Better Neighborhoods or Better Houses? The Effects of Housing Policies on Poor Households in Brazil

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Abstract

This paper evaluates the effects of a housing program that built houses for low-income families from the city of Rio de Janeiro (Brazil). We explore the lotteries used to select the program's beneficiaries to provide evidence of its effects on location, housing quality, housing costs, and household choices. The program induced households to move to less populated, more impoverished, and more distant neighborhoods. However, it increased the houses' quality in which these households lived and decreased their housing costs. Increases in other expenditures did not compensate for the decline in housing costs. Furthermore, we find the program did not influence labor force participation and income and weakly increased teenagers' enrollment. Overall, our evidence contributes to understanding the mechanisms through which housing programs affect well-being.

Keywords: *Housing Policies, Houses, Neighborhoods, Schooling, Labor Supply*

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1 Introduction

The United Nations estimates that over 800 million people live in slums located in the cities throughout the world (UN-HABITAT, 2015). The lack of sanitation, the overpopulation, and the poor public services that define these neighborhoods are thought to increase poverty, deteriorate health, and stimulate crime (Wilson, 1987; Jencks & Mayer, 1990; Glaeser, 2011; Marx et al., 2013). Throughout the world, governments have responded to this issue by offering poor households houses on peripheries (Barnhardt et al., 2017). However, to the extent that these policies relocate households further from job opportunities, there is a concern that they might have unintended consequences (Glaeser, 2011; Picarelli, 2019).

This paper contributes to the literature on the consequences of housing policies in developing countries by documenting the direct and indirect effects of a large-scale housing program called *Minha Casa Minha Vida* (hereafter, MCMV) implemented in Brazil in the 2010s. The MCMV consists of different initiatives that subsidized home purchases. Our research focuses on poor households (total income up to R$ 1,600 per month or US$ 300 at the current exchange rates) living in the municipality of Rio de Janeiro. These households were selected to receive highly subsidized apartments built specifically for the program using lotteries.[1] We explore two lotteries that took place in the year 2013 to examine the direct effects of this program on neighborhood quality, housing quality, and housing costs and its indirect effects on school enrollment, labor force participation, and income.

Our investigation uses a novel dataset linking the lotteries' official records, data of the program's contracts, geo-coded information on neighborhoods, jobs, and schools, as well as socioeconomic information from the *Cadastro Único* (Brazil's unified registry of beneficiaries of social policies) from the period 2012-2018. This dataset enables us to compare

[1]We choose Rio de Janeiro mainly for two reasons. First, it was one of the few cities in Brazil to make available the list of participants and lottery winners with name and CPF (taxpayer registration number). Second, the municipality organized general lotteries with clear rules based on the Brazilian Federal Lottery.

winners ("treatment group"), and losers ("control group") of these lotteries both before and after the lotteries occurred and the units built under the program were delivered. To ensure comparability between these groups, we focus on beneficiaries of the *Bolsa Família* program (Brazil's flagship social policy) who entered into the *Cadastro Único* before the MCMV started. Because beneficiaries of the *Bolsa Família* program must update their information in 24-month intervals, the first restriction ensures we observe most of these households multiple times. Moreover, because households were supposed to register in the *Cadastro Único* to participate in MCMV lotteries, the second restriction ensures we focus on households who entered our data because of the program. After these restrictions, we provide evidence that the treatment and the control groups' demographic and economic outcomes were comparable for the lotteries that occurred in 2013.[2]

We divide our investigation into four parts. First, we examine the program's take up. Using contract records, we estimate households in the treatment group are 54 p.p. more likely to sign a contract to purchase a house built under the MCMV program than households in the control group. Using administrative data, we estimate that these households are roughly 30 p.p. more likely to live or move to the neighborhood where the MCMV projects were built. There is no evidence these numbers decrease in the first three years after the households move, contrasting with the evidence of increasing program exit over time documented by Barnhardt et al. (2017) in India.

Second, we document the MCMV effects on neighborhood quality. Combining the MCMV's records, administrative data, and geo-coded information of neighborhoods and the location of existing schools and job opportunities, we provide evidence the program moved households to neighborhoods that are less populated, poorer, and more distant from jobs and schools.

[2]Our results are robust to using other lotteries. However, we opt to exclude them from our empirical investigation because we cannot ensure the treatment and control groups are balanced. We discuss this issue in detail in Section 3.

Third, we document the MCMV effects on housing quality and housing costs. Combining MCMV's records and administrative data, we find that households in the treatment group have houses 26% larger, 6 p.p. more likely to have wood/tile floor, and 3 p.p. more likely to be connected to the sewage system than the households in the control group. We further find these households reduce their expenditures with rents by R$ 37.8-43.8 (70-80% of the control mean). While increases in spending with utilities mitigate the reduction in rents, expenditures in general fall by R$ 28.9-33.6 (10% of the control mean). These findings highlight the heterogeneous effects of the program on houses and neighborhoods.

Fourth, to understand how the heterogeneous effects of the MCMV on houses and neighborhoods map into economic outcomes, we examine the program's short-run effects on labor supply, income, and school enrollment. Using administrative data, we find null effects of the program on school labor supply and income both immediately and some years after the treatment. The decrease in total expenditures combined with the null effect on income indicates that households might be increasing savings or investments due to the program. Furthermore, we find evidence the program increases the enrollment of teenagers. However, we find no effects on enrollment in high school and high school completion rates, indicating age-grade distortion might be growing.

The evidence provided in this paper contributes to the growing literature on the effects of housing programs. The literature on housing programs in developing countries highlight these programs often move families to more isolated neighborhoods (e.g., Barnhardt et al. (2017), Picarelli (2019), and Franklin (2019)). This might deteriorate their job prospects (e.g., Picarelli (2019)) and induce program exit (e.g., Barnhardt et al. (2017)). Consistent with this literature, we document the MCMV moves households to more isolated neighborhoods. However, we find that improvements in housing quality and decreases in housing costs – benefits not previously documented in the literature – compensate for increased isolation. Furthermore, we find no evidence of program exit or reductions in employment. Indeed, our results on economic outcomes are closer to the ones from stud-

ies in developed countries (e.g., Jacob & Ludwig (2012), Oreopoulos (2003), Jacob (2004) and Chetty et al. (2016)). However, opposite to these studies, where families were induced to move to better neighborhoods, we find null effects on economic outcomes in a setting in which households move to more isolated neighborhoods.

This paper further contributes to the literature on slums (e.g., Marx et al. (2013)). This literature emphasizes that closeness to city centers is important to ensure that poor households benefit from urban living. This is consistent with urban economic models, which predict that employment and income would decline in response to increases in the distance to job opportunities (e.g., Alonso et al. (1964)). However, our findings show that living close to city centers provided negligible benefits for households in employment and income. A possible explanation is that our effects are estimated for a set of households who did not have good labor market prospects.

Finally, this paper adds to the literature evaluating the consequences of the MCMV program. Other studies use the lotteries from Rio de Janeiro and some other selected municipalities to examine the program's effects on formal employment using data from RAIS (a matched employer-employee registry of employment). Mata & Mation (2018) and Chagas et al. (2019) find small negative effects of the MCMV on formal employment. Pacheco (2019) also find negative effects of the MCMV on formal employment right after the houses are delivered but finds these effects revert in three years. She further documents the program moves households further from job opportunities. Leape (2020) extends the former work adding more lotteries the took place in Rio de Janeiro (but balancing the treatment and control groups using a propensity-score method) and finds that moving to a MCMV unit increased the likelihood of employment by 2% after four years.[3] This literature focuses on outcomes measured using RAIS because it is hard to follow the lotteries' participants through time using other datasets. We complement this literature

[3]Less related to our work, Teixeira (2019) examine the effects of the MCMV on credit access, and Bueno et al. (2018) on political preferences.

on two dimensions. Methodologically, we provide evidence of how it is possible to use restrictions to eliminate selection of the MCMV beneficiaries into and out of the *Cadastro Único* and follow them through time in this dataset. This enables us to eliminate some of the differences between lotteries' winners and losers documented in the existing literature and conduct more thorough randomization checks.[4] Empirically, we examine the effects of the program on more outcomes. This enables us to document effects on housing quality, housing costs, formal and informal employment, and enrollment not previously studied in this program's literature.[5]

The rest of this paper is divided into six sections. Section 2 describes the institutional background of the program. Section 3 presents the data, describes the sample selection, and tests the balance of the sample. Section 5 describes the expected effects of the program. Section 6 present the results. Section 7 concludes the paper.

[4] Mata & Mation (2018) check randomization only for demographic characteristics and did not find balance on two of the six lotteries they analyze, while Chagas et al. (2019) documents *Cadastro Único* outcomes are not balanced in the lotteries he studies.

[5] This comes at the cost of restricting attention to lotteries' winners and losers of the MCMV who are also beneficiaries of the *Bolsa Família* program. This sub-population is probably poorer than the population targeted by the MCMV. We discuss this in detail in Section 6.

2 Institutional Context

This section describes the institutional background of the *Minha Casa Minha Vida* (MCMV) program focusing on the features relevant to our empirical investigation. Appendix A provides a detailed description of the program.

2.1 The *Minha Casa Minha Vida Program*

The *Minha Casa Minha Vida* (MCMV) program was created in the late 2000s to provide housing for low and middle-income households in Brazil. In the period 2009-2018, the program financed the construction of 3.95 million houses at a total cost of about R$430 billion (US$80.3 billion at the current exchange rates) (PAC, 2018).[6]

The MCMV offered different types of subsidies for households in different segments determined according to their income levels.[7] Its resources came from the federal government budget and are managed and channeled mainly by *Caixa*, a stated-owned bank specialized in mortgage financing. This bank is responsible for certifying construction companies, contracting the development of housing projects, and providing subsidies for eligible households.[8]

Roughly 30% of these houses were built and sold to households in the program's segment 1 (income up to R$ 1,600 per month or US$ 320 at the current exchange rates). Subsidies for households in this segment could go up to 90% of the unit cost. There were no down payment requirements, and monthly installments were capped at 5% of the household income (or R$ 25). Because the demand for houses built for households in this segment typically exceeded the supply of units, municipalities organized lotteries to select its

[6]Appendix Table A1 reports information on the number of units financed for urban poor households by the MCMV until 2017.

[7]Appendix Table A2 describes these subsidies in detail as well as the average value of the units built for these different groups.

[8]Table A4 reports segment 1 corresponds to 32% of the of units (constructed and under construction) and 20% of the investment in the MCMV Program. It further reports that the typical value of a unit of segment 1 is roughly 50% of the typical value of a unit in segment 2 or 3.

beneficiaries.[9]

Housing units built through MCMV must have at least two bedrooms, a living room, a kitchen, and a bathroom. Its minimum surface area is 37 m^2 (roughly 400 sq^2). These houses are built in housing projects which have from a few dozen to more than a thousand units. The location of these projects must comply with minimum requirements regarding environmental planning, sewage treatment, connection to the electricity grid and the water network, access roads, and public transportation.[10]

Households were required to register for the lotteries either online or at municipal offices. In theory, households in the *Cadastro Único* eligible for the program were registered automatically. However, in practice, it is unclear whether local governments (responsible for selecting the beneficiaries) registered these households. Indeed, we observe the that not all households eligible for the MCMV observed in the *Cadastro Único* were in the lists of lotteries. When housing projects were close to completion, local officers organized the lottery among registered households to select beneficiaries. People forcibly displaced from their homes or individuals with disabilities are prioritized in separate lotteries. Apart from this, the allocation mechanism is straightforward. If the last two digits of the participant's registration number matched the Federal Lottery draw's last two digits, the household is selected. When the units' construction finishes, winners of the lotteries are invited to sign their contracts with *Caixa*. At this moment, officials check the household's eligibility. Importantly, units cannot be legally sold or rented.

2.2 The Lotteries in the Municipality of Rio de Janeiro

Our investigation focuses on the lotteries in Rio de Janeiro, Brazil's second-largest municipality, with 6.7 million inhabitants. This municipality received 2% of the units and

[9]Housing lotteries were implemented by Ordinance n. 140 from the Ministry of Cities enacted on 2010.
[10]Appendix Figure A2 shows pictures of a typical house plan, building and surroundings of a MCMV project.

2.45% of the MCMV program's total funding in the period 2009-2018. In total, 27,843 low-income households received units from the program. This corresponds to more than 1% of the number of households of the municipality. The typical unit built in Rio de Janeiro was priced at about R$ 62,566 and had square footage of about 45 m^2.[11] We focus on this municipality for two reasons. First, Rio de Janeiro publicly released the records of the winners and losers of the lotteries that took place in the city, giving us a comparable control group to estimate causal effects. Second, the municipality is known for the long-lasting prevalence of slums in the surroundings of its most important neighborhoods (Perlman, 2010; Monteiro & Rocha, 2017).

A total of 12 lotteries occurred in the period 2011-2015.[12] Three lotteries occurred in 2011, one in 2012, two in 2013, none in 2014, and six in 2015. These 12 lotteries selected households to live in 31 different projects delivered between the years of 2012-2018.[13] . Demand exceeded the supply of units in all lotteries with 0.1% to 4.2% of the subscribers being selected. Winners were contacted by phone or letter by public officials who offered them a house of the program. Typically, there was a period of one to two years between the lotteries and the signing of the contracts.

Figure 1, Panel A depicts the location of these housing projects. It further shows the spatial distribution of the households who register for the lotteries. The projects are concentrated in the municipality's western neighborhoods while the subscribers come mostly from the municipality's western and northern neighborhoods.[14]

While we observe data from all lotteries from 2011, 2012, 2013, and 2015, our invest-

[11] We obtain the average value of the unit for Rio de Janeiro from the dataset of contracts provided by *Caixa*. The average value for Brazil is R$ 59,509

[12] Here we focus on general lotteries. There were specific lotteries for disabled and elderly, and for people living in risk areas. Information on the subscribers is public available in the website `http://www.rio.rj.gov.br/web/smhc/menu-minha-casa-minha-vida#`.

[13] Appendix Table A.3 presents details on the lotteries and the projects

[14] Appendix B reports summary statistics of projects location combining spatial data with the MCMV units location and population census data by census tract to describe the neighborhoods where the MCMV units were built.

igation focuses on the two lotteries that occurred in the year of 2013. We exclude the lotteries that occurred in 2011 due to absence of pre-program information of their winners and losers. This occurs because we start observing information on demographic and economic outcomes of most of the households in 2012. However, this is the year in which the winners of the 2011 lotteries received their units. Because we do not know exactly when households moved to the units (we approximate these dates using date on contract signature), it is not possible to test whether the winners and losers of the lotteries were comparable before the MCMV was implemented.

We exclude the lotteries that occurred in 2012 and 2015 due to a combination incomplete information and implementation problems. The 2012 housing project was invaded before the units were delivered (see Appendix A for details) and the municipality included the housing project in a later lottery that took place in January 14, 2015. The lists of subscribers of the 2015 lotteries have a number of problems (e.g., repeated identifiers, incomplete names – see Appendix A for details). This puts into question the integrity of the lotteries.[15]

Figure 1, Panel B depicts the location of the projects allocated in the 2013 lotteries and the origins of its subscribers. As most MCMV projects implemented in the municipality, the projects are located in Rio de Janeiro's western zone. The origins of the subscribers are also almost identical to the origins of the subscribers in general. This reflects the fact that the list of participants does not change much. Indeed, a large share of the households participate in multiple lotteries. Te similarities between the projects' location and the subscribers of the 2013 lotteries and the rest of the lotteries indicates the effects from these lotteries is informative of the effects of the MCMV in the municipality in general.

[15]Appendix D provide evidence it is possible to balance the lists of winners and losers of the 2011 and 2015 lotteries by resorting excluding beneficiaries not observed before the treatment and lotteries with more implementation problems. It further shows that including these lotteries does not influence our results.

3 Data Construction

3.1 Data Sources

We use data from multiple data sources. To obtain information on housing quality, expenditures, enrollment, labor force participation, and income of the lotteries' subscribers, we combine publicly-available records from the MCMV lotteries with microdata of the beneficiaries of the *Bolsa Família* program which registered in the program and, therefore, entered in the *Cadastro Único* (Brazil's unified registry of beneficiaries of social policies) before the MCMV started. To understand if and when the households selected in the lotteries program signed a contract to purchase houses constructed for the MCMV program, we match this data with official data of the program's contracts obtained from *Caixa*. Furthermore, to generate information on neighborhood quality, we merge information of the location of the households with neighborhood-level characteristics computed using the 2010 Population Census and information on distance to jobs and education institutions from Pereira et al. (2020). We describe each of these data sources in detail below.

Lotteries. Rio de Janeiro's municipal government provides the list of participants (winners and losers) in the form of PDF files.[16] It is the main source of information on "treated" and "non-treated" individuals we use in the research. We digitized this data to obtain the CPF (taxpayer registration number), the full name, and the treatment status of each individual who subscribed in the lottery. We further use the lottery records to obtain the name of the housing projects with units allocated through each lottery.

Cadastro Único. The Ministry of Citizenship's unified register of social beneficiaries provides demographic and economic information of the low-income population of Brazil. It is the main source of information on demographic, households and houses' characteristics, expenditures, and economic outcomes we use in this research.

[16] See `http://www.rio.rj.gov.br/web/smhc/menu-minha-casa-minha-vida#`.

The *Cadastro Único* was created in 2001 and, since 2003, it is the tool used for identifying and monitoring beneficiaries of the *Bolsa Família* program (Mostafa & Sátyro, 2014). While its focus is on the *Bolsa Família* beneficiaries, this registry is increasingly used to identify and monitor beneficiaries of other programs. Currently, more than 20 programs run by the Federal Government and numerous programs run by local governments use the *Cadastro Único* to track their beneficiaries.

In 2018, this dataset contained information of 23 million households, 13.8 million of which were beneficiaries of the *Bolsa Família Program*. Its data is grouped into six categories: personal identification, household identification, household characteristics, schooling, work, and income. Supplementary information on expenditures, participation in social programs, and vulnerability (homeless, engaged in child labor, etc.) has been collected either for particular groups of households or at specific dates.

We use *Cadastro Único* extractions for the period 2012-2018. Each extraction is a cross-section including the most recent information of each household from the registry. Importantly, it contains the date in which the information was updated. This will be essential to enable us to follow households included in this dataset over time. At the individual-level, we obtain the following information from the *Cadastro Único*: household identifier, CPF (taxpayer registration number)[17], NIS (social registration number), full name, demographic information (age, sex, marital status etc.), enrollment, and employment. At the household-level, we obtain the following information: household identifier, date of the update house characteristics, participation in the *Bolsa Família*, expenditures, and income per capita.

To ensure comparability between our treatment and control groups, we focus on beneficiaries of the *Bolsa Família* program (Brazil's flagship social policy). Because households must update their information every 24-months to continue eligible for the federal pro-

[17]The CPF identifying is missing for almost 50% of the individuals registered

grams, this enables us to follow a group of households over time. This will be typically the case of the households receiving the *Bolsa Família* program. Figure 2 provides evidence of these households update their information much more frequently than the other households.

Contracts. *Caixa* provides information on the mortgages signed by the beneficiaries of the MCMV program. We obtain the NIS (social registration number), the date the contract was signed, the value of the mortgage, the subsidy, and the name and address of the housing project of each beneficiary of the MCMV program. The information on the address is incomplete, but we retrieve the complete address using geocoding tools from Google Maps Geocoding API.

Neighborhoods. We use tract-level information on demographic, economic and tract characteristics from the 2010 Population Census to examine the average characteristics of the neighborhoods in which "treatment" and "control" households are located both before and after the MCMV. We extract the following indicators from the census: the share of poor households, the average household income, the share of black individuals, the average schooling, and the share of households located in streets with paved roads, the share of households located in streets with garbage collection, and the share of households located in streets with open sewage.

We also explore data on access to job opportunities and educational institutions constructed by Pereira et al. (2020). These authors combine data on firm location coming from the Ministry of Labor's administrative data (*RAIS*) and the Ministry of Education's administrative data (*Censo Escolar*) with geo-coded timetables of public transportation to built a dataset containing information on the share of employment opportunities and educational facilities accessible in 30, 60, 90, and 120 minutes at a 200m $\times$ 200m resolution. We aggregated this data at the neighborhood level.

3.2 Data Linkages

Our procedure to match the different sources of data described in the previous section has four different steps.

In the first step, we use the CPF and the name to match the lotteries' records with data from the *Cadastro Único*. We define a household as being treated if an individual of this household participated and won one of the MCMV lotteries. We define a household as being non-treated if an individual of this household participated but lost one of the MCMV lotteries.

There are two concerns with this match. The first is that the CPF is optional in the *Cadastro Único*, available for about 50-55% of the individuals. We mitigate this problem using both the CPF and the names of the individuals to match these datasets. The second concern with the match is that the *Cadastro Único* does not contain information of the full set of individuals who subscribed to the lotteries. In theory, participants must enroll in the *Cadastro Único* to participate in the lotteries. However, in practice, participants were only required to register in the *Cadastro Único* to receive the houses from the program.[18] This endogenous selection into the *Cadastro Único* might unbalance the characteristics of households in the treatment and control groups, threatening our research design. We deal with this issue by focusing on the beneficiaries of the *Bolsa Família* program who entered into the *Cadastro Único* before the first MCMV lottery in Rio de Janeiro (June 11, 2011). These restrictions ensure treatment and control households were randomly allocated in the lotteries' records and the records matched with the *Cadastro Único*. Using these restrictions, we obtain a match rate of 10.5% for the lotteries that occurred in 2013. For the lottery that occurred in October 2013, we find 60 treated households and 49,654 control households. For the one that occurred in December 2013, we find 297 treated units and

[18]For instance, our data indicates that the probability of finding households in the treatment group in any extraction of the *Cadastro Único* is much higher than the likelihood of finding households in the control group.

51,394 control units.

In the second step, we use the NIS and the name of the individuals to match the our data with the contract-level information of the MCMV.[19] We define a household as having received a house from the program if a member of the household signed a contract with *Caixa* to receive a house built by the MCMV. We found that about 57% of the treated households signed contracts to purchase the program's units.

In the third step, we use neighborhood codes from IBGE to match our data with data on neighborhood quality from the 2010 Population Census. In the baseline, there are no neighborhood codes in the *Cadastro Único* for about 15% of our data, implying we do not have neighborhood information for them. However, we do have neighborhood information for most of our sample in the post-treatment period. This is due to improvements in the *Cadastro Único* information over time.

In the fourth step, we use the more recent information to build a panel dataset containing information of the treatment and control households pre and post-treatment. For each household, we define the pre-treatment (post-treatment) periods as the observations with information updated prior to (after) April 27, 2015. This is the last date of delivery of the projects for which the households in our sample subscribed. Our empirical analysis will typically focus on the first and the last observations of each household.

Our empirical investigation focuses on *Bolsa Família*'s beneficiaries which, as reported in Figure 2, help us to track the households in our sample through time. However, there is still some attrition in our data. Indeed, we do not find roughly 30% of the households from our matched dataset. Figure 3 explains the sample construction. The black rectangle denotes the *Cadastro Único* and blue rectangle denotes the lotteries. The gray area represents the final match.

After linkages, we are left with 50 treatment (34,883 control) units for the lottery from

[19] All individuals registered in *Cadastro Único* have a NIS.

October 2013 and 224 treatment (36,080 control) units for the lottery of December 2013. We merge the lists and remove observations which appear in both. Because the lists of subscribers are remarkably similar, this reduces a lot the number of observations in our sample. Our final sample has 36,470 households which observe in the pre and post-treatment periods. The treatment group has 274 observations and the control group 36,196 observations in each period. Figure 4 reports a histogram of the year of the updates in the first pre-treatment period (which we use to test the balance of our sample) and last post-treatment period (which we use to test the MCMV's effects). Information from the pre-treatment period typically comes from the year 2011, while information from the post-treatment period is divided in the years 2015-2018 (less than 12 months, 12-24 months, and more than 24 months after the treatment).

4 Empirical Framework

Random assignment implies it is possible to estimate the effects of the MCMV comparing the outcomes of winners and losers of the program's lotteries. Our baseline specification estimates these intent-to-treat (ITT) effects using the following equation:

$$y_i = \alpha + \beta T_i + \gamma \mathbf{X}_i + \epsilon_i, \tag{1}$$

in which y_i is an outcome of interest for household i, T_i is a dummy indicating whether a member of the household i was offered a housing built under MCMV program, $\mathbf{X}_i$ is a vector of pre-determined controls included to improve precision, and ϵ_i is a error term.

The coefficient of interest in equation (1) is β. This coefficient captures the effect of being offered a house built under the MCMV program on outcome y_i. This coefficient is identified under the hypothesis that the lotteries were well-implemented, that is, T_i is not correlated with ϵ_i.

Equation (1) is estimated using household's i most recent information. However, households update their information in different periods, implying their exposure to the program is different. Thus, it is possible to estimate the intent-to-treat (ITT) for different exposures using the following equation:

$$y_i = \alpha + \sum_{s \in S} \beta_s \left(T_i \times E_{is} \right) + \gamma \mathbf{X}_i + \epsilon_i, \tag{2}$$

in which E_{is} is a dummy denoting whether the household was exposed to the program in the intervals $S = \{$0-24 months, 24+ months$\}$. This coefficient is identified under the hypotheses that the lotteries were well-implemented and the timing in which households are observed is exogenously determined. These hypotheses imply $T_i \times E_{is}$ is not correlated with ϵ_i.

4.1 Multiple Testing

Due to the large number of outcomes of interest used in our empirical investigation, inference using conventional methods will probably generate over-rejection of the null hypotheses. This happens because the FWER (Family-Wise Error Rate) – the probability of rejecting at least one null hypothesis when all the null hypothesis are true – increases when the number of hypotheses increases.

To deal with this issue, we use Romano-Wolf step-down procedure to obtain p-values corrected for multiple testing (Romano & Wolf, 2005a,b, 2016). This procedure is a more powerful method to control the FWER than other procedures (e.g., Bonferroni and Holm) that assume the test statistics are independent because it uses re-sampling (bootstrap) to incorporate information about the joint dependence structure of the test statistics of the different hypothesis being tested. It is also more general than other procedures based on re-sampling (e.g., Westfall et al. (1993)) because its algorithm is more general.

The Romano-Wolf correction has been increasingly used in empirical work (e.g., Mazzocco & Saini (2012); Gertler et al. (2014); Olken et al. (2014); Attanasio et al. (2017)). We employ this correction for the groups of outcomes for which we have more than one indicator (neighborhood quality, housing quality, housing costs). The corrected *p*-values should be interpreted as the significance level that would have to be applied to the entire family of hypotheses if we were to accept the null that the effect is zero.

4.2 Balance

To test the integrity of our research design, we estimate equation (1) using pre-treatment indicators. The results are reported in Table 1. We test for pre-treatment differences in five different groups of outcomes: demographics, neighborhood and neighbors characteristics, house characteristics, housing costs, and enrollment and employment. For each outcome, we compute the mean of the outcome for the control group (column 1), the mean

of the outcome for the treatment group (column 2), and the mean differences between the treatment and control groups (column 3). For each group of outcomes, we further report a test of joint significance of the differentes between the treatment and control groups.[20]

Table 1 reports that pre-treatment differences were negligible for all groups of outcomes. Panel A reports pre-treatment differences in demographic characteristics. There are almost no prime-aged males in our sample. More than 90% of the households are headed by females and spouses are present in only 20% of them. Heads have 39 years on average, children under the age of 6 years are present in 45% of the households, and the average household size is about 3.80. Mean differences between the treatment and the control group are economically and statistically irrelevant for all but one outcome. The exception is the number of dwellers which is 0.16 higher in the treatment than in control group. This difference is statistically significant at the 10% level. However, a joint test of significance rejects the hypothesis that these differences are jointly different from zero.

Panels B and C report pre-treatment differences in neighborhood and housing quality. Households lived in neighborhoods with close to 100,000 inhabitants, where almost 80% of the households were connected to the sewage network, 44% of the inhabitants were white, and their income was slightly over R$ 1,400 per month. Their houses had 3.8 rooms and 1.3 dorms. 98% of them had a bathroom, and 56% had either wood or tile floor. Mean differences between treatment and controls groups are minor and not significant at the usual statistical levels.

Panel D reports pre-treatment differences in housing costs. Households spent approximately R$54 on rent, R$20 with electricity, R$37 on gas, and R$ 5.5 with water and sanitation. Panel E reports pre-treatment differences in school enrollment, labor force participation, and income. 90% of the children with 6-17 years were enrolled at school. Comparable

[20]To test the joint significance of the mean differences between the treatment and control groups for each group of outcomes, we estimate the mean differences jointly using Seemingly Unrelated Regression (SUR) and test whether the differences are jointly different from zero using a chi-squared statistic.

figures are found for males and females. 51% of the (female) heads of the households with 25-64 years were employed. Mean differences between treatment and controls groups are minor and not significant at the usual statistical levels.

Taken together, the evidence from Table 1 indicates that the characteristics of the treatment and control groups of the 2013 lotteries are balanced. As discussed before, it is harder to confirm balance for the other MCMV lotteries due to a combination of missing information and implementation issues. However, in Appendix D (Tables D1 and D8), we provide evidence that the 2011 and the 2015 are reasonably balanced once we exclude households without pre-program information and lotteries with problems in the implementation.

5 The Expected Effects of the *Minha Casa Minha Vida*

Before we present the results, we briefly discuss the expected effects of the MCMV projects. We begin by laying out the expected effects of this program on neighborhood quality, housing quality, and housing costs. We then discuss how economic theory and existing evidence suggest effects on these three dimensions influence economic choices.

The geographic concentration of the MCMV projects in the peripheries documented in Section 2 suggests the program might induce households to move to worse neighborhoods. An influential body of work discusses the influence neighborhoods – through their influence on individuals' preferences, social connections, and access to public services – exert on outcomes like schooling, labor force participation, and income (Jacobs, 1970; Wilson, 1987; Jencks & Mayer, 1990; Massey & Denton, 1993; Kowarick, 2002). Recent empirical studies exploring exogenous improvements in neighborhood quality induced by housing programs in the U.S. document that better neighborhoods improve the educational outcomes of children (Chetty et al. (2016) and Chyn (2018)) but do not improve (and might even deteriorate) the labor market outcomes of adults (e.g., Katz et al. (2001), Kling et al. (2007), Jacob & Ludwig (2012), Ludwig et al. (2013)). Thus, to the extent that the MCMV induces households to move to poorer and more distant neighborhoods, we expect this mechanism to (weakly) deteriorate both the educational outcomes of children and adults' labor market outcomes.

However, the houses built under the MCMV program might be of better quality than the houses poor households typically reside in the slums of Rio de Janeiro. There is a long line of empirical studies that discuss how houses with proper sanitation, lighting, and ventilation, might positively affect individual health and well-being (e.g., Galiani & Schargrodsky (2004) and Kling et al. (2007)). In particular, access to proper sanitation has an essential role in reducing the incidence of communicable diseases due to oral contamination (Cutler & Miller, 2005; Alsan & Goldin, 2019). These effects on health might pos-

itively affect the school achievement of children (e.g., Miguel & Kremer (2004), Bleakley (2007)) and the labor supply and earnings of adults (e.g., Currie & Madrian (1999)). Thus, to the extent that the MCMV induced households to move to better houses, we expect this mechanism (weakly) to improve both the educational outcomes of children and the labor market outcomes of adults.

Moreover, the MCMV relieves households of the burden of rent. This reduction in housing expenditures represents an increase in non-labor income. Households will respond to this increase by investing more in human and physical capital and decreasing their labor supply. Empirical evidence from other settings suggest poor households typically respond to increases in non-labor income by investing more both on human and physical capital (e.g., Gertler et al. (2012) and Blattman et al. (2014)). In line with these studies, Kumar (2019) finds positive effects on human capital investments of subsidized housing lotteries in Mumbai (India) despite these lotteries induced households to move to worse neighborhoods. She interprets these effects as a consequence of income effects esteeming from the program's subsidies. Empirical evidence also suggests that poor households respond to increase in non-labor income by reducing their labor supply (e.g., Alzúa et al. (2016)).[21] Thus, to the extent that the MCMV reduces housing expenditures, we expect this mechanism to (weakly) improve the educational outcomes of children and to (weakly) deteriorate the labor market outcomes of adults.

We expect the effects of the MCMV on economic outcomes to reflect the combination of the neighborhood, house, and income effects described in the previous paragraphs.[22] We use our extremely detailed data on neighborhoods and households to investigate how

[21]It is important to note that in the presence of credit constraints, households might increase their labor supply in response to increases in non-labor income. See Banerjee et al. (2020) for evidence on this.

[22]A fourth mechanism highlighted in the literature is that housing programs influence economic decisions by changing tenure security. Moving from slums with poorly defined property rights to projects with well-defined property rights might influence households' economic decisions as suggested by evidence from previous land titling programs (Field, 2007; Galiani & Schargrodsky, 2010). However, we do not expect this mechanism to be relevant in our setting since households cannot sell or formally rent the houses built under the MCMV program.

the MCMV indeed influenced neighborhood quality, housing quality, housing costs, and their combined effect on school enrollment of the children, labor force participation of the adults, and the household's overall income.

6 Results

We present our results in three parts. We begin by discussing MCMV's take-up. We then document the program's effects on neighborhood quality, housing quality, and housing costs. Finally, we examine whether these changes in neighborhood quality, housing quality, and housing costs influence labor force participation of adults, income, and schooling decisions.

6.1 Take-up

The first row of Table 2 reports the share of the control households who signed contracts with *Caixa* (column 1), the share of treated households who signed contracts with *Caixa* (column 2), and the difference in these probabilities (column 3). The control mean is 0% and the treatment mean is 54%. This 54 p.p. difference is highly significant, thereby indicating the lotteries did increase the probability the households benefits from the MCMV program. Furthermore, it is worth noting the control mean indicates there are no "always takers" of the 2013 lotteries, while the treatment mean indicates that "never takers" amount to 46% of the subscribers of these lotteries.

While useful, the contract-level information does not enable us to examine whether the households who signed contracts indeed live in the units built by the MCMV. Indeed, it is possible that households abandon the MCMV houses after a period. Moreover, the contract-level information does not enable us to understand whether the program moved the households to other neighborhoods or simply re-located them in their neighborhood or origin.

Thus, we investigate other measures of take-up built using information of the households' location. The remaining rows of Table 2 reports the results. 6-7% of the treatment and control households lived in the neighborhoods of *Cosmos* and *Santíssimo* (where the units allocated in the 2013 lotteries were built) before the program. This probability in-

creases to 8% for the controls households and to 40% of the treatment households after the program. We further document that 5% of the control households and 35% of the treatment households moved to these neighborhoods in the period of analysis. These measures indicate a take up of 31-32 percentage points.

One concern with policies that move households to other neighborhoods is whether households quit the program as their exposure to it increases. We estimate equation (2) to obtain the effects of the MCMV on the probability of moving to the neighborhoods in which the program's houses were built in different time horizons. As shown in Figure 5, the probability of moving to these neighborhoods increases with the program's exposure. Hence, there is no evidence of program exit. This contrasts with the evidence of increasing program exit over time documented by Barnhardt et al. (2017) for a program in Mumbai (India).

Together, our measures indicate the program's take-up is between 31-54%. These figures are in the range of the rates estimated in the literature. They are higher than the 19%-48% take-up of housing vouchers found in studies analyzing experiments in the U.S. (Rubinowitz & Rosenbaum, 2002; Kling et al., 2007; Jacob & Ludwig, 2012) but are lower than the 66% take-up of houses found in Mumbai (India) (Barnhardt et al., 2017).

6.2 Neighborhood Quality, Housing Quality, and Housing Costs

Table 3 reports the effects of the MCMV on neighborhood quality. Panel A examines whether the program moved households to different neighborhoods, Panel B examines whether the program moved households to locations with different neighbors, and Panel C reports whether the program moved households to locations closer or further from job opportunities and schools. Each row reports the results for a different outcome of interest. Column 1 presents the mean of the control group, column 2 reports the results of a bivariate regression of outcome of interest on a treatment indicator, and column 3 adds

a control for the outcome measured in the baseline. Inference is based on Romano-Wolf p-values corrected for multiple testing.

Panel A shows that the MCMV moved households to neighborhoods that were less populated. The population of the neighborhoods in which the households from the treatment group reside is roughly 12-17,000 smaller than the population of the neighborhoods in which the households from the control group reside. However, the neighborhoods in which treatment and controls households live are no different in terms of access to the sewer network and slightly better in terms of access to the water network. Indeed, using a neighborhood index combining these three variables[23], we find only weak evidence the program moved families to worse neighborhoods in terms of population and infrastructure. The differences between the treatment and control group are small, being significant at the 10% level in the specification without controls and not significant in the specification with controls.

Panel B shows that the MCMV moved households to neighborhoods with a lower share of white residents, labor force participation, and income. The typical head of the household of the neighborhoods in which treatment units live is 2.1 p.p. less likely to be white, 1.1 p.p. less likely to work, and receives R$ 104-106 less than the typical head of the household of the neighborhoods in which control units live. Indeed, using a neighbors index combining these four variables, we find that the program moves households to neighborhoods with resident with worse outcomes.

The findings from Panels A and B indicate that the the MCMV moved households to neighborhoods less populated and with worse socioeconomic according to the 2010 Population Census. However, one concern with these measures is that they do not capture the changes in these neighborhoods that might have occurred after 2010. While this has

[23]We perform a principal component analysis of the neighborhood variables, and and define the neighborhood index as the first principal component. We use the same strategy to build the other indexes used in this section.

the benefit of insuring re-location of treatment households contaminates neighborhood quality, it has the cost of not picking up other changes in neighborhood quality that might have happened after 2010.

Panel C deals with this issue by examining whether the program moved households to neighborhoods closer or further to job opportunities and schools in the post-treatment period. We find the treatment group lives in neighborhoods in which the share of job opportunities (schools) accessible (using public transportation) in less than 90 minutes is 4-6 p.p. (1-3 p.p.) smaller than the in the neighborhoods in which the control group lives. For job opportunities, these results are statistically significant at the 1% level in all specifications while, for educational facilities, these results are statistically significant at the 1% level using controls and at the 10% level using controls.

Together, these results provide robust evidence that the MCMV induced households to re-locate to worse and more distant neighborhoods. This movement is predicted to decrease the consumption of amenities and decrease income net of transportation costs (Alonso et al., 1964; Straszhem, 1987; Glaeser, 2000). This indicates that consumption-maximizing households will choose to move to worse and more distant neighborhoods only if increases in housing quality or decreases in housing costs compensates them for the losses in the consumption of amenities and income.

Tables 4 and 5 test these conjectures. Table 4 reports the effects of the MCMV on housing quality. It tests the effects of the program on the following outcomes: a dummy indicating whether the house has wood or tile floor, a dummy indicating whether the house's sidewalk is paved, a dummy indicating whether the house is connected to the sewage network, the number of rooms, the number of bedrooms, a dummy indicating whether the house has metered electricity, and a housing index. The structure of the table is identical to the structure of Table 3.

We find the program moves households to better houses: the probability of having a

wood or tile floor increases by 7 p.p. ($\approx$ 12% of the control mean), the probability of having a paved sidewalk increases by 7 p.p. ($\approx$ 8% of the control mean), and the probability of being connected to the sewage network increases by 3 p.p. ($\approx$ 3% of the control mean). There is also evidence the MCMV moves households to bigger houses. The number of bedrooms increases by 0.19-0.20 ($\approx$ 15% of the control mean) and the number of rooms increases by 0.34-0.35 ($\approx$ 10% of the control mean). This provides compelling evidence that the program positively affected the quality of the house in terms of size and construction materials and moved families to places with better infrastructure. Furthermore, we find the program also induced the formalization of the households by increasing the probability of the household having metered electricity (as opposed to a irregular connection) by 11-12 p.p. ($\approx$ 20% of the control mean). This reinforces the interpretation the program moves households from slums (or other informal settlements) closer to the city center to apartments located in the outskirts of the city. Together, estimates obtained using a house index built combining all outcomes discussed above indicate that the MCMV increases housing quality by about 0.34-0.39 standard deviations.

Table 5 reports the effects of the MCMV on housing costs. It tests the effects of the program on the following outcomes: expenditures with rent, expenditures with water, expenditures with electricity, expenditures with gas, and total expenditures. The structure of the table is identical to the structure of Table 3. The table shows that increases in housing quality are not the only benefit households obtain from the MCMV program. The program also reduces housing costs significantly. The treatment group spends R$37.8-43.8 per month less in rent than the control group. It is possible this decreases in rents is at least partially compensated by increases in other housing costs. For instance, the increase in the number of rooms and the decrease in illegal connections might mechanically increase the expenditures with water and electricity. Indeed, we find water expenditures are about R$ 5.7-5.8 and electricity expenditures R$12 higher in the treatment group compared to the control group. The former effect is statistically significant at the 5% level while the latter

is significant at the 10% level. Interestingly, however, gas expenditures decline by about R$6.0-6.1. This is consistent with the MCMV moving households out of slums in which drug dealers and/or paramilitaries monopolize the gas distribution, thereby increasing its price.

The magnitude of the effects on water, electricity, and gas expenditures indicates the MCMV generated net decreases in housing costs. Moreover, there is no evidence that other expenditures (e.g., food) increase significantly. As a consequence, we find that the treatment reduces total expenditures by R$ 28.9-33.6. This effect is statistically significant at the 5% level. This indicates the program had a sizable income effect. To get a sense of the magnitude of this effect, it is useful to compute Wald (IV) estimates of the effects of the MCMV subsidies on expenditures. The midpoint of the take up estimates reported before is 0.42, implying the that receiving a house from the MCMV program reduces costs by almost R$75. This effect corresponds to one quarter of the household's reported expenditures.

Appendix C report the effects of the MCMV on neighborhood quality (Figure C1) and housing quality and costs (Figure C2). The effects on neighborhood quality are stable. Interestingly, the effects on the index of housing quality and on housing costs move in opposite directions. The effects on the index of housing quality increase from 0.30 to 0.45 standard deviations. The effects on housing and total costs, on their turn, decline significantly from R$ 40 (R$ 50) to less than R$ 20 (R$ 10) per month.

6.3 Labor Force Participation, Income, and Schooling

Our findings so far indicate that the MCMV moved households to worse neighborhoods but to better and less expensive houses. To understand whether theses chances influence economic choices, we examine the program's effects on female labor force participation, household income, and schooling decisions.

We begin by analyzing the effects of the MCMV on the employment of adults. We expect the deterioration of neighborhood quality and the declines in housing costs to (weakly) decrease employment and the improvements in housing quality to (weakly) increase employment. Table 6 presents the results. As discussed in section 4, we do not observe adult males in our sample of *Bolsa Família* beneficiaries. Thus, we focus on female employment. Panel A uses the labor force participation of the head of the household as the outcome of interest while Panel B uses the share of adult females that work as the outcome of interest. Both panels report results for prime-aged females in general (25-64 years) and for younger (25-44 years) and older (45-64 years) women.

We find no effects of the MCMV on female employment in general. The coefficients are close to zero in most of the specifications. Point estimates are typically positive for younger women but negative for older women. Our results are consistent to the findings of Pacheco (2019) that suggests no persistent impact of the MCMV on employment in the formal market. She finds a negative effect of the program on employment. However, this effect diminishes over time and disappears after three years.[24]

Then, we examine the effects of the MCMV on income. We expect the effects of the program on income to be qualitatively similar than the effects on employment. Table D13 reports the results. There is no effect on wages of the head of the household, total wages of the household, and income per capita. This is consistent with the absence of effects on employment in general. However, it is worth noting the effects on income represent the combined effects of changes in labor supply in the extensive margin (documented in Table 6), changes in the labor supply in the intensive margin (for which there is no information), and changes in hourly wages (for which there is no information). Thus, the null effect on income suggests the responses in these other margins are not relevant as well.

[24] Pacheco (2019) suggests that there was an adaptation by the people drawn by the program through accessibility via individual motorized transport. This evidence is corroborated by work of Mata & Mation (2018) that shows an increase in the purchase of motorcycles by MCMV participants.

The combination of the decrease in expenditures documented before with the stability in income indicates that households disposable income increased due to the MCMV. This is suggestive evidence that the program might be increasing investments (in durable goods, small businesses etc.) or savings, thereby increasing income and consumption in the long run. This increase in investments is consistent with the evidence from Gertler et al. (2012) who document that poor households respond to permanent income increases by increasing investments.

Finally, we analyze the effects of the MCMV on schooling decisions. We expect the deterioration of neighborhood quality to (weakly) decrease enrollment and the improvements in housing quality and the decline in housing costs to (weakly) increase enrollment. Table 8 reports the results. It presents the effects of the MCMV on enrollment both for children in general as well as for boys and girls separately. The gender split is motivated by previous studies that finds that girls' school outcomes respond much more than boys' to housing programs (e.g., Kling et al. (2005)) and other interventions (e.g., Anderson (2008)). Notice that the number of observations is different in each row because the number of households with school-aged children in general, boys, and girls is different. We find some evidence that the MCMV increases the enrollment of teenagers. However, this does not translate into increases in the enrollment of teenagers on high school nor on increases in high school graduation rates among young adults. These pieces of evidence indicate the program might be increasing age-grade distortion.

7 Conclusion

This paper contributes to the literature on the consequences of housing policies in low and middle-income countries by documenting the direct and indirect effects of a large-scale housing program called *Minha Casa Minha Vida* (MCMV) on poor households from the city of Rio de Janeiro (Brazil). We explore two lotteries used to select beneficiaries which took place in 2013 to investigate this program's direct effects of this program on neighborhood quality, housing quality, and housing costs and its indirect effects on school enrollment, labor force participation, and income.

Combining multiple sources of information, we are able to track winners (treatment group) and losers (control group) of these lotteries over time. We find that 34-54% of the households in the treatment group purchase and move to the highly subsidized houses built by the program. We then document the MCMV moved these households to neighborhoods that are less populated, poorer, and more distant from schools and job opportunities but to houses that are larger and of better quality. Moreover, we find that the program decreases significantly housing costs.

Turning to economic outcomes, our findings the suggest that, despite moving households to more distant and isolated neighborhoods, there is no evidence the MCMV decreases children's school enrollment, adults' labor supply, and the household's overall income in the short run. This indicates evidence that either improvements in housing quality and declines in housing costs are compensating the deterioration in neighborhood quality or that neighborhood quality does not affect economic outcomes in the short run. Furthermore, our evidence suggests the declines in housing costs are not generating increases in current expenditures with transportation and food. This is suggestive that households are investing or saving more. Documenting these responses and investigating how they influence households in the long run is an important agenda for future research.

The evidence provided in this paper contributes to the growing literature on the effects of housing programs on poor households. Our findings on economic outcomes are consistent with other studies which find null effects of housing programs on labor force participation and income (e.g., Jacob & Ludwig (2012), Oreopoulos (2003), Jacob (2004) and Chetty et al. (2016) for the U.S., Barnhardt et al. (2017) for India, and Franklin (2019) for Ethiopia). However, in our setting, households moved to worse neighborhoods, while households moved to better neighborhoods in the settings of the aforementioned studies. Moreover, we find no evidence of increases in program exit over time like Barnhardt et al. (2017) and document significant gains in terms of housing quality and reduced housing expenditures not documented previously. These findings highlight the importance of other mechanisms in shaping the effects of housing policies on poor households.

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Table 1: Descriptive Statistics and Randomization Check

	(1)	(2)	(3)	(4)
	Control	Treatment	T-C	N
Panel A: Demographics				
Female head	0.96	0.97	0.01	36470
	[0.18]	[0.17]	(0.01)	
Age	38.72	38.27	-0.45	36470
	[9.37]	[8.80]	(0.53)	
Spouse (0/1)	0.20	0.20	-0.00	36470
	[0.40]	[0.40]	(0.02)	
Children 0-6 (0/1)	0.45	0.46	0.01	36470
	[0.50]	[0.50]	(0.03)	
Dwellers	3.80	3.96	0.16*	36470
	[1.54]	[1.52]	(0.09)	
Joint significance test (p-value)			0.633	
Panel B: Neighborhoods				
Population (in 1000s)	102.18	97.63	-4.55	31615
	[92.37]	[90.85]	(6.09)	
Sewage	0.78	0.77	-0.01	31615
	[0.21]	[0.22]	(0.01)	
Water	0.99	0.99	0.00	31615
	[0.03]	[0.02]	(0.00)	
Sh. Work (head)	0.86	0.86	0.00	31615
	[0.03]	[0.03]	(0.00)	
Avg. Income (head)	1417.8	1430.1	12.35	31615
	[725.6]	[705.8]	(47.34)	
Sh. white	0.44	0.44	0.00	31615
	[0.10]	[0.11]	(0.01)	
Joint significance test (p-value)			0.874	

Descriptive Statistics and Randomization Check (continuation)

	(1)	(2)	(3)	(4)
	Control	Treatment	T-C	N
Panel C: Housing Quality				
Wood/Tile (0/1)	0.55	0.56	0.01	36470
	[0.50]	[0.50]	(0.03)	
Sewage (0/1)	0.90	0.91	0.00	36470
	[0.30]	[0.29]	(0.02)	
Paving (0/1)	0.68	0.69	0.01	36470
	[0.46]	[0.46]	(0.03)	
Electricity (meter 0/1)	0.56	0.57	0.01	35983
	[0.50]	[0.50]	(0.03)	
Dorms	1.32	1.35	0.02	31316
	[0.87]	[0.54]	(0.04)	
Rooms	3.83	3.85	0.02	35983
	[1.53]	[1.03]	(0.06)	
Dwellers per room	1.09	1.12	0.03	35983
	[0.61]	[0.62]	(0.04)	
Joint significance test (p-value)			0.395	
Panel D: Housing Costs				
Rent	54.76	63.28	8.52	32329
	[111.38]	[127.11]	(8.30)	
Electricity	20.25	20.65	0.40	32329
	[57.58]	[33.42]	(2.17)	
Gas	37.50	36.06	-1.44	32329
	[46.44]	[11.86]	(0.77)	
Water	5.51	6.26	0.75	32329
	[16.05]	[15.74]	(1.03)	
Joint significance test (p-value)			0.366	
Panel E: Enrollment and LFP				
School enrollment (%)	0.89	0.91	0.01	32758
	[0.25]	[0.22]	(0.01)	
Female LFP (Head, 25-64)	0.51	0.52	0.01	28919
	[0.50]	[0.50]	(0.03)	
Joint significance test (p-value)			0.532	

Notes: Column 1 reports the mean of each indicator in the control group. Column 2 reports the mean of each indicator in the treatment group. Column 3 reports mean differences between the treatment groups and the control group. Column 4 reports the number of observations of each indicator. Sample is restricted to households observed in the *Cadastro Único* pre and post-treatment. Standard deviations are reported in brackets and robust standard errors are reported in parentheses. ***p<0.01; **p<0.05; *p<0.10

Table 2: Take-up

	(1)	(2)	(3)
	Control	Treatment	T-C
Signed	0.00	0.57	0.57***
	[0.00]	[0.50]	(0.03)
Lives in MCMV Neighborhood (pre)	0.06	0.07	0.00
	[0.24]	0.24]	(0.02)
Lives in MCMV Neighborhood (post)	0.08	0.40	0.32***
	[0.27]	[0.49]	(0.03)
Moved to MCMV Neighborhood	0.05	0.35	0.31***
	[0.21]	[0.48]	(0.03)
N	36196	274	36470

Notes: Column 1 reports the mean of each take-up indicator in the control group. Column 2 reports the mean of each take-up indicator in the treatment group. Column 3 reports mean differences between the treatment groups and the control group. Sample is restricted to households observed in the *Cadastro Único* pre and post-treatment. Standard deviations are reported in brackets and robust standard errors are reported in parentheses. ***p<0.01; **p<0.05; *p<0.10

Table 3: Neighborhood Quality

	(1)	(2)	(3)	(4)
	Control Mean	Bivariate	Baseline	N
Panel A: Neighborhood				
Population	102.18	-17.32***	-12.55***	36470
	(92.37)	(4.38)	(4.68)	
		[0.005]	[0.010]	
Sewage	0.775	0.007	0.010	36470
	(0.206)	(0.013)	(0.009)	
		[0.589]	[0.292]	
Water	0.986	0.005***	0.003**	36470
	(0.027)	(0.001)	(0.001)	
		[0.007]	[0.027]	
Neighborhood Index	-0.000	-0.088*	-0.048	36470
	(1.000)	(0.053)	(0.053)	
Panel B: Neighbors				
LFP (Head)	0.859	-0.011***	-0.011***	36470
	(0.034)	(0.002)	(0.002)	
		[0.002]	[0.002]	
Income (Head)	1417.77	-104.02***	-106.67***	36470
	(725.59)	(37.63)	(34.28)	
		[0.005]	[0.007]	
White (%)	0.442	-0.022***	-0.021***	36470
	(0.100)	(0.006)	(0.006)	
		[0.002]	[0.002]	
Neighbors Index	0.000	-0.253***	-0.262***	36470
	(1.000)	(0.060)	(0.060)	
Panel C: Access to Opportunities				
Jobs: 90 minutes	0.277	-0.037***	-0.061***	36470
	(0.198)	(0.012)	(0.011)	
		[0.005]	[0.002]	
Schools: 90 minutes	0.274	-0.012*	-0.031***	36470
	(0.131)	(0.006)	(0.006)	
		[0.067]	[0.002]	

Notes: Each row reports the results for a different outcome. Column 1 reports the control mean. Column 2 reports the coefficient of a bivariate regression of each outcome on a treatment dummy. Column 3 add the outcome measure in the baseline as a control. Sample is restricted to households observed in the *Cadastro Único* pre and post-treatment. Robust standard errors are reported in parentheses and Romano-Wolf *p*-values correcting for multiple testing in each group of outcomes are reported in brackets. ***p<0.01; **p<0.05; *p<0.10

Table 4: Housing Quality

	(1)	(2)	(3)	(4)
	Control Mean	Bivariate	Baseline	N
Wood/Tile Floor (0/1)	0.55	0.07***	0.07***	36470
	(0.50)	(0.02)	(0.02)	
		[0.01]	[0.00]	
Paving (0/1)	0.68	0.07***	0.07***	36470
	(0.46)	(0.02)	(0.02)	
		[0.00]	[0.00]	
Sewage (0/1)	0.90	0.03***	0.03**	36470
	(0.30)	(0.30)	(0.30)	
		[0.01]	[0.02]	
Dorms	1.32	0.20***	0.19***	35903
	(0.87)	(0.03)	(0.03)	
		[0.00]	[0.00]	
Rooms	3.83	0.35***	0.34***	35903
	(1.53)	(0.06)	(0.05)	
		[0.00]	[0.00]	
Electricity - meter (0/1)	0.56	0.12***	0.11***	35903
	(0.50)	(0.03)	(0.03)	
		[0.00]	(0.00)	
House Index	-0.11	0.39***	0.34***	35903
	(1.09)	(0.05)	(0.05)	

Notes: Each row reports the results for a different outcome. Column 1 reports the control mean. Column 2 reports the coefficient of a bivariate regression of each outcome on a treatment dummy. Column 3 add the outcome measure in the baseline as a control. Sample is restricted to households observed in the *Cadastro Único* pre and post-treatment. Robust standard errors are reported in parentheses and Romano-Wolf p-values correcting for multiple testing are reported in brackets. ***p<0.01; **p<0.05; *p<0.10

Table 5: Housing Costs

	(1)	(2)	(3)	(4)
	Control Mean	Bivariate	Baseline	N
Rent	54.76	-37.84**	-43.80***	36470
	(111.38)	(9.09)	(10.93)	
		[0.02]	[0.01]	
Water	5.51	5.81**	5.74**	36470
	(16.05)	(2.17)	(2.29)	
		[0.02]	[0.01]	
Electricity	20.25	12.40*	12.85*	36470
	(57.58)	(4.30)	(4.55)	
		[0.08]	[0.10]	
Gas	37.50	-6.11**	-6.00**	36470
	(46.44)	(1.43)	(1.46)	
		[0.02]	[0.03]	
Total	296.79	-28.92*	-33.59**	36470
	[199.32]	[16.85]	[16.24]	

Notes: Each row reports the results for a different outcome. Column 1 reports the control mean. Column 2 reports the coefficient of a bivariate regression of each outcome on a treatment dummy. Column 3 add the outcome measure in the baseline as a control. Sample is restricted to households observed in the *Cadastro Único* pre and post-treatment. Robust standard errors are reported in parentheses and Romano-Wolf *p*-values correcting for multiple testing are reported in brackets. ***p<0.01; **p<0.05; *p<0.10

Table 6: Female LFP

	(1)	(2)	(3)	(4)
	Control Mean	Bivariate	Baseline	N
Panel A: Head (0/1)				
25-64	0.44	0.02	0.00	33022
	(0.50)	(0.03)	(0.03)	
25-44	0.45	0.04	0.02	19483
	(0.50)	(0.04)	(0.04)	
45-64	0.40	-0.02	-0.03	13539
	(0.49)	(0.05)	(0.05)	
Panel B: All (%)				
25-64	0.424	0.02	0.02	33581
	(0.49)	(0.03)	(0.03)	
25-44	0.434	0.04	0.04	21356
	(0.49)	(0.04)	(0.04)	
45-64	0.370	-0.02	-0.08	13975
	(0.48)	(0.05)	(0.06)	

Notes: Panel A reports the effects of the MCMV on the labor force participation of the heads of household. Panel A reports the effects of the MCMV on the labor force participation of adults in general. Column 1 reports the control mean. Column 2 reports the coefficient of a bivariate regression of each outcome on a treatment dummy. Column 3 add the outcome measure in the baseline as a control. Sample is restricted to households observed in the *Cadastro Único* pre and post-treatment. Robust standard errors are reported in parentheses. ***p<0.01; **p<0.05; *p<0.10

Table 7: Income

	(1)	(2)	(3)	(4)
	Control Mean	Bivariate	Baseline	N
Wage (Head)	273.30	-0.64	-2.97	35278
	(394.01)	(23.93)	(24.86)	
Wage (Household)	327.08	-3.78	0.20	35278
	(449.50)	(27.45)	(26.85)	
Income per capita	159.37	-12.54	-13.62	36470
	(199.60)	(11.97)	(11.36)	

Notes: Each row reports the results for a different outcome. Column 1 reports the control mean. Column 2 reports the coefficient of a bivariate regression of each outcome on a treatment dummy. Column 3 add the outcome measure in the baseline as a control. Sample is restricted to households observed in the *Cadastro Único* pre and post-treatment. Robust standard errors are reported in parentheses. ***p<0.01; **p<0.05; *p<0.10

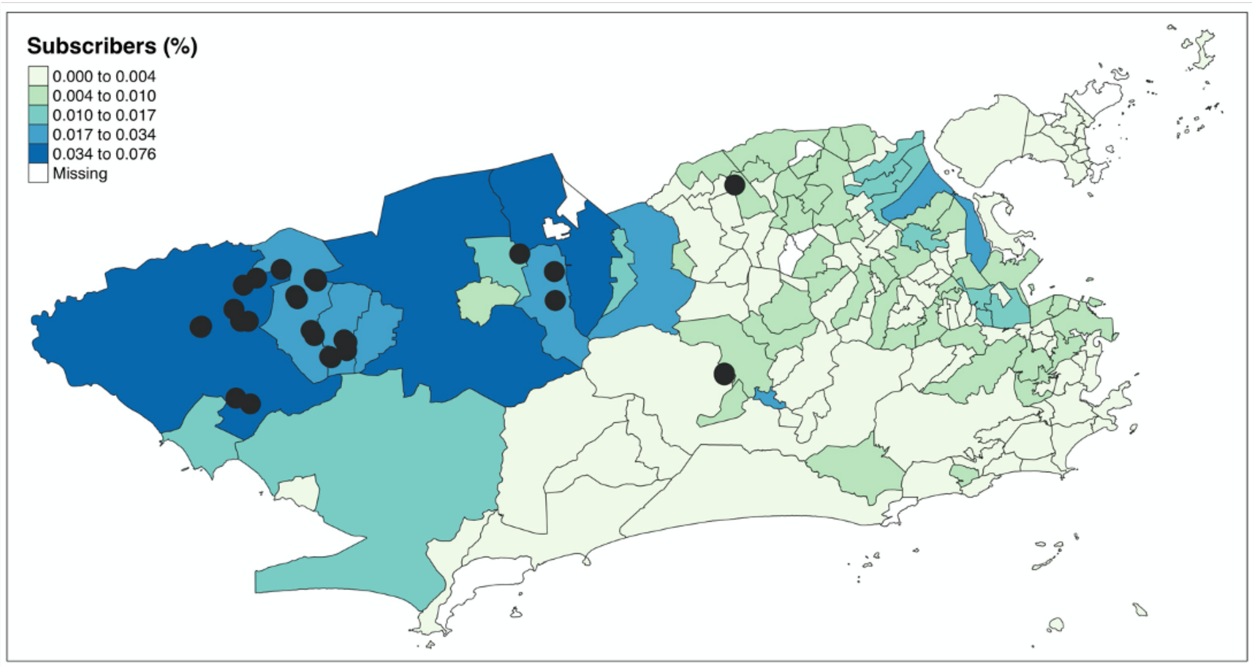
Table 8: Education

	(1) Control Mean	(2) Bivariate	(3) Baseline	(4) N
Enrollment, 4-18	0.89	0.01	0.01	28982
	(0.25)	(0.01)	(0.01)	
Boys, 4-18	0.89	0.01	0.02*	20300
	(0.28)	(0.01)	(0.01)	
Girls, 4-18	0.90	-0.01	-0.00	19727
	(0.27)	(0.02)	(0.02)	
Pre-School, 4-6	0.62	-0.02	0.03	5639
	(0.48)	(0.09)	(0.09)	
Enrollment, 7-15	0.96	-0.00	-0.01	22788
	(0.17)	(0.01)	(0.01)	
Boys, 7-15	0.96	-0.00	-0.01	14391
	(0.19)	(0.02)	(0.02)	
Girls, 7-15	0.96	-0.01	-0.01	13908
	(0.19)	(0.02)	(0.02)	
Elementary, 7-15	0.86	0.01	0.01	22788
	(0.30)	(0.01)	(0.01)	
Boys, 7-15	0.86	0.01	0.00	14391
	(0.33)	(0.02)	(0.02)	
Girls, 7-15	0.86	0.01	0.00	13908
	(0.33)	(0.02)	(0.02)	
Enrollment, 16-18	0.94	0.03**	0.07***	13845
	(0.23)	(0.01)	(0.01)	
Boys, 16-18	0.94	0.04**	0.06***	7610
	(0.23)	(0.01)	(0.01)	
Girls, 16-18	0.94	0.02	0.09***	7111
	(0.23)	(0.02)	(0.02)	
High School, 16-18	0.33	0.03	0.10	13845
	(0.46)	(0.05)	(0.10)	
Boys, 16-18	0.29	-0.05	-0.14	7610
	(0.45)	(0.06)	(0.14)	
Girls, 16-18	0.36	0.02	-0.04	7157
	(0.47)	(0.06)	(0.13)	
High School Graduate, 19-24	0.32	0.00	-0.07	12828
	(0.45)	(0.05)	(0.09)	
Boys, 19-24	0.26	-0.02	-0.20	7015
	(0.43)	(0.06)	(0.15)	
Girls, 19-24	0.36	0.02	-0.04	7157
	(0.47)	(0.06)	(0.13)	

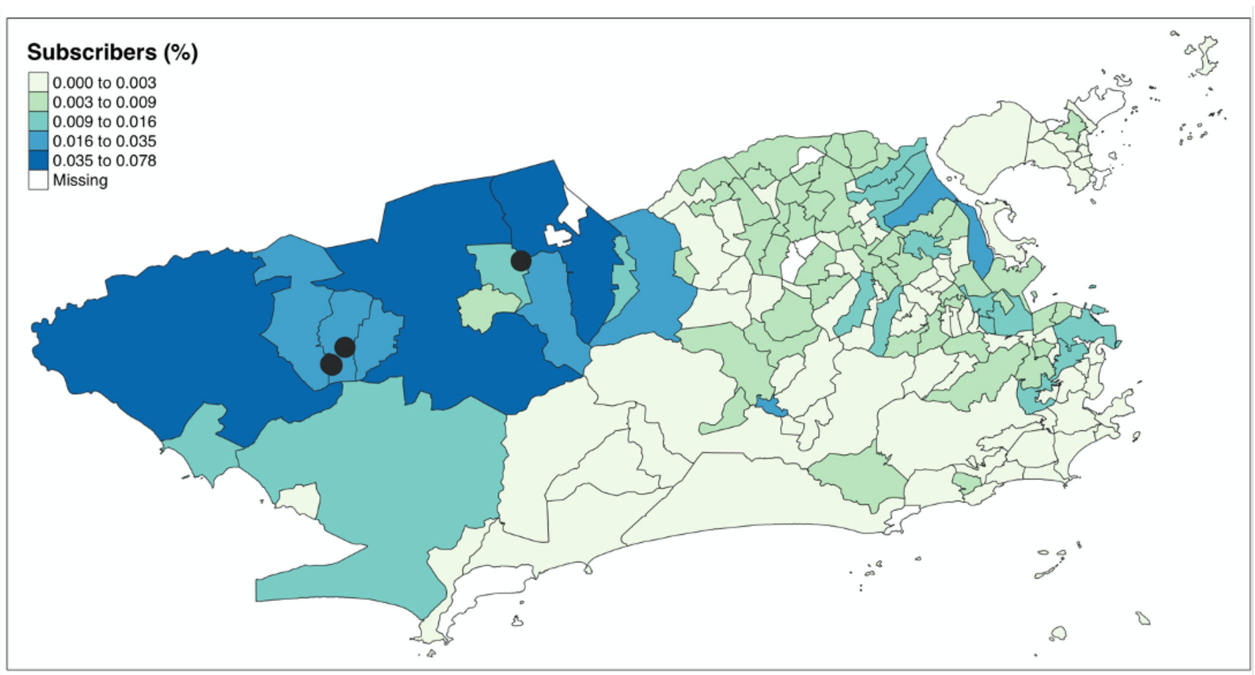
Notes: Each row reports the results for a different outcome. Column 1 reports the control mean. Column 2 reports the coefficient of a bivariate regression of each outcome on a treatment dummy. Column 3 add the outcome measure in the baseline as a control. Sample is restricted to households observed in the *Cadastro Único* pre and post-treatment. Robust standard errors are reported in parentheses. ***p<0.01; **p<0.05; *p<0.10

Figure 1: Projects' Location and Origins of Subscribers

(a) **All lotteries**

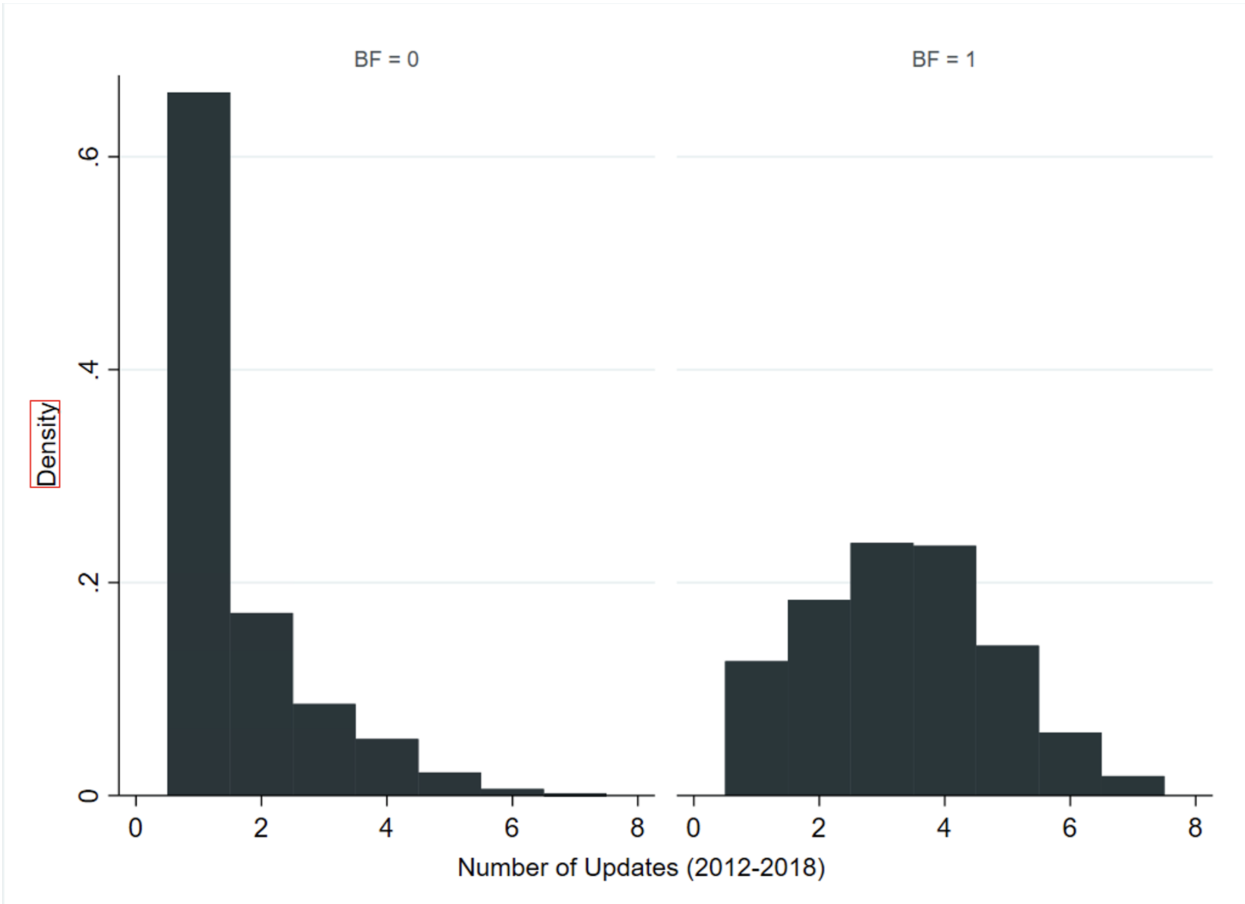


(b) **Sample lotteries**



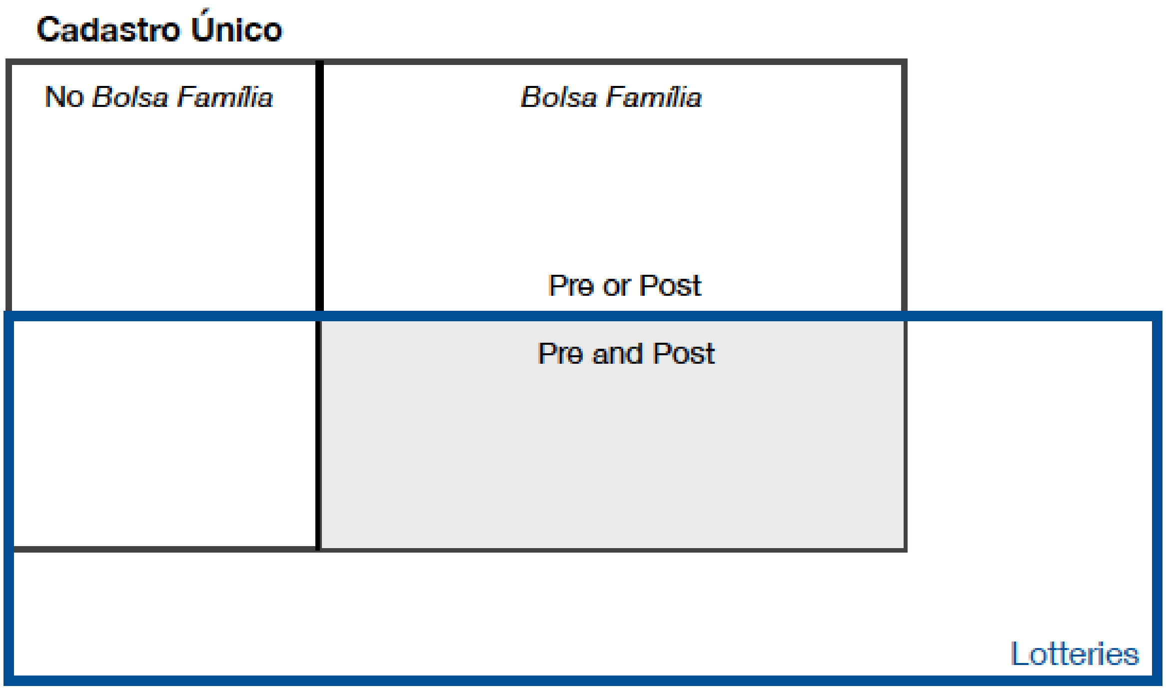
Note: Panel A plots the location of the MCMV units allocated through the regular lotteries that occurred during the period 2011-2015 and the neighborhood of residence of their subscribers. Panel B plots the location of the MCMV units allocated through the two lotteries used in our empirical investigation and the neighborhood of residence of their subscribers.

Figure 2: Updates



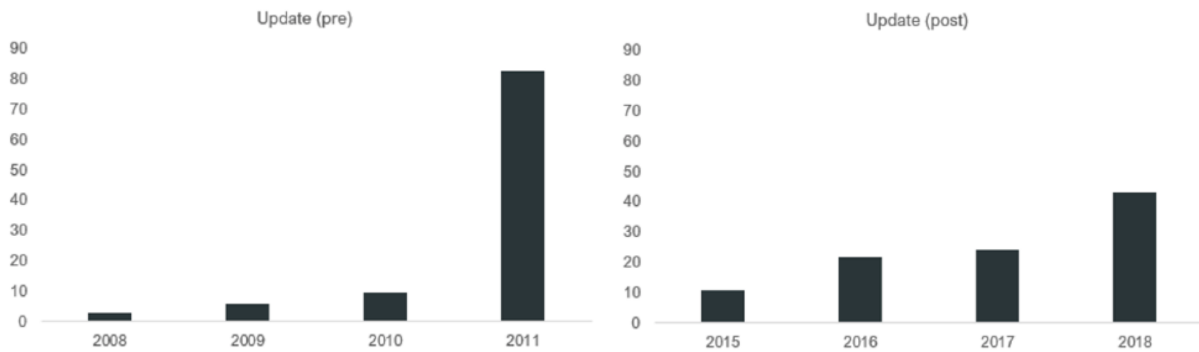
Notes: The figure reports the number of updates in the *Cadastro Único* by *Bolsa Família* status.

Figure 3: Sample Construction



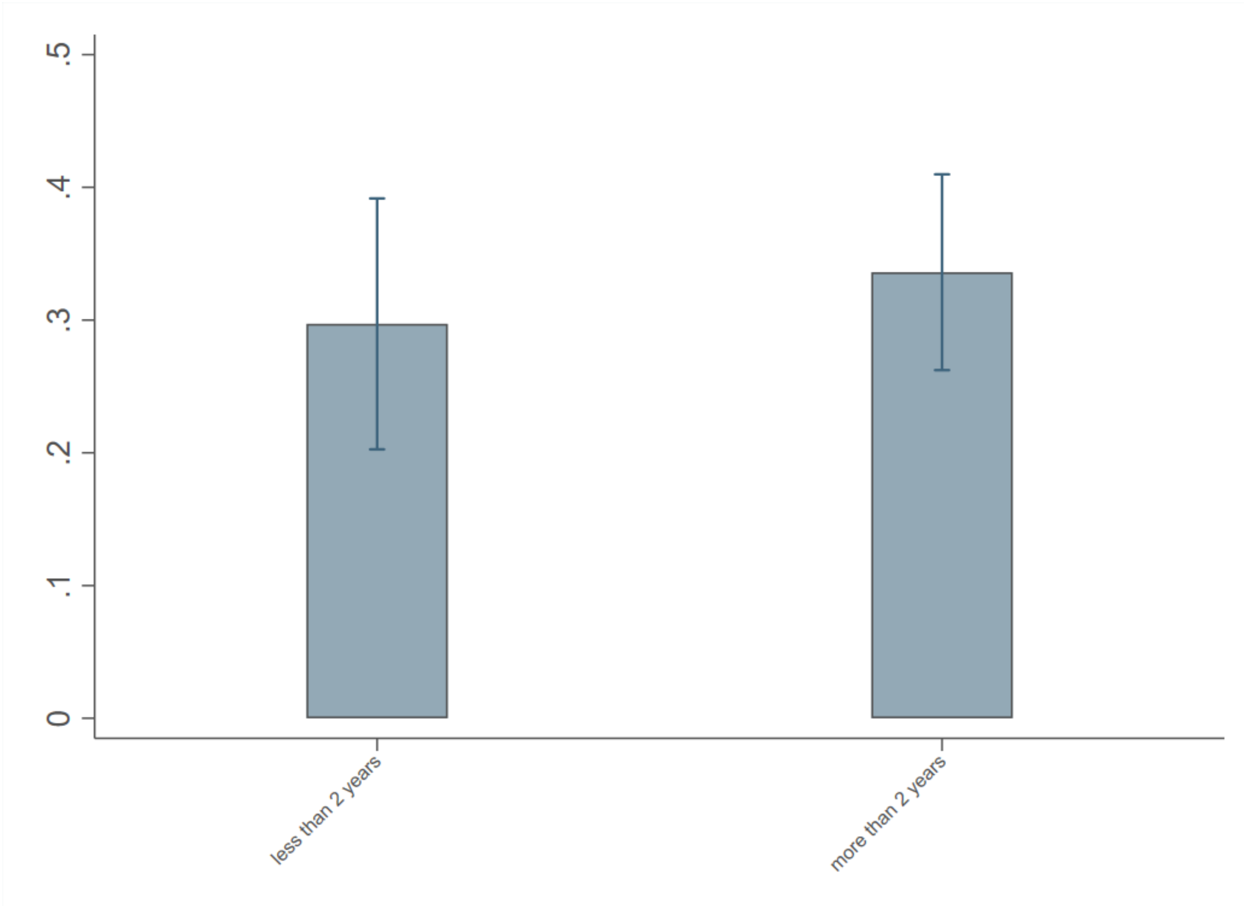
Notes: The depicts the sample construction. The black rectangle denotes the *Cadastro Único* and the blue rectangle the list of subscribers of the lotteries. The gray area represents the final sample.

Figure 4: Updates (pre and post treatment)



Notes: The figure reports the the year of the updates in the first pre-treatment period (used to test the balance of our sample) and last post-treatment period (used to test MCMV's effects). Sample is restricted to households observed in the *Cadastro Único* pre and post-treatment.

Figure 5: The Evolution of Take-Up



Notes: The figure plots the coefficients obtained from estimating equation (2) using a dummy indicating of whether household moved to the neighborhoods in which the program's houses were built as dependent variable. The bars denote the coefficient and the capped lines their 95% confidence intervals.

Appendix to "Better Neighborhoods or Better Houses?"

A MCMV Description

In the main text, we present the aspects of the *Minha Casa Minha Vida* (MCMV) program more relevant to our empirical investigation. In this appendix, we provide a more complete description of the program. We begin by describing its rules, financing, and scale. We then describe the program in Rio de Janeiro (Brazil) and the lotteries used to select its participants.

A.1 The *Minha Casa Minha Vida Program*

Creation. The *Minha Casa Minha Vida* (MCMV) program was created by the Federal Law n. 11,977 in 2009. Its aim is to provide housing for low and middle-income households in Brazil. In the period 2009-2018, the program financed the construction of about 5.5 million houses at a total cost of R$464 billion (US$ 92.8 billion at the current exchange rates).

Segment 1. As mentioned in section 2, the MCMV offered different types of subsidies for households depending on the family's income level. These different brackets are shown in Table A2. In the program's segments 2 and 3, private developers sell units directly for households with income below R$ 5,000 (about US$ 1,250) with *Caixa* offering mortgages with subsidized rates. In segment 1, municipal governments allocate units to households with income below R$ 1,600 (about US$ 400) with *Caixa* financing the construction. Subsidies for segment 1 could go up to 90% of the construction cost. There were no down payment requirements, and monthly installments were capped at 5% of the household income (or R$ 25). Our investigation focuses on segment 1 of the MCMV program due to its focus on the poor population and participants' randomized assignment. There were three different initiatives focused on building houses for households poor households eligible for subsidies of the program's segment 1: MCMV-FAR, MCMV-

Sub-50, and MCMV-Entities. This paper focuses on MCMV-FAR which targeted poor households living in municipalities with more than 50,000 inhabitants. This modality concentrated more than 85% of the units built for segment 1.[25] The program's investments were more intensive in the country's largest municipalities due to the concentration of households living in inappropriate houses. Figure A1 shows the geographic distribution of the program in Brazil. Table A1 shows the number of MCMV contracts signed by year from 2010 to 2017.[26]

Funding. The program's resources come from the federal government budget.[27] These resources are managed and channeled mainly by *Caixa*, a stated-owned bank specialized in mortgage financing.[28] *Caixa* is also the financial institution responsible for most social programs of the Federal Government like the *Bolsa Família* (conditional cash transfer).

Execution. Private developers present the project to *Caixa*, and the bank is responsible for certifying construction companies, contracting the development of housing projects, and providing funding subsidized for eligible households. Municipalities are responsible for selecting the beneficiaries, guaranteeing compliance with urban regulation, guaranteeing the provision of infrastructure and public goods nearby housing projects, and improving the feasibility of developments, for instance, by donating land or providing tax cuts.

Application. Households were required to register for the lotteries either online or at municipal offices. In theory, households in the *Cadastro Único* (an administrative registry for managing the payment of federal government programs) eligible for the program were

[25]The MCMV-Entities also targeted households living in municipalities with more than 50,000 inhabitants. However, unlike the MCMV-FAR, the projects' execution and the selection of beneficiaries occurs through social movements. The MCMV-*Sub-50* initiative targeted poor households living in municipalities with less than 50,000 inhabitants.

[26]According to data on signed contracts provided by *Caixa*, the 309 contracts signed in 2009 were from the MCMV-Entities modality.

[27]The federal government transferred resources to three funds (FAR, FDS and FGTS - the FFF funds) to subside housing mortgages, to fund *FGHab* to provide guarantees for those mortgages, and to BNDES to finances urban infrastructure.

[28]*Caixa* is Brazil's largest mortgage lender, responsible for about 70% of Brazil's home mortgages.

registered automatically. However, it is unclear whether local governments (responsible for selecting the beneficiaries) registered these households in practice. We observe in the data is the beneficiaries eventually register in the *Cadastro Único*. Local officers organized lotteries among registered households to select beneficiaries. Households removed to construct infrastructure projects or individuals with disabilities are prioritized in the lotteries.

Lotteries. Housing lotteries were implemented by Ordinance n. 140 from the Ministry of Cities (from Abril 2010). For each housing project, at least 6% of housing units should be allocated to people with special needs and older people. If there is excess demand for these two groups, lotteries must also be used. Only families affected by natural disasters and reallocated due to federal-level infrastructure projects do not need to apply for lotteries to receive housing units. Every lottery must indicate a waiting list corresponding to 30% of the number of winners. The Federal Law n. 11,977 created three nationally defined priority criteria: families living in risk-prone areas, female-headed families, and families with people with disabilities. The law also allowed local governments to stipulate (up to) three additional priority criteria. Some municipalities have chosen local priority criteria; others have not. Lotteries can use numbers drawn from the results of other lotteries, or municipalities can carry out lotteries by themselves (that usually takes place in sports arenas and is supervised by a *Caixa* worker). For instance, Rio de Janeiro uses results from a famous national lottery run by *Caixa*, and separate lists of the general lotteries (with no priority criteria) and the lists of the special lotteries (with priority criteria).

Winners. When the units' construction finishes, all households selected to receive a housing unit of a particular housing project are invited to sign their contracts and receive their units on the same date. Units are identical and, given the large pool of applicants, selected households are unlikely to know each other. Thus, households typically do not reallocate units among themselves. Lottery results must be published in official registers (*"Diários Oficiais"*). After enrolling winners and the waiting list in *Cadastro Único*, municip-

alities send the list to *Caixa*. The bank then verifies compliance with the income threshold and other data by using different registries. When compliance is verified, *Caixa* authorizes the credit.

Subsidy. The design of housing subsidies is such that monthly installments should be several times lower than rent values. The lower the household income, the greater the subsidy. Subsidies are considerable: if total household income is within the segment 1 range, up to 90% of the housing price is subsidized. Subsidies were also designed to reach a wide range of the population. For instance, the segment 1 income range corresponded to the percentile 63 of the income distribution according to 2010 Brazil's 2010 Population Census. Every beneficiary must pay monthly installments (reduced by subsidies), lasting up to 120 months. Mortgage installments are set to be 5% of households' gross income. They are adjusted annually by a below-market interest rate, usually below inflation, to provide negative real interest rates (Resolution 477, October 2013). If the borrower does not pay the installments or uses units for other purposes, *Caixa* forecloses the unit.[29]

Houses. The MCMV program's housing units must have at least two bedrooms, a living room, a kitchen, and a bathroom. Its minimum surface area is 37 m^2 (roughly 400 sq^2). These houses are built in housing projects from a few dozen to more than one thousand units. MCMV's law established minimum requirements for the project's location. Projects should be located either inside the current urban network or in expansion areas indicated in the municipality's current urban planning. Moreover, these projects must comply with minimum requirements regarding environmental planning, sewage treatment, the electricity grid, the water network, access roads, and public transportation.[30] There is a price cap for housing units set by the federal government, which differs by state, municipal size, and housing type (house or apartment). The price cap influences the feasibility

[29]The comprehensive legislation regarding the PMCMV can be found at https://www.caixa.gov.br/Downloads/habitacao-minha-casa-minha-vida/_Legislacao_FAR.pdf.

[30]These requirements were instituted by the Provisional Measure 459 enacted in March 2009. This provisional measure was later converted into the Law #12,424 enacted in June 2011.

of housing projects and thus interferes with their location and scale. In large-size municipalities, where available land is scarce and more expensive, most housing projects are higher-density developments in the suburbs or surrounding municipalities with inadequate provision of urban infrastructure and public services ((Habitat, 2013)). In this scenario, a housing development usually comprises hundreds of housing units, so hundreds of families move virtually simultaneously to suburb areas. Figure A2 shows a MCMV house and its surroundings in Rio de Janeiro.

A.2 The Lotteries in the Municipality of Rio de Janeiro

Our investigation focuses on the lotteries in Rio de Janeiro, Brazil's second-largest municipality, with 6.7 million inhabitants. This municipality received 2% of the units and 2.45% of the MCMV program's total funding in 2009-2018. In total, 27,843 low-income households received units from the program. This corresponds to more than 1% of the number of families of the municipality. The typical unit built in Rio de Janeiro was priced at about R$ 51,644.00 and had square footage of about 45 m^2. We focus on this municipality for two reasons. First, the municipality publicly released the winners' and losers' records of the lotteries. Second, the municipality is known for the long-lasting prevalence of slums in the surroundings of its most important neighborhoods (Perlman, 2010; Monteiro & Rocha, 2017).

We analyze the general lotteries' list (with no priority criteria) from 2011 to 2015, corresponding to contracts signed between 2012-2017. A total of 11 general lotteries occurred in the period 2011-2015.[31] Three lotteries occurred in 2011, one in 2012, two in 2013, none in 2014, and five in 2015 (three of them considered age as a priority criterion in the selection process). Demand exceeded the supply of units in all lotteries, with 0.1% to 4.2% of the subscribers being selected. These 12 chosen lotteries households to live in 32 different

[31] We focus on general lotteries. There were specific lotteries for the disabled and elderly and for people living in risk areas. Information on the subscribers is publicly available on the website http://www.rio.rj.gov.br/web/smhc/menu-minha-casa-minha-vida#.

projects delivered between the years of 2012-2017. Figure A3 shows the location of these housing projects are spatially concentrated in the municipality's western zone.

As mentioned before, to select the beneficiaries, Rio de Janeiro uses results from a nationwide famous lottery run by *Caixa*. For these general lotteries, the allocation mechanism is straightforward. If the last two digits of the participant's registration number matched the Federal Lottery draw's last two digits, the household is selected. Applications are free of charge, and participants must not be the owner of a housing unit. Non-winners automatically participate in future lotteries. Winners who chose to withdraw from the rest of the process also automatically participate in future lotteries. Figure A5 shows a notice of the December 21, 2013 lottery that occurred in Rio de Janeiro indicating the Federal Lottery result that would determine the winners among the participants.

Table A4 presents information on the 10 lotteries from 2011 to 2015 for the low-income population (general lotteries) that we analyze in this paper. The houses delivered throughout 2012-2015 were clustered in the western zone of Rio de Janeiro. Only the region of Santa Cruz received 18 out of 26 units of Segment 1 of MCMV considered in these notices.

As explained in the main text, we use only data on the 2013 lottery. The 2011 lotteries selected beneficiaries of houses which were delivered during the year of 2012, the first year for which we observe the outcomes of most of the treatment and control households in our data. This precludes us from testing whether the treatment and control units we find in our match procedure were comparable before the MCMV happened. The 2012 lottery selected beneficiaries for for 240 houses to be constructed in Guadalupe in north of the municipality of Rio de Janeiro. However, the project was invaded after completion, first by 200 low-income families that lived in a slum nearby and, later, by armed gangs. These invasions had widespread media coverage[32], delayed the delivery of the units June 2015[33], and led to the organization of another lottery to select beneficiaries. It is not clear

[32] https://cutt.ly/ahpATJs; https://cutt.ly/KhpAOlo

[33] We obtain this information from the contract-level data of the program

how this lottery the took into account the 2012's lottery. This precludes us from using it.

The 2015 lotteries also had a series of problems. The lottery from notice 004/2015, which occurred on January 21, 2015, has 1848 duplicates in CPF. Besides, we observe several winners duplicated in the list of subscribers, with different registration numbers (the registration number is used to define the winner according to the Federal lottery). There are also several people whose digits were drawn in the Federal lottery and, still, they are not in the list of winners.[34] Therefore, we are not confident we can use these registers given this evidence that the lists of winners are not compatible with the exogenous rule for the lotteries.

Despite these issues, in the appendix C, we provide evidence that adjusting the lists of subscribers from the 2011 and 2015 lotteries and including them in our analysis does not change much the results. For 2011, we obtain reasonably balanced lists of winners and losers by excluding the households which we only observe after the MCMV houses were delivered. For 2015, we obtain reasonably balanced lists of winners and losers by excluding the more problematic lotteries. We then show the impacts of the MCMV estimated using these lotteries are qualitatively and quantitatively similar to the impacts estimated using all lotteries.

Table A3 presents the number of subscribers and winners on each lottery. Subscribers that were not selected remain on the list in subsequent raffles. The number of subscribers is much higher than the number of winners, representing from 0.1% to 4.2% of the total number of subscribers. The share of winners falls over the years (except in 2015(5)), and the main reason for that is that the waiting lists are cumulative - people who do not win a lottery remain on the list to participate in the subsequent raffle.

[34] In the 2015 notices, there are 942 people enrolled whose registration number ended in numbers selected in the Federal lotteries but did not appear in the winner's list

Table A1: Number of Signed Contracts by year

Year	# Houses	% Signed Contracts
2010	9986	1.1%
2011	102956	11.3%
2012	145713	15.9%
2013	133955	14.6%
2014	167268	18.3%
2015	170535	18.6%
2016	152013	16.6%
2017	32314	3.5%

Notes: The table presents the number of MCMV signed contracts by year for the urban population in Brazil, 2009-2017.

Table A2: Income threshold for eligibility

Monthly Family Income	**Benefits**
Up to R$ 1,600.00 (Faixa 1)	Up to 90% of the value of the property. The portion paid by the beneficiary is 5% of the monthly income with a minimum benefit of R$ 25 (divided into 120 months), without interest.
Up to R$ 3,100.00 (Faixa 2)	Subsidy with 5% interest per year.
Up to R$ 5,000.00 (Faixa 3)	Subsidy with 6%-7% interest per year.

Notes: Information compiled using data from the Ministry of Cities (2017)

Table A3: Number of subscribers by lottery

Year	Winners	Losers	Total
2011 (1)	2,983	295,149	298,132
2011 (2)	6,505	318,788	325,293
2011 (3)	14,055	337,343	351,398
2012	414	413,774	414,188
2013 (1)	566	471,902	472,468
2013 (2)	2,457	489,173	491,630
2015 (1)	3,337	664,958	668,295
2015 (2)	275	552,588	552,863
2015 (3)	2,226	554,184	556,410
2015 (4)	1,111	554,034	555,145
2015 (5)	7,305	554,719	562,024
2015 (6)	569	568,599	569,168

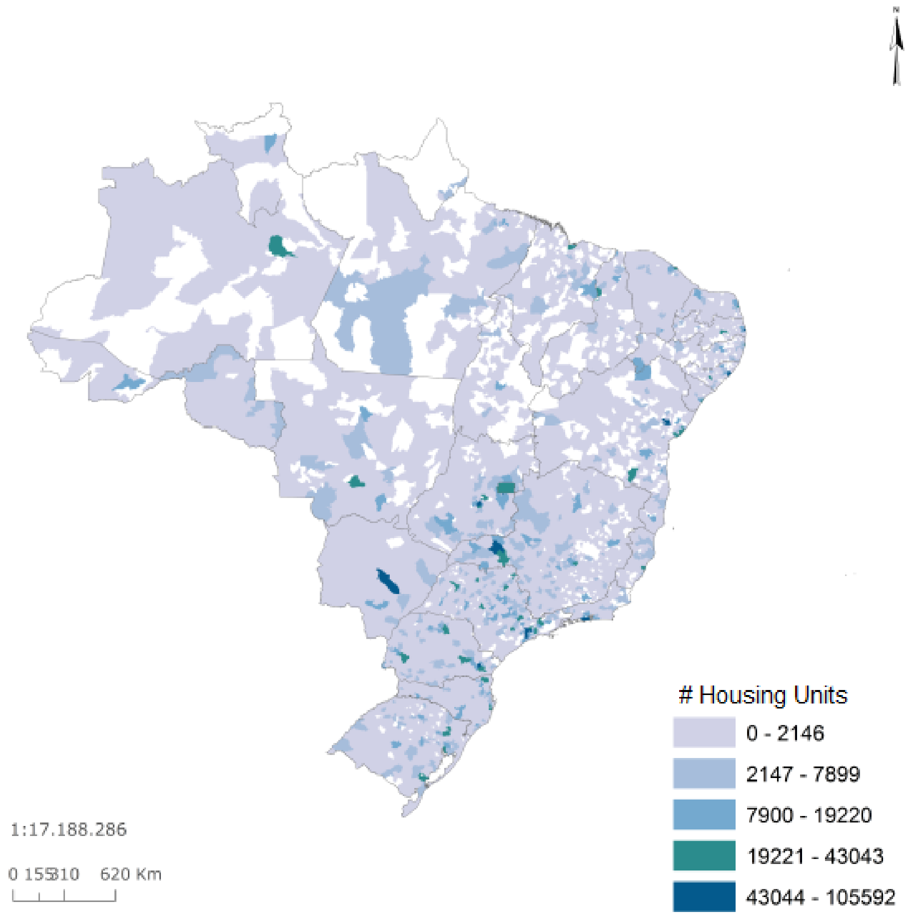
Notes: The table reports the number of winners (column 1), losers (column 2), and subscribers (column 3) of each of the general MCMV lotteries that occurred from 2011 to 2015 in the municipality of Rio de Janeiro (RJ).

Table A4: Lotteries Details

Notice	Project Name	Lottery date	Construction Year	Signature
2011/003	Park Imperial	11/06/2011	2009	23/10/2012
	Park Royal		2009	24/10/2012
	Destri		2009	09/01/2012
	Toledo		2009	28/06/2012
	Rio Bonito		2010	29/10/2012
	Estoril		2009	29/05/2012
2011/006	Sevilha	13/08/2011	2009	25/06/2012
	Taroni		2009	11/01/2012
	Cascais		2009	30/07/2012
	Toledo		2009	28/06/2012
2011/009	Vidal	02/11/2011	2009	11/04/2012
	Évora		2009	11/07/2012
	Zaragoza		2009	09/07/2012
	Park Imperial		2009	23/10/2012
	Park Royal		2009	24/10/2012
	Toledo		2009	28/06/2012
	Estoril		2009	29/05/2012
	Sevilha		2009	25/06/2012
	Cascais		2009	30/05/2012
2013/003	Vivendas das Garças	02/10/2013	2011	23/10/2014
2013/006	Recanto do Paçuaré I	21/12/2013	2011	27/04/2015
	Recanto do Paçuaré I I		2011	27/04/2015
	Vivenda dos Pintassilgos		2012	24/10/2014
	Vivenda das Gaivotas		2012	22/04/2015
2015/004	Mikonos	21/01/2015	2011	24/12/2015
	Dellos		2011	20/04/2016
	Santorine		2011	30/03/2016
	Vivenda das Cotovias		2012	04/05/2016
	Vivenda das Coleirinhas		2012	11/05/2016
	Vivenda dos Colibris		2013	13/05/2016
2015/007	Recanto do Paçuaré I	07/03/2015	2011	27/04/2015
	Recanto do Paçuaré II		2011	27/04/2015
2015/018	Mikonos	11/04/2015	2011	24/12/2015
	Dellos		2011	20/04/2016
	Santorini		2011	30/03/2016
2015/019	Vivendas das Cotovias	15/04/2015	2012	04/05/2016
	Vivendas das Coleirinhas		2012	11/05/2016
	Vivendas dos Colibris		2013	13/05/2016

Notes: The table reports the date of each lottery we use in our empirical investigation. It further reports the name of projects allocated in each of these lotteries, the year their construction started, and the dates in which contracts started to be signed with beneficiaries.

Figure A1: Geographic Distribution of Housing Units



Notes: The figure reports the regional distribution of the number of MCMV signed contracts using administrative data provided by Caixa (2017).

Figure A2: MCMV units in Rio de Janeiro

(a) Buildings

(b) Living Room

(c) Kitchen

(d) Buildings and Surroundings

Notes: House plan and housing units built through MCMV in Rio de Janeiro.

Figure A3: Projects'Location by Census Tract

Notes: Location of the units drafted through lotteries that occurred from 2011 to 2015 in the municipality of Rio de Janeiro.

Figure A4: 2013/006 Notice

PREFEITURA DA CIDADE DO RIO DE JANEIRO
SECRETARIA MUNICIPAL DE HABITAÇÃO

EDITAL DE DIVULGAÇÃO DE RESULTADO DE SORTEIO REFERENTE AO EDITAL 006/2013 PUBLICADO NO DIÁRIO OFICIAL DO MUNICIPIO EM 20/12/2013

A Prefeitura da Cidade do Rio de Janeiro, através da Secretaria Municipal de Habitação, torna público o resultado do sorteio da extração da Loteria Federal nº. 04.825 da Caixa Econômica Federal – CAIXA, realizado às 18:00 horas do dia 21/12/2013.

Resultado do 1º. Prêmio	10.352
Resultado do 2º. Prêmio	45.790
Resultado do 3º. Prêmio	87.091
Resultado do 4º. Prêmio	88.678
Resultado do 5º. Prêmio	88.701

Conforme prevê o Edital 006/2013 publicado no Diário Oficial do Município em 20/12/2013, foram sorteados os candidatos cujos três últimos algarismos do número que lhes foi atribuído corresponder às centenas 352, 790, 091, 678 e 701.
Posteriormente, os candidatos sorteados receberão no endereço cadastrado, carta-convite para comparecimento à reunião, onde serão informados acerca de todas as regras do PMCMV, em especial critérios de enquadramento, documentação necessária e prazo-limite para entrega da documentação, o qual, se descumprido, caracterizará desistência.

Notes: Image from notice of the December 21, 2013 general lottery from Rio de Janerio.

Figure A5: Eviction in MCMV housing project - Guadalupe

Notes: Image from the *Guadalupe* housing project during its eviction in November 2014. Image from TV Globo, obtained in https://noticias.uol.com.br/album/2014/11/12/predios-do-minha-casa-minha-vida-sao-invadidos-no-rio.htm?foto=1.

B MCMV Locations

In this section, we combine geo-coded information of the MCMV projects' with tract-level information of the Population Census 2010 to describe the neighborhoods where the MCMV units were built. Figure B1 panel a shows the distribution of income across the city, panel b the share of whites, panel c shows in yellow the census tracts that do not have full access to sewage, and panel d shows in yellow streets that has paved sidewalk. The location of these residential complexes is concentrated in areas with low-income families and with little infrastructure.

Table B1 presents several features for locations with no MCMV projects (column (1)), for areas with MCMV projects (column(2)), the difference between census tracts with and without projects, and the difference of theses variables within neighborhoods. Panel A of Table B1 has information on the average income and the share of female and literates. The average income of census tracts with no projects is R$ 813,94 higher than the average income of census tracts with projects. The percentage of whites is ten percentage points larger in locations with no projects. Females represent 47% of residents in census tracts without projects, and 44% of residents in places with MCMV projects and literates represent 97% and 96%, respectively. The share of females and literates are not significantly different. As column (3) shows, while the locations with no projects have higher income, the average characteristics within an area are similar between residents.

Panel B of Table B1 has information on street identification, the share of streets in the census tract with a paved sidewalk, maintenance hole, and share of tree-lined streets. The Table shows that locations with no projects have more roads with name identification than places with MCMV projects (difference of 13 percentage points). The percentage of streets with maintenance holes in locations with no projects is 15 percentage points higher than in areas with no projects. Finally, sites with no projects have more tree-lined streets than locations with MCMV projects (13 percentage points of difference). In all variables tested,

areas with no projects have fewer public services than places with projects. Again, we see in column (3) that while the sites with no projects have less public services offer, the average characteristics within a location is similar between residents.

Panel C of Table B1 has information on the share of renters, the share of households with water sanitation, and the share of households with sewage sanitation. Locations with no projects have more renters (8 percentage points) and a higher share of households with sewage sanitation (14 percentage points). The difference within a location is substantially different in terms of sewage, as shown in column (4).

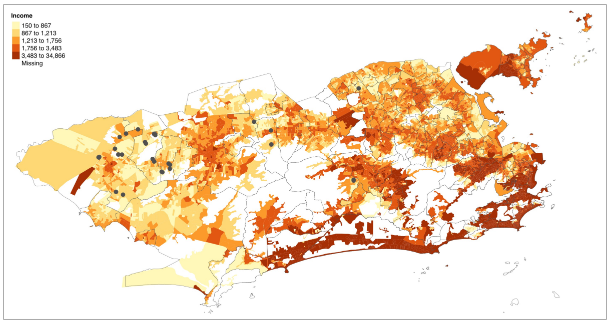
Table B1: Census Tracts with and without MCMV projects

	No Projects	Projects	Diff.	Diff. (within)
	(1)	(2)	(3)	(4)
Panel A: Neighbors				
Income	2374.32	1100.01	-1274.31***	25.26
	[2375.57]	[285.48]	(55.67)	(63.45)
White	0.54	0.38	-0.16***	0.02
	[0.21]	[0.09]	(0.02)	(0.02)
Female	0.47	0.44	-0.03	-0.01
	[0.11]	[0.12]	(0.02)	(0.02)
Literate	0.97	0.96	-0.01	0.01
	[0.05]	[0.04]	(0.01)	(0.01)
Panel B: Neighborhood				
Street Id.	0.14	0.43	0.30***	0.10*
	[0.27]	[0.34]	(0.06)	(0.06)
Sidewalk	0.11	0.41	0.30***	0.16***
	[0.27]	[0.37]	(0.07)	(0.06)
Manhole	0.14	0.45	0.32***	0.16**
	[0.28]	[0.38]	(0.07)	(0.07)
Trees	0.24	0.55	0.31***	-0.04
	[0.35]	[0.37]	(0.06)	(0.07)
Panel C: Houses				
Rental	0.22	0.11	-0.11***	-0.02
	[0.13]	[0.07]	(0.01)	(0.01)
Water	0.98	0.98	0.00	0.00
	[0.10]	[0.03]	(0.01)	(0.01)
Sewage	0.90	0.63	-0.27***	-0.17***
	[0.22]	[0.34]	(0.06)	(0.06)
Observations	10,247	34	10,247	10,247

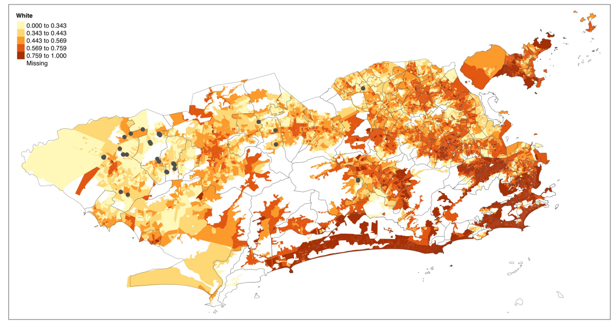
Notes: Column 1 reports the reports the mean of the outcome for census tracts without projects, column 2 for census tracts with projects, column 3 reports the differences in means between these census tracts, column 4 reports the within-neighborhood differences in means between these census tracts. Standard deviations are reported in brackets and standard errors in parenthesis. ***p<0.01; **p<0.05; *p<0.10

Figure B1: MCMV housing projects and Neighborhood characteristics

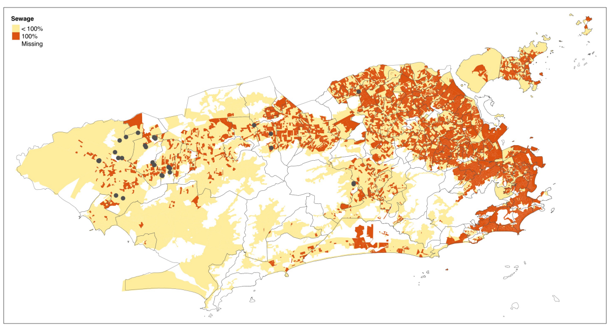
(a) Income



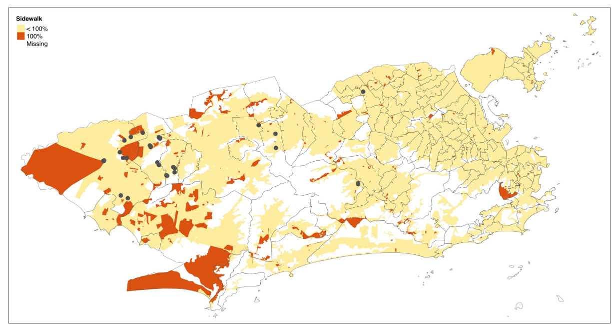
(b) Share of whites



(c) Sewage



(d) Paved Sidewalk

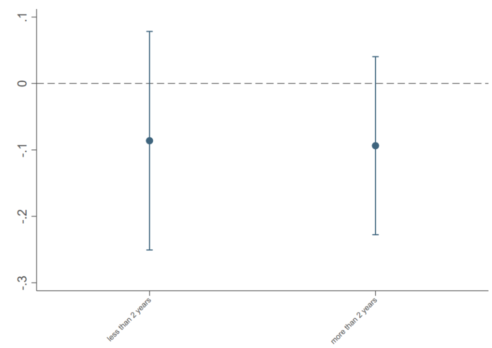


Note: Each panel reports the spatial distribution of a different socioeconomic at the census-tract level in the municipality of Rio de Janeiro. The black dots represent the location of the MCMV projects.

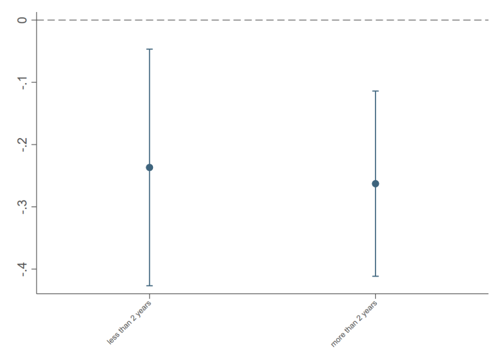
C Exposure Effects

Figure C1: Neighborhoods

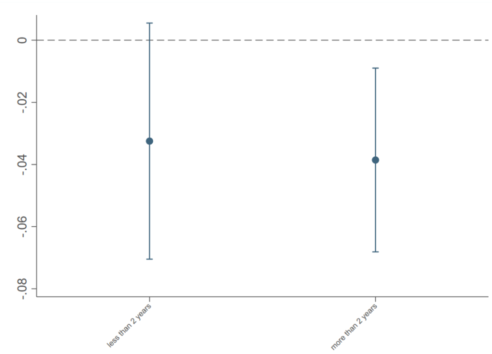
(a) Neighborhood index



(b) Neighbors index



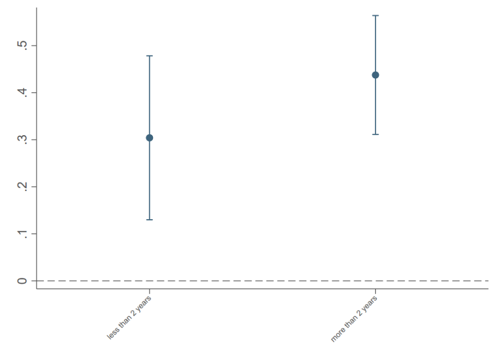
(c) Job accessibility



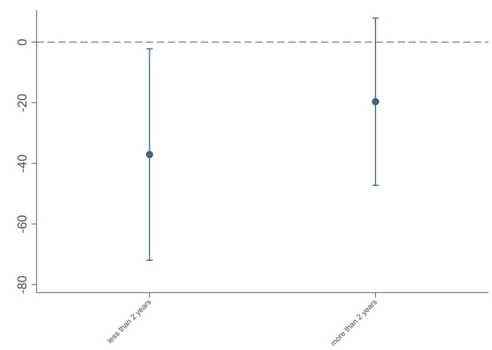
Notes: The figure plots the coefficients obtained from estimating equation (2) using a different indicators of neighborhood quality as dependent variables. The point denote the coefficient and the capped lines their 95% confidence intervals.

Figure C2: Housing Quality and Costs

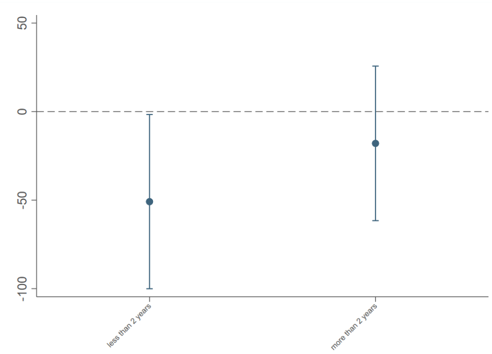
(a) House index



(b) Housing Costs



(c) Total Costs



Notes: The figure plots the coefficients obtained from estimating equation (2) using a different indicators of housing quality and costs as dependent variables. The point denote the coefficient and the capped lines their 95% confidence intervals.

D Results using Other Lotteries

Tables D1-D7 replicate the effects of the MCMV for the 2011 lotteries. Table D1 restricts the sample to households which updates their records before the first date of delivery of the units allocated using these lotteries. The other tables use the full sample.

Table D1: Descriptive Statistics and Randomization Check

	(1)	(2)	(3)	(4)
	Control	Treatment	T-C	N
Panel A: Demographics				
Female head	0.96	0.95	-0.00	15069
	[0.20]	[0.21]	(0.01)	
Age	38.80	39.02	0.22	15069
	[9.56]	[9.38]	(0.33)	
Spouse (0/1)	0.23	0.22	-0.01	15069
	[0.42]	[0.42]	(0.01)	
Children 0-6 (0/1)	0.42	0.40	-0.02	15070
	[0.49]	[0.49]	(0.02)	
Dwellers	3.69	3.75	0.06	15070
	[1.52]	[1.45]	(0.05)	
Joint significance test (p-value)			0.457	
Panel B: Neighborhoods				
Population (in 1000s)	108.45	99.57	-8.89**	10402
	[94.79]	[90.67]	(3.79)	
Sewage	0.78	0.78	0.00	10402
	[0.20]	[0.19]	(0.01)	
Water	0.99	0.98	-0.00*	10402
	[0.03]	[0.04]	(0.00)	
Sh. Work (head)	0.86	0.86	0.00	10402
	[0.03]	[0.03]	(0.00)	
Avg. Income (head)	1399.76	1451.65	51.89*	10402
	[678.93]	[649.53]	(27.14)	
Sh. white	0.44	0.45	0.01**	10402
	[0.09]	[0.10]	(0.00)	
Joint significance test (p-value)			0.131	

Descriptive Statistics and Randomization Check (continuation)

	(1)	(2)	(3)	(4)
	Control	Treatment	T-C	N
Panel C: Housing Quality				
Wood/Tile (0/1)	0.43	0.43	-0.00	15070
	[0.50]	[0.50]	(0.02)	
Sewage (0/1)	0.89	0.90	0.01	15070
	[0.32]	[0.30]	(0.01)	
Paving (0/1)	0.54	0.55	0.01	15070
	[0.50]	[0.50]	(0.02)	
Electricity (meter 0/1)	0.58	0.57	-0.01	14860
	[0.49]	[0.49]	(0.02)	
Dorms	1.34	1.32	-0.03	10280
	[0.70]	[0.53]	(0.02)	
Rooms	3.78	3.82	0.04	14858
	[1.49]	[1.68]	(0.06)	
Dwellers per room	1.09	1.10	0.01	14858
	[0.66]	[0.65]	(0.02)	
Joint significance test (p-value)			0.520	
Panel D: Housing Costs				
Rent	55.97	60.39	4.42	11066
	[106.45]	[111.05]	(4.48)	
Electricity	21.34	22.40	1.07	11764
	[38.44]	[35.61]	(1.41)	
Gas	36.25	34.32	-1.93	13280
	[53.43]	[12.40]	(0.65)	
Water	6.05	6.52	0.47	10914
	[15.32]	[16.17]	(0.66)	
Joint significance test (p-value)			0.473	
Panel E: Enrollment and LFP				
School Enrollment (%)	0.86	0.85	-0.01	13206
	[0.29]	[0.30]	(0.01)	
LFP (Head, 25-64)	0.54	0.56	0.03	9252
	[0.50]	[0.50]	(0.02)	
Joint significance test (p-value)			0.479	

Notes: Column 1 reports the mean of each indicator in the control group. Column 2 reports the mean of each indicator in the treatment group. Column 3 reports mean differences between the treatment groups and the control group. Column 4 reports the number of observations of each indicator. Sample is restricted to households observed in the *Cadastro Único* pre and post-treatment. Standard deviations are reported in brackets and robust standard errors are reported in parentheses. ***p<0.01; **p<0.05; *p<0.10

Table D2: Neighborhood Quality

	(1)	(2)	(3)	(4)
	Control Mean	Bivariate	Baseline	N
Panel A: Neighborhood				
Population	104.548	-0.607	1.591	28542
	(93.534)	(2.062)	(1.454)	
		[0.756]	[0.501]	
Sewage	0.776	0.008	0.004	28542
	(0.203)	(0.004)	(0.003)	
		[0.224]	[0.501]	
Water	0.987	-0.001	0.001	28542
	(0.026)	(0.001)	(0.001)	
		[0.494]	[0.501]	
Neighborhood Index	-0.008	0.020	0.022	28542
	[1.008]	[0.022]	[0.022]	
Panel B: Neighbors				
LFP (head)	0.860	-0.005***	-0.005***	28542
	(0.033)	(0.001)	(0.001)	
		[0.002]	[0.002]	
Income (head)	1421.942	-38.834**	-44.917***	28542
	(720.219)	(15.989)	(10.390)	
		[0.032]	[0.002]	
White (%)	0.444	-0.010 ***	-0.010***	28542
	(0.100)	(0.002)	(0.002)	
		[0.002]	[0.002]	
Neighbors Index	0.026	-0.114 **	-0.105**	28542
	[1.012]	[0.024]	[0.024]	
Panel C: Access to Opportunities				
Jobs: 90 minutes	0.283	-0.020 ***	-0.019 ***	28542
	(0.197)	(0.005)	(0.003)	
		[0.002]	[0.002]	
Schools: 90 minutes	0.277	-0.008 ***	-0.011 ***	28542
	(0.131)	(0.003)	(0.002)	
		[0.007]	[0.002]	

Notes: Each row reports the results for a different outcome. Column 1 reports the control mean. Column 2 reports the coefficient of a bivariate regression of each outcome on a treatment dummy. Column 3 add the outcome measure in the baseline as a control. Sample is restricted to households observed in the *Cadastro Único* pre and post-treatment. Robust standard errors are reported in parentheses and Romano-Wolf *p*-values correcting for multiple testing in each group of outcomes are reported in brackets. ***p<0.01; **p<0.05; *p<0.10

Table D3: Housing Quality

	(1)	(2)	(3)	(4)
	Control Mean	Bivariate	Baseline	N
Wood/Tile Floor (0/1)	0.53	0.04***	0.04***	28647
	(0.50)	(0.01)	(0.01)	
		[0.00]	[0.00]	
Paving (0/1)	0.66	0.02**	0.01	28647
	(0.47)	(0.01)	(0.01)	
		[0.02]	[0.25]	
Sewage (0/1)	0.90	0.01	0.01	28647
	(0.30)	(0.30)	(0.30)	
		[0.11]	[0.25]	
Dorms	1.33	0.11***	0.11***	28180
	(0.75)	(0.01)	(0.01)	
		[0.00]	[0.00]	
Rooms	3.83	0.18***	0.15***	28180
	(1.50)	(0.02)	(0.02)	
		[0.00]	[0.00]	
Electricity - meter (0/1)	0.58	0.07***	0.06***	28180
	(0.49)	(0.01)	(0.01)	
		[0.00]	[0.00]	
House Index	-0.13	0.20***	0.20***	28180
	(1.06)	(0.02)	(0.02)	

Notes: Each row reports the results for a different outcome. Column 1 reports the control mean. Column 2 reports the coefficient of a bivariate regression of each outcome on a treatment dummy. Column 3 add the outcome measure in the baseline as a control. Sample is restricted to households observed in the *Cadastro Único* pre and post-treatment. Robust standard errors are reported in parentheses and Romano-Wolf p-values correcting for multiple testing are reported in brackets. ***p<0.01; **p<0.05; *p<0.10

Table D4: Housing Costs

	(1)	(2)	(3)	(4)
	Control Mean	Bivariate	Baseline	N
Rent	59.27	-14.52*	-17.70***	28657
	(114.80)	(3.94)	(3.94)	
		[0.01]	[0.00]	
Water	5.90	3.56***	3.72***	28647
	(16.19)	(0.69)	[0.72)	
		[0.00]	[0.00]	
Gas	37.61	-1.89*	-1.89*	28647
	(53.70)	(0.69)	(0.72)	
		[0.08]	[0.10]	
Electricity	21.39	6.31	6.34	28647
	(64.15)	(2.59)	(2.86)	
		[0.12]	[0.13]	
Total	298.99	-0.44	-3.54	28647
	(296.78)	(7.23)	(7.19)	

Notes: Each row reports the results for a different outcome. Column 1 reports the control mean. Column 2 reports the coefficient of a bivariate regression of each outcome on a treatment dummy. Column 3 add the outcome measure in the baseline as a control. Sample is restricted to households observed in the *Cadastro Único* pre and post-treatment. Robust standard errors are reported in parentheses and Romano-Wolf *p*-values correcting for multiple testing are reported in brackets. ***p<0.01; **p<0.05; *p<0.10

Table D5: Female LFP

	(1)	(2)	(3)	(4)
	Control Mean	Bivariate	Baseline	N
Panel A: Head (0/1)				
25-64	0.43	0.01	0.01	26305
	[0.49]	(0.01)	(0.01)	
25-44	0.44	0.01	0.00	15356
	[0.50]	(0.02)	(0.02)	
45-64	0.39	0.02	0.01	10949
	[0.49]	(0.02)	(0.02)	
Panel B: All (%)				
25-64	0.415	0.01	0.00	26869
	[0.485]	(0.01)	(0.01)	
25-44	0.424	0.01	0.01	16857
	[0.492]	(0.02)	(0.02)	
45-64	0.366	0.02	0.00	11385
	[0.481]	(0.02)	(0.02)	

Notes: Panel A reports the effects of the MCMV on the labor force participation of the heads of household. Panel A reports the effects of the MCMV on the labor force participation of adults in general. Column 1 reports the control mean. Column 2 reports the coefficient of a bivariate regression of each outcome on a treatment dummy. Column 3 add the outcome measure in the baseline as a control. Sample is restricted to households observed in the *Cadastro Único* pre and post-treatment. Robust standard errors are reported in parentheses. ***p<0.01; **p<0.05; *p<0.10

Table D6: Income

	(1)	(2)	(3)	(4)
	Control Mean	Bivariate	Baseline	N
Wage (head)	283.52	10.10	-0.84	28368
	[396.74]	(11.83)	(12.99)	
Wage (Household)	340.89	8.74	-7.11	28368
	[451.32]	(13.23)	(13.01)	
Income per capita	168.36	1.05	-3.44	28647
	[200.97]	(4.65)	(4.64)	

Notes: Each row reports the results for a different outcome. Column 1 reports the control mean. Column 2 reports the coefficient of a bivariate regression of each outcome on a treatment dummy. Column 3 add the outcome measure in the baseline as a control. Sample is restricted to households observed in the *Cadastro Único* pre and post-treatment. Robust standard errors are reported in parentheses. ***p<0.01; **p<0.05; *p<0.10

Table D7: Education

	(1)	(2)	(3)	(4)
	Control Mean	Bivariate	Baseline	N
Enrollment, 4-18	0.89	-0.01	-0.01 *	22610
	[0.25]	(0.00)	(0.00)	
Boys, 4-18	0.89	-0.01	-0.01	15675
	[0.28]	(0.01)	(0.01)	
Girls, 4-18	0.90	-0.01	-0.01	15235
	[0.28]	(0.01)	(0.01)	
Pre-School, 4-6	0.61	-0.03	-0.06	4251
	[0.48]	(0.05)	(0.05)	
Enrollment, 7-15	0.96	-0.00	-0.00	17461
	[0.18]	(0.00)	(0.00)	
Boys, 7-15	0.95	-0.00	0.00	11003
	[0.20]	(0.00)	(0.00)	
Girls, 7-15	0.96	-0.01	-0.01	10563
	[0.19]	(0.01)	(0.01)	
Elementary, 7-15	0.85	-0.01	-0.01	17461
	[0.32]	(0.01)	(0.01)	
Boys, 7-15	0.85	0.00	0.01	11003
	[0.34]	(0.01)	(0.01)	
Girls, 7-15	0.85	-0.02	-0.02	10563
	[0.34]	(0.01)	(0.01)	
Enrollment, 16-18	0.94	-0.01	0.00	10770
	[0.23]	(0.02)	(0.02)	
Boys, 16-18	0.94	-0.02	0.01	5942
	[0.24]	(0.03)	(0.03)	
Girls, 16-18	0.94	-0.01	-0.03	5526
	[0.23]	(0.04)	(0.04)	
High School, 16-18	0.32	0.01	0.02	10770
	[0.45]	(0.02)	(0.03)	
Boys, 16-18	0.28	0.00	0.02	5942
	[0.44]	(0.03)	(0.06)	
Girls, 16-18	0.34	-0.02	0.04	5405
	[0.47]	(0.03)	(0.06)	
High School graduate, 19-24	0.31	0.00	0.05	9863
	[0.45]	(0.02)	(0.03)	
Boys, 19-24	0.26	0.02	0.03	5470
	[0.43]	(0.03)	(0.06)	
Girls, 29-24	0.34	-0.02	0.04	5405
	[0.47]	(0.03)	(0.06)	

Notes: Each row reports the results for a different outcome. Column 1 reports the control mean. Column 2 reports the coefficient of a bivariate regression of each outcome on a treatment dummy. Column 3 add the outcome measure in the baseline as a control. Sample is restricted to households observed in the *Cadastro Único* pre and post-treatment. Robust standard errors are reported in parentheses. ***p<0.01; **p<0.05; *p<0.10

Tables D8 -D14 replicate the effects of the MCMV for the 2015 lotteries. The sample is restricted to the four lotteries without known implementation issues.

Table D8: Descriptive Statistics and Randomization Check

	(1)	(2)	(3)	(4)
	Control	Treatment	T-C	N
Panel A: Demographics				
Female head	0.96	0.97	0.00	42728
	[0.18]	[0.17]	(0.01)	
Age	38.57	39.14	0.57	42728
	[9.36]	[9.23]	(0.41)	
Spouse (0/1)	0.21	0.18	-0.02	42728
	[0.40]	[0.39]	(0.02)	
Children 0-6 (0/1)	0.46	0.45	-0.00	42729
	[0.50]	[0.50]	(0.02)	
Dwellers	3.80	3.82	0.02	42729
	[1.54]	[1.45]	(0.06)	
Joint Test (p-value)			0.177	
Panel B: Neighborhoods				
Population (in 1000s)	100.69	102.62	1.93	37060
	[91.53]	[95.29]	(4.55)	
Sewage	0.77	0.77	-0.00	37060
	[0.21]	[0.21]	(0.01)	
Water	0.99	0.98	-0.00	37060
	[0.03]	[0.03]	(0.00)	
Sh. Work (head)	0.86	0.86	0.00	37060
	[0.03]	[0.03]	(0.00)	
Avg. Income (head)	1415.31	1468.85	53.54	37060
	[732.79]	[750.71]	(35.83)	
Sh. white	0.44	0.45	0.01	37060
	[0.10]	[0.10]	(0.00)	
Joint Test (p-value)			0.116	

Descriptive Statistics and Randomization Check (continuation)

	(1)	(2)	(3)	(4)
	Control	Treatment	T-C	N
Panel C: Housing Quality				
Wood/Tile (0/1)	0.55	0.50	-0.04**	42728
	[0.50]	[0.50]	(0.02)	
Sewage (0/1)	0.90	0.90	-0.00	42728
	[0.30]	[0.31]	(0.01)	
Paving (0/1)	0.68	0.65	-0.03	42728
	[0.47]	[0.48]	(0.02)	
Electricity (meter 0/1)	0.56	0.58	0.02	42146
	[0.50]	[0.49]	(0.02)	
Dorms	1.32	1.30	-0.03	36706
	[0.84]	[0.50]	(0.02)	
Rooms	3.83	3.73	-0.10*	42147
	[1.51]	[1.09]	(0.05)	
Dwellers per room	1.09	1.12	0.03	42146
	[0.61]	[0.63]	(0.03)	
Joint Test (p-value)			0.101	
Panel C: Housing Costs				
Rent	53.96	56.23	2.27	37894
	[110.95]	[116.15]	(5.48)	
Electricity	20.02	21.11	1.09	38698
	[54.99]	[39.36]	(1.86)	
Gas	37.47	37.38	-0.10	40619
	[46.79]	[12.07]	(0.59)	
Water	5.36	5.11	-0.26	37727
	[15.88]	[14.31]	(0.68)	
Joint Test (p-value)			0.633	
Panel D: Enrollment and LFP				
Enrollment (sh)	0.89	0.88	-0.01	39034
	[0.25]	[0.27]	(0.01)	
LFP (female, 25a64)	0.51	0.52	0.01	33843
	[0.50]	[0.50]	(0.02)	
Joint Test (p-value)			0.867	

Notes: Column 1 reports the mean of each indicator in the control group. Column 2 reports the mean of each indicator in the treatment group. Column 3 reports mean differences between the treatment groups and the control group. Column 4 reports the number of observations of each indicator. Sample is restricted to households observed in the *Cadastro Único* pre and post-treatment. Standard deviations are reported in brackets and robust standard errors are reported in parentheses. ***p<0.01; **p<0.05; *p<0.10

Table D9: Neighborhood Quality

	(1)	(2)	(3)	(4)
	Control Mean	Bivariate	Baseline	N
Panel A: Neighborhood				
Population	100.692	13.642***	13.762***	42714
	(91.526)	(4.117)	(3.594)	
		[0.005]	[0.002]	
Sewage	0.771	0.001	0.002	42714
	(0.208)	(0.009)	(0.007)	
		[0.918]	[0.833]	
Water	0.986	-0.000	0.001	42714
	(0.028)	(0.001)	(0.001)	
		[0.918]	[0.716]	
Neighborhood Index	-0.005	0.093**	0.098**	42714
	(1.000)	(0.044)	(0.044)	
Panel B: Neighbors				
LFP (head)	0.858	-0.007***	-0.007***	42714
	(0.034)	(0.002)	(0.002)	
		[0.002]	[0.002]	
White (%)	0.442	-0.015***	-0.020***	42714
	(0.101)	(0.004)	(0.004)	
		[0.005]	[0.002]	
Income (head)	1415.310	-35.513	-68.993***	42714
	(732.787)	(32.517)	(18.791)	
		[0.262]	[0.002]	
Neighbors Index	0.020	-0.148**	-0.208**	42714
	(1.013)	(0.045)	(0.045)	
Panel C: Access to Opportunities				
Jobs: 90 minutes	0.274	-0.028***	-0.041***	42714
	(0.198)	(0.009)	(0.006)	
		[0.005]	[0.002]	
Schools: 90 minutes	0.271	-0.018***	-0.024***	42714
	(0.132)	(0.006)	(0.004)	
		[0.005]	[0.002]	

Notes: Each row reports the results for a different outcome. Column 1 reports the control mean. Column 2 reports the coefficient of a bivariate regression of each outcome on a treatment dummy. Column 3 add the outcome measure in the baseline as a control. Sample is restricted to households observed in the *Cadastro Único* pre and post-treatment. Robust standard errors are reported in parentheses and Romano-Wolf *p*-values correcting for multiple testing in each group of outcomes are reported in brackets. ***p<0.01; **p<0.05; *p<0.10

Table D10: Housing Quality

	(1)	(2)	(3)	(4)
	Control Mean	Bivariate	Baseline	N
Wood/Tile Floor (0/1)	0.55	0.04**	0.06***	42728
	(0.50)	(0.02)	(0.02)	
		[0.06]	[0.00]	
Paving(0/1)	0.68	0.04***	0.05***	42728
	(0.47)	(0.02)	(0.01)	
		[0.04]	[0.00]	
Sewage (0/1)	0.90	0.01	0.01	42728
	(0.30)	(0.30)	(0.30)	
		[0.43]	[0.30]	
Dorms	1.32	0.07***	0.09***	42728
	(0.84)	(0.02)	(0.02)	
		[0.02]	[0.00]	
Rooms	3.83	0.17***	0.20***	42728
	(1.51)	(0.04)	(0.04)	
		[0.00]	[0.00]	
Electricity - meter (0/1)	0.56	0.08***	0.07***	42728
	(0.50)	(0.02)	(0.02)	
		[0.00]	[0.00]	
House Index	-0.11	0.17***	0.23***	42728
	(1.09)	(0.04)	(0.04)	

Notes: Each row reports the results for a different outcome. Column 1 reports the control mean. Column 2 reports the coefficient of a bivariate regression of each outcome on a treatment dummy. Column 3 add the outcome measure in the baseline as a control. Sample is restricted to households observed in the *Cadastro Único* pre and post-treatment. Robust standard errors are reported in parentheses and Romano-Wolf *p*-values correcting for multiple testing are reported in brackets. ***p<0.01; **p<0.05; *p<0.10

Table D11: Housing Costs

	(1)	(2)	(3)	(4)
	Control Mean	Bivariate	Baseline	N
Rent	53.96	-27.33*	-31.97*	42728
	(110.95)	(6.69)	(6.69)	
		[0.09]	[0.08]	
Water	5.36	4.16*	4.66*	42728
	(15.88)	(1.24)	(1.31)	
		[0.08]	[0.08]	
Gas	37.47	-2.90	-2.80	42728
	(46.79)	(1.10)	(1.14)	
		[0.22]	[0.23]	
Electricity	20.02	22.65	25.06	42728
	(54.99)	(15.51)	(17.57)	
		[0.22]	[0.23]	
Total	296.01	2.50	2.98	42728
	(200.36)	(19.87)	(19.10)	
Cost Index	-0.22	0.04	0.06	42728
	(0.64)	(0.05)	(0.05)	

Notes: Each row reports the results for a different outcome. Column 1 reports the control mean. Column 2 reports the coefficient of a bivariate regression of each outcome on a treatment dummy. Column 3 add the outcome measure in the baseline as a control. Sample is restricted to households observed in the *Cadastro Único* pre and post-treatment. Robust standard errors are reported in parentheses and Romano-Wolf *p*-values correcting for multiple testing are reported in brackets. ***p<0.01; **p<0.05; *p<0.10

Table D12: Female LFP

	(1)	(2)	(3)	(4)
	Control Mean	Bivariate	Baseline	N
Panel A: Head (0/1)				
25-64	0.44	-0.02	-0.02	39692
	[0.50]	(0.02)	(0.02)	
25-44	0.45	-0.04	-0.04	23582
	[0.50]	(0.03)	(0.03)	
45-64	0.40	0.01	0.01	16110
	[0.49]	(0.03)	(0.04)	
Panel B: All (%)				
25-64	0.424	-0.01	-0.01	40359
	[0.486]	(0.02)	(0.02)	
25-44	0.435	-0.04	-0.04	25846
	[0.494]	(0.03)	(0.03)	
45-64	0.371	0.02	-0.05	16641
	[0.482]	(0.03)	(0.04)	

Notes: Each row reports the results for a different outcome. Column 1 reports the control mean. Column 2 reports the coefficient of a bivariate regression of each outcome on a treatment dummy. Column 3 add the outcome measure in the baseline as a control. Sample is restricted to households observed in the *Cadastro Único* pre and post-treatment. Robust standard errors are reported in parentheses. ***p<0.01; **p<0.05; *p<0.10

Table D13: Income

	(1)	(2)	(3)	(4)
	Control Mean	Bivariate	Baseline	N
Wage (head)	273.44	-17.33	-18.49	42368
	[395.47]	(17.15)	(18.26)	
Wage (Household)	328.04	-20.74	-20.71	42368
	[449.86]	(19.95)	(19.45)	
Income per capita	158.36	11.48	10.94	42729
	[197.70]	(9.22)	(9.20)	

Notes: Each row reports the results for a different outcome. Column 1 reports the control mean. Column 2 reports the coefficient of a bivariate regression of each outcome on a treatment dummy. Column 3 add the outcome measure in the baseline as a control. Sample is restricted to households observed in the *Cadastro Único* pre and post-treatment. Robust standard errors are reported in parentheses. ***p<0.01; **p<0.05; *p<0.10

Table D14: Education

	(1)	(2)	(3)	(4)
	Control Mean	Bivariate	Baseline	N
Enrollment, 4-18	0.89	-0.00	-0.00	34057
	[0.25]	(0.01)	(0.01)	
Boys, 4-18	0.89	-0.01	-0.00	23908
	[0.28]	(0.01)	(0.01)	
Girls, 4-18	0.89	0.00	-0.00	23171
	[0.28]	(0.01)	(0.01)	
Pre-School, 4-6	0.62	-0.00	-0.05	6694
	[0.48]	(0.08)	(0.08)	
Enrollment, 7-15	0.96	0.00	0.00	26843
	[0.17]	(0.00)	(0.00)	
Boys, 7-15	0.96	-0.00	0.01 ***	16969
	[0.19]	(0.00)	(0.00)	
Girls, 7-15	0.96	0.01 ***	0.01 ***	16398
	[0.19]	(0.00)	(0.00)	
Elementary, 7-15	0.86	-0.00	0.01	26843
	[0.31]	(0.01)	(0.01)	
Boys, 7-15	0.86	-0.00	0.01	16969
	[0.33]	(0.02)	(0.01)	
Girls, 7-15	0.86	0.01	-0.01	16398
	[0.33]	(0.02)	(0.02)	
Enrollment, 16-18	0.94	-0.02	-0.08 *	16208
	[0.23]	(0.04)	(0.04)	
Boys, 16-18	0.94	-0.00	0.07 ***	8951
	[0.23]	(0.01)	(0.01)	
Girls, 16-18	0.94	-0.05	-0.19 **	8284
	[0.23]	(0.09)	(0.09)	
High School, 16-18	0.34	-0.00	-0.02	16208
	[0.46]	(0.03)	(0.06)	
Boys, 16-18	0.29	0.02	0.17	8951
	[0.45]	(0.05)	(0.14)	
Girls, 16-18	0.35	0.04	0.04	8332
	[0.47]	(0.05)	(0.11)	
High School graduate, 19-24	0.32	0.01	0.07	14963
	[0.45]	(0.04)	(0.07)	
Boys, 19-24	0.26	0.00	0.16	8208
	[0.43]	(0.05)	(0.12)	
Girls, 29-24	0.35	0.04	0.04	8332
	[0.47]	(0.05)	(0.11)	

Notes: Each row reports the results for a different outcome. Column 1 reports the control mean. Column 2 reports the coefficient of a bivariate regression of each outcome on a treatment dummy. Column 3 add the outcome measure in the baseline as a control. Sample is restricted to households observed in the *Cadastro Único* pre and post-treatment. Robust standard errors are reported in parentheses. ***p<0.01; **p<0.05; *p<0.10