.460)	
Commute cost (cond)	5.836	1.482**	0.679	3.362**	0.04
		(0.732)	(0.740)	(1.315)	
Takes a minibus to work	0.070	-0.009	-0.027**	0.013	0.01
		(0.010)	(0.012)	(0.013)	
Walks to work	0.052	0.001	0.006	-0.006	0.35
		(0.008)	(0.011)	(0.009)	
Factory job	0.005	0.005*	0.005	0.006	0.88
		(0.003)	(0.004)	(0.004)	
Construction job	0.019	-0.008*	-0.008	-0.007	0.95
		(0.004)	(0.006)	(0.005)	

Note: Each row represents a regression of the named outcome on whether the household won the lottery using the ANCOVA specification in Equation 1. Column shows the main effect for all individuals. Columns 3-5 compares the treatment effects for household members with different characteristics. Column (3) shows the effect for heads of households, Column (4) the effects for all other members. Column (5) shows the test for equality of the coefficients between heads and other members.

Table A32: Individual health – all adults- endline 1

			ITT Estimate Lottery		
Outcome	N (1)	Control mean (2)	Coeff (3)	Std. Err. (4)	Sharpened q-value (5)
Health condition index	5,379	0.011	-0.040	0.033	0.661
Malaria	5,379	0.002	-0.001	0.001	0.834
Diarrhea	5,379	0.008	-0.004	0.002	0.612
Physical	5,379	0.011	0.004	0.004	0.661
Dental	5,379	0.004	0.002	0.002	0.793
Eye	5,379	0.008	0.001	0.003	0.834
Skin	5,379	0.004	-0.002	0.002	0.774
Asthma	5,379	0.008	-0.005**	0.002	0.564
ENT	5,379	0.009	0.004	0.004	0.661
Tuberculosis	5,379	0.001	-0.002**	0.001	0.564
HighBloodPressure	5,379	0.011	0.002	0.003	0.795
Diabetes	5,379	0.008	0.005	0.003	0.612
HeartProblems	5,379	0.003	0.001	0.002	0.834
Commoncold	5,379	0.044	0.007	0.008	0.774
Typhoid	5,379	0.007	-0.001	0.003	0.834
Back pain	5,379	0.009	0.003	0.003	0.774
Goiter	5,379	0.001	-0.001	0.001	0.661
Jardia	5,379	0.002	-0.002	0.001	0.612
Kidney infection	5,379	0.008	0.000	0.003	0.999
Other	5,379	0.026	0.000	0.005	0.980
Ilness prevent normal activities	5,202	0.085	0.002	0.010	0.926
Ilness prevent activities (employed)	2,302	0.092	-0.005	0.013	0.834
Ilness prevent activities (working age)	3,620	0.086	-0.004	0.011	0.834
Sought health care (condition on sickness)	903	0.857	-0.021	0.030	0.795

Note: Each row represents a regression of the named outcome on whether the household won the lottery using the ANCOVA specification in Equation 1. Column 5 shows an sharpened q-value to control the false discovery rate.

Table A33: Individual health –children - endline 1

Outcome	N	Control mean	ITT Estimate Lottery Coeff	Std. Err.	Sharpened q-value
	(1)	(2)	(3)	(4)	(5)
Health condition index	1,849	-0.086	-0.063	0.044	0.493
Malaria	1,849	0.001	-0.002	0.002	0.509
Diarrhea	1,849	0.012	-0.008	0.005	0.493
Physical	1,849	0.005	0.000	0.003	0.988
Dental	1,849	0.005	-0.005	0.003	0.493
Eye	1,849	0.002	0.003	0.003	0.509
Skin	1,849	0.005	-0.002	0.004	0.683
Asthma	1,849	0.004	-0.005**	0.003	0.493
ENT	1,849	0.011	0.006	0.008	0.599
Tuberculosis	1,849	0.000	0.000	0.000	0.509
HighBloodPressure	1,849	0.000	0.000	0.000	0.493
Diabetes	1,849	0.001	-0.001	0.001	0.606
HeartProblems	1,849	0.003	-0.004	0.003	0.509
Commoncold	1,849	0.075	0.011	0.017	0.509
Typhoid	1,849	0.002	0.004	0.004	0.493
Back pain	1,849	0.000	0.000	0.000	0.511
Goiter	1,849	0.000	0.000	0.000	0.606
Jardia	1,849	0.002	-0.001	0.001	0.745
Kidney infection	1,849	0.000	0.002	0.002	0.493
Other	1,849	0.016	-0.006	0.006	
Ilness prevent normal activities	1,796	0.069	0.010	0.015	
Ilness prevent activities (employed)	56	0.000	0.000	0.000	
Ilness prevent activities (working age)	349	0.035	0.008	0.022	
Sought health care (condition on sickness)	261	0.808	-0.086	0.063	

Note: Each row represents a regression of the named outcome on whether the household won the lottery using the ANCOVA specification in Equation 1. Column 5 shows an sharpened q-value to control the false discovery rate.

A4.9 Main results by moving in status (specification 2) for Endline 1 only [Section 5]

Table A34: Effects of winning the lottery on movers and non-movers: consumption, housing, and location. Endline 1

Outcome	N	Control mean	ITT Lottery	By Moving Decision: Mover	Stayer	Equality pval
	(1)	(2)	(3)	(4)	(5)	(6)
Housing quality index	1,290	-0.05	0.61***	1.43***	-0.07	0.00
			(0.07)	(0.11)	(0.07)	
Distance from city centre	1,290	5.40	4.28***	8.97***	0.48	0.00
			(0.30)	(0.35)	(0.35)	
Housing consumption	1,290	81.96	0.53	5.67	-2.45	0.19
			(3.48)	(6.22)	(4.07)	
Transport expenditure	1,290	12.26	3.39***	8.32***	0.02	0.00
			(1.09)	(2.03)	(1.13)	
Consumption (no housing & transport)	1,290	142.20	-0.44	-13.50	-8.24	0.67
			(6.73)	(13.07)	(6.97)	
Non-housing Asset index	1,228	0.06	-0.04	0.18	-0.12	0.02
			(0.08)	(0.14)	(0.09)	

Note: This table shows the ITT estimates of winning the housing lottery side-by-side with heterogeneous effects for households that move into their units and those that stay (do not move). ITT results in Column 3 come from one regression, the decomposition in Columns 4-6 come from a separate regression, which uses Equation 2 to separately identify these groups, using movers from later lottery rounds for those that moved in after the first round. Column 6 presents the p-value for a test of equality between the results in Column 4 and Column 5.

Table A35: Effects of winning the lottery on movers and non-movers: labour market outcomes. Endline 1

			ITT	By Moving Decision		
Outcome	N	Control mean	Lottery	Mover	Stayer	Equality pval
	(1)	(2)	(3)	(4)	(5)	(6)
Household labour market index	1,290	0.02	-0.07	-0.03	-0.03	0.97
			(0.07)	(0.13)	(0.08)	
Earnings per working age adult	1,290	85.44	-1.88	1.27	-2.13	0.74
			(5.74)	(10.84)	(6.14)	
Total employed per working age adult	1,280	0.67	-0.02	-0.00	-0.01	0.85
			(0.02)	(0.04)	(0.02)	
Hours worked per working age adult	1,280	29.40	-1.20	-1.09	-0.01	0.61
			(1.18)	(2.20)	(1.33)	

Note: This table shows the ITT estimates of winning the housing lottery side-by-side with heterogeneous effects for households that move into their units and those that stay (do not move). ITT results in Column 3 come from one regression, the decomposition in Columns 4-6 come from a separate regression, which uses Equation 2 to separately identify these groups, using movers from later lottery rounds for those that moved in after the first round. Column 6 presents the p-value for a test of equality between the results in Column 4 and Column 5.

Table A36: Effects of winning the lottery on movers and non-movers: individual labour. Endline 1

		ITT	By Moving Decision		
Outcome	Control mean	Lottery	Moved	Stayed	Equality pval
	(1)	(2)	(3)	(4)	(5)
Did any work in the last 7 days	0.633	-0.022	-0.043	-0.005	0.29
		(0.019)	(0.037)	(0.020)	
Wage-employed work in the last 7 days	0.445	-0.021	-0.054	-0.011	0.28
		(0.020)	(0.041)	(0.022)	
Self-employed work in the last 7 days	0.121	0.001	0.019	-0.006	0.38
		(0.015)	(0.029)	(0.016)	
Individual monthly earnings (USD)	82.075	-0.495	-1.144	-0.397	0.92
		(4.476)	(8.220)	(4.747)	
Individual hours worked in the last 7 days	29.817	-1.255	-2.491	-0.139	0.22
		(1.006)	(1.982)	(1.114)	
Permanent work	0.291	-0.016	-0.090**	-0.012	0.03
		(0.019)	(0.037)	(0.021)	
White collar-work	0.186	0.004	-0.044	0.001	0.14
		(0.016)	(0.031)	(0.017)	
Permament white-collar work	0.321	-0.011	-0.079**	-0.009	0.05
		(0.019)	(0.037)	(0.021)	
Switched occupations (40 main occupations)	0.479	0.025	0.077	0.003	0.29
		(0.037)	(0.072)	(0.041)	
Works in areas near housing sites	0.070	0.026**	0.047**	0.007	0.08
		(0.013)	(0.024)	(0.014)	
Works close to home	0.051	-0.028***	-0.033*	-0.021*	0.49
		(0.010)	(0.019)	(0.011)	
Works in own home	0.058	0.017	0.026	0.015	0.67
		(0.012)	(0.026)	(0.013)	
Commute time (cond)	60.295	15.790***	36.277***	-4.490	0.00
		(3.347)	(6.203)	(3.384)	
Commute cost (cond)	8.788	3.393***	10.048***	-0.472	0.00
		(1.015)	(1.798)	(1.057)	
Factory job	0.011	-0.003	-0.014	-0.000	0.14
		(0.005)	(0.010)	(0.005)	
Construction job	0.078	0.003	0.003	-0.000	0.90
		(0.012)	(0.024)	(0.014)	

Note: This table shows the ITT estimates of winning the housing lottery side-by-side with heterogeneous effects for households that move into their units and those that stay (do not move). ITT results in Column 3 come from one regression, the decomposition in Columns 4-6 come from a separate regression, which uses Equation 2 to separately identify these groups, using movers from later lottery rounds for those that moved in after the first round. Column 6 presents the p-value for a test of equality between the results in Column 4 and Column 5.

Table A37: Effects of winning the lottery on movers and non-movers: consumption, housing, and location. Endline 1

Outcome	N	Control mean	ITT Lottery	By Moving Decision: Mover	By Moving Decision: Stayer	Equality pval
	(1)	(2)	(3)	(4)	(5)	(6)
Subjective wellbeing (ladder)	1,287	4.28	-0.07	-0.19	-0.16	0.90
			(0.13)	(0.26)	(0.14)	
Total number of social ties	1,279	11.37	-3.27***	-4.07***	-3.41***	0.56
			(0.68)	(1.26)	(0.72)	
Social ties in local neighbourhood	1,289	6.55	-3.62***	-3.87***	-3.31***	0.39
			(1.16)	(1.35)	(1.13)	
Can turn to neighbours for advice	1,227	1.80	-0.26**	-0.33	-0.24*	0.70
			(0.12)	(0.26)	(0.13)	
Felt lonely	1,246	1.52	-0.07	-0.03	-0.07	0.80
			(0.07)	(0.14)	(0.07)	
Needed help and couldn't find with friends	1,246	1.65	0.15*	0.09	0.20**	0.46
			(0.08)	(0.15)	(0.09)	
Satisfied with social life in neighbourhood (1/0)	1,290	0.81	-0.02	-0.11*	0.02	0.03
			(0.03)	(0.06)	(0.03)	
Satisfied with neighbours	1,290	3.30	-0.06	-0.14	-0.02	0.24
			(0.05)	(0.10)	(0.06)	
Beliefs: neighbours' contribution to pub. goods	1,099	-0.02	0.05	0.12	0.03	0.55
			(0.08)	(0.16)	(0.09)	
Arguments with neighbours	1,227	0.41	-0.11*	-0.29**	-0.08	0.11
			(0.06)	(0.14)	(0.07)	
Household is a member of at least one iddir	1,290	0.55	0.13***	0.30***	0.04	0.00
			(0.03)	(0.07)	(0.04)	
Community meetings participation	1,290	0.37	0.10***	0.33***	-0.04	0.00
			(0.04)	(0.07)	(0.04)	
Respondent has leadership role in community	1,290	0.04	0.02	0.06*	-0.00	0.04
			(0.02)	(0.03)	(0.02)	
Index of public goods	1,290	-0.00	-0.21***	-0.28*	-0.11	0.24
			(0.08)	(0.16)	(0.09)	
Clinic/hospital quality	1,290	3.24	-0.15***	-0.23**	-0.08	0.11
			(0.05)	(0.10)	(0.05)	
Primary school quality	1,290	3.06	-0.05	-0.04	-0.02	0.83
			(0.04)	(0.08)	(0.05)	
Index of neighbourhood amenities	1,231	0.02	-0.21***	-0.68***	0.14*	0.00
			(0.08)	(0.15)	(0.08)	
Neighbourhood has *less* smell of drains or sewerage	1,245	-0.01	0.07	-0.01	0.11	0.41
			(0.08)	(0.16)	(0.08)	
Neighbourhood has working streetlights	1,290	0.40	-0.12***	-0.37***	0.02	0.00
			(0.04)	(0.07)	(0.04)	
Less debris/rubble lying around neighhbourhood	1,287	2.69	-0.24***	-0.51***	0.04	0.00
			(0.06)	(0.11)	(0.06)	
Condition of piping and sewerage system	1,235	-0.01	-0.01	-0.17	0.13	0.05
			(0.08)	(0.16)	(0.09)	
Feels safe at night	1,244	5.72	0.07	-0.02	0.06	0.44
			(0.06)	(0.10)	(0.06)	
Preference to stay	1,290	3.24	0.56***	1.20***	0.11	0.00
			(0.11)	(0.22)	(0.12)	

Note: This table shows the ITT estimates of winning the housing lottery side-by-side with heterogeneous effects for households that move into their units and those that stay (do not move). ITT results in Column 3 come from one regression, the decomposition in Columns 4-6 come from a separate regression, which uses Equation 2 to separately identify these groups, using movers from later lottery rounds for those that moved in after the first round. Column 6 presents the p-value for a test of equality between the results in Column 4 and Column 5.

A4.10 Main results by moving in status – ML Method (Endlines 1 and 2)

Table A38: Effects of winning the lottery and moving house on consumption, housing, and location. Endline 1

			ITT	By Moving Decision		
Outcome	N	Control mean	Lottery	Moved	Stayed	Equality pval
	(1)	(2)	(3)	(4)	(5)	(6)
Housing quality index	1,426	-0.05	0.67***	1.00***	-0.14	0.00
			(0.05)	(0.23)	(0.18)	
Distance from city centre	1,426	5.40	4.40***	9.26***	0.70**	0.00
			(0.27)	(0.27)	(0.35)	
Housing consumption	1,426	77.83	2.95	5.94**	-3.19	0.00
			(1.83)	(2.78)	(2.30)	
Transport expenditure	1,426	12.26	3.22***	7.75***	-0.58	0.00
			(0.76)	(1.19)	(1.50)	
Consumption (no housing & transport)	1,426	142.20	4.86	13.44	1.99	0.15
			(5.00)	(8.19)	(6.70)	
Non-housing Asset index	1,352	0.06	-0.06	0.01	-0.21***	0.02
			(0.06)	(0.08)	(0.08)	

Note: This table shows the ITT estimates of winning the housing lottery side-by-side with heterogeneous effects for households that move into their units and those that stay (do not move). ITT results in Column 3 come from one regression, the decomposition in Columns 4-6 come from a separate regression, which uses Equation 3 to look at outcomes for mover and non-movers from the 10th round while controlling for a rich set of baseline covariates that predict whether households move in or not. Column 6 presents the p-value for a test of equality between the results in Column 4 and Column 5.

Table A39: Effects of winning the lottery and moving house on consumption, housing, and location. Endline 2

Outcome	N (1)	Control mean (2)	ITT Lottery (3)	By Moving Decision Moved (4)	Stayed (5)	Equality pval (6)
Housing quality index	1,370	0.29	0.66***	0.92***	-0.16	0.00
			(0.09)	(0.28)	(0.27)	
Distance from city centre	1,370	6.07	4.34***	9.33***	-0.10	0.00
			(0.29)	(0.32)	(0.18)	
Housing consumption	1,370	103.36	20.81***	29.66***	7.04	0.00
			(4.04)	(4.50)	(5.14)	
Transport expenditure	1,370	14.95	2.58	5.42**	-1.21	0.00
			(1.91)	(2.30)	(2.81)	
Consumption (no housing & transport)	1,370	143.20	9.32	5.11	12.59	0.41
			(8.75)	(10.94)	(10.55)	
Non-housing Asset index	1,370	-0.02	0.03	-0.10	-0.16*	0.41
			(0.03)	(0.09)	(0.09)	

Note: This table shows the ITT estimates of winning the housing lottery side-by-side with heterogeneous effects for households that move into their units and those that stay (do not move). ITT results in Column 3 come from one regression, the decomposition in Columns 4-6 come from a separate regression, which uses Equation 3 to look at outcomes for mover and non-movers from the 10th round while controlling for a rich set of baseline covariates that predict whether households move in or not. Column 6 presents the p-value for a test of equality between the results in Column 4 and Column 5.

Table A40: Effects of winning the lottery and moving house on household labour market outcomes. Endline 1

Outcome	N (1)	Control mean (2)	ITT Lottery (3)	By Moving Decision Moved (4)	Stayed (5)	Equality pval (6)
Household labour market index	1,426	0.02	-0.04	0.18	0.04	0.41
			(0.05)	(0.15)	(0.14)	
Earnings per working age adult	1,426	85.44	1.36	6.13	-6.08	0.34
			(3.98)	(11.60)	(11.08)	
Total employed per working age adult	1,415	0.67	-0.02	-0.01	-0.00	0.80
			(0.02)	(0.02)	(0.02)	
Hours worked per working age adult	1,415	29.40	-1.16	-0.59	1.42	0.24
			(0.86)	(1.52)	(1.50)	

Note: This table shows the ITT estimates of winning the housing lottery side-by-side with heterogeneous effects for households that move into their units and those that stay (do not move). ITT results in Column 3 come from one regression, the decomposition in Columns 4-6 come from a separate regression, which uses Equation 3 to look at outcomes for mover and non-movers from the 10th round while controlling for a rich set of baseline covariates that predict whether households move in or not. Column 6 presents the p-value for a test of equality between the results in Column 4 and Column 5.

Table A41: Effects of winning the lottery and moving house on household labour market outcomes. Endline 2

Outcome	N	Control mean	ITT Lottery	By Moving Decision: Moved	By Moving Decision: Stayed	By Moving Decision: Equality pval
	(1)	(2)	(3)	(4)	(5)	(6)
Household labour market index	1,370	-0.02	-0.04	0.12	-0.28	0.02
			(0.09)	(0.21)	(0.21)	
Earnings per working age adult	1,370	69.43	4.58	11.45	-6.48	0.19
			(6.43)	(17.70)	(17.38)	
Total employed per working age adult	1,359	0.50	-0.03	0.00	-0.08**	0.01
			(0.03)	(0.04)	(0.04)	
Hours worked per working age adult	1,359	24.02	-1.43	0.84	-2.68	0.08
			(1.76)	(2.41)	(2.54)	

Note: This table shows the ITT estimates of winning the housing lottery side-by-side with heterogeneous effects for households that move into their units and those that stay (do not move). ITT results in Column 3 come from one regression, the decomposition in Columns 4-6 come from a separate regression, which uses Equation 3 to look at outcomes for mover and non-movers from the 10th round while controlling for a rich set of baseline covariates that predict whether households move in or not. Column 6 presents the p-value for a test of equality between the results in Column 4 and Column 5.

Table A42: Effects of winning by moving on neighbourhood & social outcomes (endline 1)

Outcome	N (1)	Control mean (2)	ITT Lottery (3)	By Moving Decision Moved (4)	Stayed (5)	Equality pval (6)
Subjective wellbeing (ladder)	1,426	4.28	-0.04 (0.14)	-0.16 (0.30)	0.06 (0.13)	0.53
Total number of social ties	1,414	11.37	-2.25*** (0.45)	-1.48** (0.71)	-1.88*** (0.70)	0.56
Social ties in local neighbourhood	1,425	6.55	-2.56*** (0.64)	-2.89*** (0.68)	-2.32*** (0.63)	0.01
Can turn to neighbours for advice	1,426	1.80	-0.20** (0.09)	-0.26** (0.11)	-0.16 (0.10)	0.39
Felt lonely	1,375	1.52	-0.07 (0.05)	-0.09 (0.06)	-0.06 (0.06)	0.71
Needed help and couldn't find with friends	1,375	1.65	0.18*** (0.06)	0.17** (0.07)	0.20*** (0.07)	0.74
Satisfied with social life in neighbourhood (1/0)	1,426	0.81	0.01 (0.02)	-0.04 (0.03)	0.04* (0.02)	0.01
Satisfied with neighbours	1,426	3.30	-0.09** (0.04)	-0.13*** (0.05)	-0.07 (0.04)	0.23
Beliefs: neighbours' contribution to pub. goods	1,311	-0.02	0.07 (0.06)	0.09 (0.07)	0.06 (0.06)	0.70
Arguments with neighbours	1,426	0.41	-0.12*** (0.04)	-0.17*** (0.05)	-0.09* (0.05)	0.15
Household is a member of at least one iddir	1,426	0.55	0.13*** (0.02)	0.24*** (0.03)	0.04 (0.03)	0.00
Community meetings participation	1,426	0.37	0.11*** (0.03)	0.30*** (0.03)	-0.04 (0.03)	0.00
Respondent has leadership role in community	1,426	0.04	0.01 (0.01)	0.03** (0.02)	-0.00 (0.01)	0.05
Index of public goods	1,426	-0.00	-0.23*** (0.06)	-0.38*** (0.07)	-0.11* (0.06)	0.00
Clinic/hospital quality	1,426	3.24	-0.15*** (0.04)	-0.23*** (0.04)	-0.09** (0.04)	0.00
Primary school quality	1,426	3.06	-0.06* (0.03)	-0.11*** (0.04)	-0.02 (0.03)	0.01
Index of neighbourhood amenities	1,358	0.02	-0.23*** (0.06)	-0.68*** (0.08)	0.12* (0.07)	0.00
Neighbourhood has *less* smell of drains or sewerage	1,374	-0.01	0.10* (0.06)	0.04 (0.07)	0.15** (0.07)	0.16
Neighbourhood has working streetlights	1,426	0.40	-0.13*** (0.03)	-0.32*** (0.03)	0.01 (0.03)	0.00
Less debris/rubble lying around neighhbourhood	1,422	2.69	-0.29*** (0.04)	-0.66*** (0.07)	0.00 (0.05)	0.00
Condition of piping and sewerage system	1,362	-0.01	-0.04 (0.06)	-0.20** (0.08)	0.09 (0.07)	0.00
Feels safe at night	1,370	5.72	0.02 (0.04)	0.04 (0.05)	0.02 (0.05)	0.64
Preference to stay	1,426	3.24	0.64*** (0.08)	1.18*** (0.08)	0.22** (0.09)	0.00

Note: This table shows the ITT estimates of winning the housing lottery side-by-side with heterogeneous effects for households that move into their units and those that stay (do not move). ITT results in Column 3 come from one regression, the decomposition in Columns 4-6 come from a separate regression, which uses Equation 3 to look at outcomes for mover and non-movers from the 10th round while controlling for a rich set of baseline covariates that predict whether households move in or not. Column 6 presents the p-value for a test of equality between the results in Column 4 and Column 5.

Table A43: Effects of winning by moving on neighbourhood & social outcomes (endline 2)

Outcome	N	Control mean	ITT Lottery	By Moving Decision: Moved	Stayed	Equality pval
	(1)	(2)	(3)	(4)	(5)	(6)
Subjective wellbeing (ladder)	1,365	4.48	0.51*** (0.16)	0.66*** (0.20)	0.45** (0.20)	0.21
Total number of social ties	1,358	4.99	-1.19* (0.64)	-0.20 (1.05)	-0.63 (1.08)	0.56
Social ties in local neighbourhood	1,370	2.80	-0.54* (0.32)	-0.64* (0.34)	-0.44 (0.39)	0.57
Can turn to neighbours for advice	1,298	2.64	-0.03 (0.06)	-0.17 (0.18)	-0.21 (0.17)	0.81
Felt lonely	876	1.72	-0.39*** (0.12)	-0.42*** (0.13)	-0.34** (0.13)	0.39
Needed help and couldn't find with friends	876	1.81	-0.46*** (0.12)	-0.48*** (0.13)	-0.43*** (0.13)	0.56
Satisfied with social life in general	1,370	3.31	0.08 (0.07)	0.13* (0.07)	0.02 (0.07)	0.03
Satisfied with social life in neighbourhood	1,370	3.23	0.11 (0.07)	0.16** (0.07)	0.06 (0.07)	0.05
Beliefs: neighbours' contribution to pub. goods (index)	803	0.02	-0.06 (0.12)	-0.12 (0.18)	0.12 (0.19)	0.12
Arguments with neighbours	838	2.27	-0.24*** (0.06)	-0.12 (0.13)	-0.16 (0.14)	0.67
Household is a member of at least one iddir	1,370	0.67	0.08** (0.04)	0.14*** (0.04)	0.02 (0.04)	0.00
Community meetings participation	1,370	2.64	0.23*** (0.08)	0.48*** (0.09)	-0.02 (0.09)	0.00
Respondent has leadership role in community	1,370	0.02	-0.00 (0.01)	-0.00 (0.01)	-0.00 (0.01)	0.86
Index of public goods	1,370	0.03	-0.10 (0.09)	-0.05 (0.09)	-0.16* (0.09)	0.09
Clinic/hospital quality	1,370	2.97	0.03 (0.05)	-0.01 (0.05)	0.07 (0.05)	0.03
Primary school quality	1,370	2.88	-0.03 (0.05)	-0.05 (0.06)	-0.01 (0.06)	0.30
Public space quality	1,370	2.97	0.09* (0.05)	0.09* (0.05)	0.10** (0.05)	0.77
Index of neighbourhood amenities	1,370	-0.06	0.19** (0.09)	0.29*** (0.09)	0.10 (0.09)	0.01
Neighbourhood has *less* smell of drains or sewerage	1,370	-0.02	0.33*** (0.09)	0.45*** (0.10)	0.20** (0.10)	0.00
Neighbourhood has working streetlights	1,370	0.24	-0.00 (0.03)	-0.03 (0.06)	0.03 (0.06)	0.23
Less debris/rubble lying around neighhbourhood	1,370	2.42	0.06 (0.06)	0.12* (0.06)	0.01 (0.07)	0.02
Condition of piping and sewerage system	1,370	-0.03	0.17* (0.09)	0.29*** (0.10)	0.04 (0.10)	0.00
Feels safe at night	1,370	5.54	0.21** (0.09)	0.30*** (0.09)	0.13 (0.10)	0.02
Overall neighbourhood rating	1,370	5.33	0.39** (0.18)	0.95*** (0.20)	-0.17 (0.19)	0.00
Proud of neighbourhood	1,370	3.77	0.24*** (0.09)	0.41*** (0.10)	0.07 (0.10)	0.00
Preference to stay	1,370	3.52	0.26** (0.11)	0.54*** (0.11)	-0.03 (0.12)	0.00

Note: This table shows the ITT estimates of winning the housing lottery side-by-side with heterogeneous effects for households that move into their units and those that stay (do not move). ITT results in Column 3 come from one regression, the decomposition in Columns 4-6 come from a separate regression, which uses Equation 3 to look at outcomes for mover and non-movers from the 10th round while controlling for a rich set of baseline covariates that predict whether households move in or not. Column 6 presents the p-value for a test of equality between the results in Column 4 and Column 5.

Table A44: Effects of winning the lottery and moving house on children's education outcomes. Endline 2

Outcome	Control mean (1)	ITT Lottery (2)	By Moving Decision: Moved (3)	By Moving Decision: Stayed (4)	Equality pval (5)
Enrolled (all < 30)	0.656	-0.004	0.000	-0.009	0.66
		(0.020)	(0.022)	(0.022)	
Enrolled (all < 18)	0.958	-0.001	0.011	-0.012	0.18
		(0.017)	(0.018)	(0.020)	
Enrolled (primary age, < 15)	0.970	-0.006	0.009	-0.019	0.19
		(0.019)	(0.020)	(0.024)	
Enrolled in highschool or higher (all 15 – 19)	0.613	0.053	0.038	0.071	0.56
		(0.057)	(0.063)	(0.064)	
Enrolled in tertiary (all 19 – 24)	0.242	-0.006	-0.002	-0.010	0.90
		(0.055)	(0.061)	(0.064)	
Enrolled in University (all 19 – 24)	0.203	-0.031	-0.009	-0.057	0.38
		(0.051)	(0.057)	(0.059)	
Completed highschool (all > 18)	0.703	0.019	0.043	-0.011	0.31
		(0.048)	(0.055)	(0.055)	
Completed degree (all > 24)	0.564	-0.076	-0.071	-0.083	0.90
		(0.090)	(0.101)	(0.103)	
Completed or enrolled in highschool (all > 14)	0.762	0.023	0.030	0.014	0.66
		(0.036)	(0.041)	(0.040)	
Grade in most recent year of school (all < 19)	79.368	1.477	1.984	0.907	0.44
		(1.166)	(1.307)	(1.409)	
Days absent from school in last 30 (all < 18)	0.928	-0.356*	-0.304	-0.407*	0.50
		(0.187)	(0.192)	(0.212)	
Aspires to tertiary education (all < 18)	0.906	0.024	0.030*	0.018	0.14
		(0.016)	(0.016)	(0.016)	
Confidently aspires to tertiary education (all < 18)	0.836	0.073**	0.088***	0.060*	0.26
		(0.029)	(0.031)	(0.032)	

Note: This table shows the ITT estimates of winning the housing lottery side-by-side with heterogeneous effects for households that move into their units and those that stay (do not move). ITT results in Column 3 come from one regression, the decomposition in Columns 4-6 come from a separate regression, which uses Equation 3 to look at outcomes for mover and non-movers from the 10th round while controlling for a rich set of baseline covariates that predict whether households move in or not. Column 6 presents the p-value for a test of equality between the results in Column 4 and Column 5.

Table A45: Effects of winning a late lottery very recently on children's education - Endline 2

Outcome	N	Control mean	ITT Estimate Lottery Coeff	Std. Err.	Sharpened q-value
	(1)	(2)	(3)	(4)	(5)
Enrolled (all < 30)	1,898	0.676	-0.054**	0.024	0.122
Enrolled (all < 18)	1,025	0.978	-0.034*	0.018	0.177
Enrolled (primary age, < 15)	675	0.986	-0.012	0.015	0.655
Enrolled in highschool or higher (all 15 – 19)	476	0.690	-0.061	0.075	0.655
Enrolled in tertiary (all 19 – 24)	498	0.282	-0.128*	0.070	0.177
Enrolled in University (all 19 – 24)	498	0.225	-0.179***	0.064	0.067
Completed highschool (all > 18)	665	0.753	-0.042	0.056	0.655
Completed degree (all > 24)	257	0.558	0.047	0.095	0.809
Completed or enrolled in highschool (all > 14)	1,141	0.822	-0.099**	0.040	0.086
Grade in most recent year of school (all < 19)	733	81.328	-0.273	1.473	0.925
Days absent from school in last 30 (all < 18)	993	0.635	-0.017	0.185	0.928
Aspires to tertiary education (all < 18)	1,025	0.989	-0.015	0.016	0.655
Confidently aspires to tertiary education (all < 18)	1,025	0.923	0.008	0.031	0.925

Note: This table shows the ITT estimates of winning the housing lottery side-by-side with heterogeneous effects for households that move into their units and those that stay (do not move). ITT results in Column 3 come from one regression, the decomposition in Columns 4-6 come from a separate regression, which uses Equation 3 to look at outcomes for mover and non-movers from the 10th round while controlling for a rich set of baseline covariates that predict whether households move in or not. Column 6 presents the p-value for a test of equality between the results in Column 4 and Column 5.

A4.11 Heterogeneous treatment effects by allocated site - First Endline

Table A46: Heterogeneous treatment effects by location of allocated site: household consumption and location (First Endline)

Outcome	N	CM	Differential effects by km from City Centre 0-4	6-12	16-2	25-30	pval
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Housing quality index	1,525	-0.05	0.34***	0.46***	0.71***	0.58***	0.003
			(0.10)	(0.14)	(0.06)	(0.07)	
Distance from city centre	1,525	5.40	0.93*	3.40***	4.33***	4.84***	0.000
			(0.55)	(0.77)	(0.32)	(0.39)	
Transport expenditure	1,525	12.26	-1.18	0.53	4.10***	2.13*	0.003
			(1.50)	(2.08)	(0.87)	(1.06)	
Consumption (no housing & transport)	1,525	142.20	9.75	15.99	10.20	-9.26	0.031
			(9.74)	(13.28)	(5.57)	(6.75)	
Non-housing Asset index	1,450	0.06	-0.14	-0.05	-0.06	-0.11	0.840
			(0.11)	(0.15)	(0.06)	(0.08)	

Note: Each row represents a regression of the named outcome on which housing site the household was assigned to, with non-lottery winners as the omitted category, as in specification 4. Columns 3 to 6 show the ITT effect of winning a government house in the distance band indicated in the column header. Column 7 provides the p-value for a joint test of equality of the four site-specific coefficients in Columns 3 to 6.

Table A47: Heterogeneous treatment effects by location of allocated site: household labour supply (First Endline)

Outcome	N	CM	Differential effects by km from City Centre 0-4	6-12	16-2	25-30	pval
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Household labour market index	1,525	0.02	-0.17	0.01	0.04	-0.11	0.104
			(0.10)	(0.14)	(0.06)	(0.07)	
Earnings per working age adult	1,525	85.44	-27.37***	-3.24	6.41	-5.05	0.001
			(8.22)	(11.41)	(4.80)	(5.82)	
Total employed per working age adult	1,525	0.67	0.03	0.03	-0.01	-0.04	0.165
			(0.03)	(0.05)	(0.02)	(0.02)	
Hours worked per working age adult	1,525	29.40	-1.61	-0.61	-0.26	-2.13	0.513
			(1.74)	(2.41)	(1.02)	(1.23)	

Note: Each row represents a regression of the named outcome on which housing site the household was assigned to, with non-lottery winners as the omitted category, as in specification 4. Columns 3 to 6 show the ITT effect of winning a government house in the distance band indicated in the column header. Column 7 provides the p-value for a joint test of equality of the four site-specific coefficients in Columns 3 to 6.

Table A48: Heterogeneous treatment effects by location of allocated site: household social and neighbourhood outcomes (First Endline)

			Differential effects by km from City Centre				
Outcome	N	CM	0-4	6-12	16-2	25-30	pval
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Subjective wellbeing (ladder)	1,525	4.28	0.56	0.68	-0.01	-0.21	0.257
			(0.42)	(0.59)	(0.25)	(0.30)	
Total number of social ties	1,525	11.37	-3.27***	-1.39	-2.38***	-2.17***	0.484
			(0.83)	(1.15)	(0.48)	(0.58)	
Satisfied with social life in neighbourhood	1,525	0.81	0.02	-0.00	0.03	0.01	0.839
			(0.04)	(0.06)	(0.02)	(0.03)	
Satisfied with neighbours	1,525	3.30	0.07	-0.04	-0.08*	-0.13**	0.087
			(0.07)	(0.09)	(0.04)	(0.05)	
Arguments with neighbours	1,525	0.41	-0.07	0.03	-0.12**	-0.18***	0.339
			(0.08)	(0.12)	(0.05)	(0.06)	
Household is a member of at least one iddir	1,525	0.55	-0.15***	0.14**	0.14***	0.11***	0.000
			(0.05)	(0.07)	(0.03)	(0.03)	
Index of public goods	1,525	-0.00	-0.12	-0.27*	-0.34***	-0.08	0.004
			(0.10)	(0.14)	(0.06)	(0.07)	
Index of neighbourhood amenities	1,525	0.01	0.04	-0.26	-0.29***	-0.15	0.015
			(0.10)	(0.16)	(0.07)	(0.08)	
Index of crime and security	1,525	-0.03	0.33***	0.20	-0.03	0.20***	0.000
			(0.10)	(0.14)	(0.06)	(0.07)	

Note: Each row represents a regression of the named outcome on which housing site the household was assigned to, with non-lottery winners as the omitted category, as in specification 4. Columns 3 to 6 show the ITT effect of winning a government house in the distance band indicated in the column header. Column 7 provides the p-value for a joint test of equality of the four site-specific coefficients in Columns 3 to 6.

A4.12 Heterogeneous treatment effects by allocated site - Second Endline

Table A49: Heterogeneous treatment effects by location of allocated site: household consumption and location (Second Endline)

			Differential effects by km from City Centre				
Outcome	N	CM	0-4	6-12	16-2	25-30	pval
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Housing quality index	1,597	0.29	0.63***	0.64***	0.67***	0.66***	0.980
			(0.12)	(0.13)	(0.09)	(0.10)	
Distance from city centre	1,597	6.07	0.97*	2.67***	3.84***	5.99***	0.000
			(0.50)	(0.57)	(0.41)	(0.45)	
Transport expenditure	1,597	14.95	-0.77	1.46	3.96**	1.82	0.076
			(2.20)	(2.52)	(1.80)	(1.98)	
Consumption (no housing & transport)	1,597	143.20	40.19***	42.01***	10.24	6.63	0.001
			(11.84)	(13.31)	(9.39)	(10.37)	
Non-housing Asset index	1,597	-0.02	0.00	0.10**	0.04	-0.01	0.009
			(0.03)	(0.04)	(0.03)	(0.03)	

Note: Each row represents a regression of the named outcome on which housing site the household was assigned to, with non-lottery winners as the omitted category, as in specification 4. Columns 3 to 6 show the ITT effect of winning a government house in the distance band indicated in the column header. Column 7 provides the p-value for a joint test of equality of the four site-specific coefficients in Columns 3 to 6.

Table A50: Heterogeneous treatment effects by location of allocated site: household labour supply (Second Endline)

			Differential effects by km from City Centre				
Outcome	N	CM	0-4	6-12	16-2	25-30	pval
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Household labour market index	1,597	-0.02	-0.17	-0.07	0.04	-0.12	0.086
			(0.11)	(0.13)	(0.09)	(0.10)	
Earnings per working age adult	1,597	69.43	-14.97*	12.23	7.74	4.92	0.004
			(8.13)	(9.31)	(6.64)	(7.33)	
Total employed per working age adult	1,597	0.50	-0.03	-0.09*	-0.00	-0.09**	0.018
			(0.04)	(0.05)	(0.03)	(0.04)	
Hours worked per working age adult	1,597	24.02	-2.60	-4.05	-0.50	-4.06*	0.096
			(2.17)	(2.49)	(1.77)	(1.96)	

Note: Each row represents a regression of the named outcome on which housing site the household was assigned to, with non-lottery winners as the omitted category, as in specification 4. Columns 3 to 6 show the ITT effect of winning a government house in the distance band indicated in the column header. Column 7 provides the p-value for a joint test of equality of the four site-specific coefficients in Columns 3 to 6.

Table A51: Heterogeneous treatment effects by location of allocated site: household social and neighbourhood outcomes (Second Endline)

			Differential effects by km from City Centre				
Outcome	N	CM	0-4	6-12	16-2	25-30	pval
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Subjective wellbeing (ladder)	1,597	4.48	-0.06	-0.10	0.86***	0.03	0.000
			(0.19)	(0.22)	(0.16)	(0.17)	
Total number of social ties	1,597	4.99	-3.38***	-1.09	-2.53***	1.65***	0.000
			(0.64)	(0.74)	(0.53)	(0.58)	
Satisfied with social life in general	1,597	3.31	0.02	-0.15	0.06	0.08	0.025
			(0.08)	(0.09)	(0.07)	(0.07)	
Satisfied with social life in neighbourhood	1,597	3.23	0.01	0.03	0.12	0.10	0.263
			(0.09)	(0.09)	(0.07)	(0.08)	
Arguments with neighbours	1,040	2.27	-0.15**	0.34***	-0.23***	-0.25***	0.000
			(0.07)	(0.08)	(0.06)	(0.07)	
Household is a member of at least one iddir	1,597	0.67	0.04	0.16***	0.09*	0.04	0.089
			(0.05)	(0.06)	(0.04)	(0.04)	
Index of public goods	1,597	0.03	0.20*	0.44***	-0.08	-0.18*	0.000
			(0.11)	(0.14)	(0.09)	(0.09)	
Index of neighbourhood amenities	1,597	-0.06	0.22**	0.11	0.16	0.17	0.805
			(0.11)	(0.12)	(0.09)	(0.10)	
Index of crime and security	1,040	0.17	0.11	0.08	0.26*	0.14	0.473
			(0.16)	(0.18)	(0.13)	(0.15)	
Overall neighbourhood rating	1,597	5.33	0.15	-0.33	0.54***	0.13	0.001
			(0.23)	(0.25)	(0.20)	(0.21)	
Proud of neighbourhood	1,597	3.77	0.11	-0.27**	0.25**	0.30***	0.000
			(0.11)	(0.11)	(0.09)	(0.10)	

Note: Each row represents a regression of the named outcome on which housing site the household was assigned to, with non-lottery winners as the omitted category, as in specification 4. Columns 3 to 6 show the ITT effect of winning a government house in the distance band indicated in the column header. Column 7 provides the p-value for a joint test of equality of the four site-specific coefficients in Columns 3 to 6.

Table A52: Heterogeneous treatment effects by location of allocated site: housing quality outcomes (Second Endline)

Outcome	N	CM	Differential effects by km from City Centre				pval
			0-4	6-12	16-2	25-30	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Housing quality index	1,597	0.29	0.62***	0.63***	0.66***	0.66***	0.978
			(0.12)	(0.13)	(0.09)	(0.10)	
Formal wall	1,370	0.44	0.29***	0.15	0.21***	0.24***	0.625
			(0.10)	(0.11)	(0.05)	(0.05)	
Formal floor	1,370	0.89	0.03	0.07	0.09***	0.06	0.439
			(0.06)	(0.07)	(0.03)	(0.03)	
Private formal water source	1,370	0.70	0.08	0.12	0.04	0.05	0.833
			(0.09)	(0.09)	(0.04)	(0.04)	
Improved toilet (shared < 5 others)	1,370	0.50	0.45***	0.18*	0.25***	0.20***	0.069
			(0.10)	(0.11)	(0.05)	(0.05)	
Cooks with electricity	1,370	0.88	0.08	0.08	0.08***	0.00	0.008
			(0.06)	(0.06)	(0.03)	(0.03)	
Cooks indoors	1,370	0.55	0.02	0.01	0.03	0.04*	0.868
			(0.04)	(0.04)	(0.02)	(0.02)	
Number of people per room	1,298	4.19	-0.15	0.11	-0.64***	-0.52**	0.204
			(0.42)	(0.44)	(0.19)	(0.21)	

Note: Each row represents a regression of the named outcome on which housing site the household was assigned to, with non-lottery winners as the omitted category, as in specification 4. Columns 3 to 6 show the ITT effect of winning a government house in the distance band indicated in the column header. Column 7 provides the p-value for a joint test of equality of the four site-specific coefficients in Columns 3 to 6.

A4.13 Robustness: Second endline results using Rounds 10, 11, and 12 as treatment

Table A53: Effects of winning the lottery and moving house on consumption, housing, and location using alternative definition of treatment (Endline 2)

Outcome	N (1)	Control mean (2)	ITT Lottery (3)
Housing quality index	1,370	0.000	0.647*** (0.084)
Distance from city centre	1,370	6.441	3.663*** (0.276)
Transport expenditure	1,370	14.440	2.174 (1.883)
Consumption (no housing & transport)	1,370	137.497	9.722 (8.544)
Non-housing Asset index	1,370	-0.039	0.025 (0.028)
Housing amenities index	876	-0.357	0.473*** (0.125)

Note: This table shows the robustness of the ITT results to redefining the treatment variable (Won Housing Lottery) to include households who had won previous subsequent lotteries (11 and 12, as well as 10). The results presented are estimated using specification 1.

Table A54: Effects of winning the lottery and moving house on individual labour supply using alternative definition of treatment (Endline 2)

			ITT Estimate Lottery		
Outcome	N	Control mean	Coeff	Std. Err.	Sharpened q-value
	(1)	(2)	(3)	(4)	(5)
Did any work in the last 7 days	3,493	0.435	-0.027	0.026	0.647
Wage-employed work in the last 7 days	3,493	0.340	-0.044*	0.025	0.563
Self-employed work in the last 7 days	3,493	0.095	0.017	0.017	0.647
Total earnings in the last month	3,493	59.420	2.333	5.452	0.813
Individual hours worked in the last 7 days	3,493	20.727	-1.260	1.327	0.647
Permanent work	3,493	0.250	-0.038	0.024	0.563
White-collar work	3,493	0.154	-0.005	0.018	0.883
Permament white-collar work	3,493	0.259	-0.037	0.025	0.563
Switched between self/wage employment	1,220	0.266	0.066	0.048	0.584
Switched occupations	775	0.520	-0.009	0.060	0.883
Works in areas near housing sites	3,493	0.044	0.008	0.012	0.739
Works close to home	3,493	0.049	-0.014	0.013	0.647
Works in own home	3,493	0.010	-0.001	0.005	0.883
Commute time (cond)	978	40.732	6.828*	4.001	0.563
Commute cost (cond)	1,735	5.880	-1.285	1.771	0.739
Takes a minibus to work	3,493	0.071	-0.007	0.016	0.813
Walks to work	3,493	0.053	-0.009	0.014	0.739

Note: This table shows the robustness of the ITT results to redefining the treatment variable (Won Housing Lottery) to include households who had won previous subsequent lotteries (11 and 12, as well as 10). The results presented are estimated using specification 1.

Table A55: Effects of winning the lottery and moving house on children's education using alternative definition of treatment (Endline 2)

			ITT Estimate Lottery		
Outcome	N	Control mean	Coeff	Std. Err.	Sharpened q-value
	(1)	(2)	(3)	(4)	(5)
Enrolled (all < 30)	2,055	0.655	-0.043*	0.025	0.265
Enrolled (all < 18)	1,182	0.957	-0.039**	0.019	0.265
Enrolled (primary age, < 15)	915	0.969	-0.051**	0.020	0.162
Enrolled in highschool or higher (all $15 - 19$)	476	0.617	0.030	0.074	0.811
Enrolled in tertiary (all $19 - 24$)	498	0.244	-0.077	0.075	0.561
Enrolled in University (all $19 - 24$)	498	0.204	-0.130*	0.073	0.265
Completed highschool (all > 18)	755	0.709	0.014	0.062	0.869
Completed degree (all > 24)	257	0.574	0.017	0.099	0.869
Completed or enrolled in highschool (all > 14)	1,141	0.768	-0.023	0.047	0.807
Grade in most recent year of school (all < 19)	734	79.425	1.350	1.602	0.650
Days absent from school in last 30 (all < 18)	1,067	0.941	-0.349	0.240	0.356
Aspires to tertiary education (all < 18)	1,182	0.908	0.010	0.015	0.722
Confidently aspires to tertiary education (all < 18)	1,182	0.837	0.051	0.036	0.356

Note: This table shows the robustness of the ITT results to redefining the treatment variable (Won Housing Lottery) to include households who had won previous subsequent lotteries (11 and 12, as well as 10). The results presented are estimated using specification 1.

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