Housing Policies and Social Mobility*

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Abstract

We leverage lottery and administrative data to study the effects of a large-sized housing program on educational and labor market outcomes. Brazil's "My House My Life" program heavily subsidizes homeownership, albeit in remote areas, for millions of low-income families. We document that children of lottery-winner households move to worse schools. Moreover, school absences increase significantly. When assessing the longer-run consequences on labor market outcomes, we find that children of winner households have lower labor market participation when reaching adulthood. While children present worse outcomes, we show that adults adopt adaptation measures that offset potential adverse effects. Our findings have far-reaching implications, highlighting the need to design and target housing policies to stimulate important drivers of social mobility.

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1 Introduction

An emerging theme in policy-making is to what extent housing policies can work as an instrument for stimulating social mobility and decreasing inequalities. Over time, the policy debate has shifted from the traditional role of housing policies—the need to boost affordability of adequate housing units—to a more comprehensive view that also takes into account the role of local amenities in creating human capital and promoting upward mobility. However, there is little systematic evidence on whether and how housing policies affect social mobility. The existing literature either lacks credible identification strategies or pays no attention to the pathways through which housing policies affect social mobility.[1]

This paper investigates how a large housing program affects education and future labor market outcomes of children of beneficiary families. The program—called "My House My Life"—heavily subsidizes homeownership for low-income families in Brazil. The housing program has been one of the world's largest programs during the past decades, with four million beneficiaries living in recently built housing units, often located in remote areas. One of the main characteristics of the program is that subsidies can be massive and account for up to 90% of the housing unit market value.

The large-sized program we study is a suitable setting for studying how housing policies affect education and labor market outcomes for at least four reasons. First, like several programs worldwide, the program we study provides social housing in cheaper, remote areas. The rapid urbanization in many low- and middle-income countries (e.g., in Africa) may require a large amount of public funds for social social. Given the restricted fiscal capacity in many low- and middle-income countries, understanding the effects of providing social housing in cheaper, remote locations is policy-relevant. Second, since billions of people live in substandard housing conditions in developing countries (e.g., more than one billion people live in slum settlements (United Nations, 2020)) and in marginalized areas of rich countries, the housing policy we study may be informative for a sizeable part of the world's population. Third, the large sample size from a program at scale allows us to perform analyses to understand who is affected by the policy that previous studies could not undertake. Fourth, it selects beneficiaries through lotteries, which we explore in our research design.

We start by analyzing the effects on education. Housing programs usually interfere with the location of households and children's schools. Conceptually, the effects of any housing program on education are ambiguous, depending on the relative quality of the new and old schools. This means that even in our setting of a housing program

[1] We define social mobility as the ability to move from a lower to a higher level of education or level of income. In this paper, we work with intragenerational mobility.

building units in remote locations, these changes do not necessarily always come at an educational cost. Moreover, even when the new schools are lower quality, the effects on educational outcomes may be offset by other factors, such as improvements in housing quality and parents' compensating behaviors. Therefore, understanding the educational consequences of housing policies is ultimately an empirical analysis and context-specific.

We leverage comprehensive lottery and administrative data to study the effects of the large-sized housing program on education. Bringing detailed data allow us to analyze both school-level and individual-level educational outcomes. Using the lottery results, we compare the educational outcomes of children in winner families to those in non-winner families. Specifically, in our empirical strategy, we estimate a Local Average Treatment Effect (LATE) using the housing lottery results as an instrumental variable for moving to a housing unit of the program.

We document three main results. Tracking the exact school pre- and post-lottery in a large and connected set of registries, we show that beneficiaries are more likely to switch schools and enroll their children in schools near the housing projects. This is consistent with the projects being located in remote areas and, thus, families need to enroll children in nearby schools.[2] Second, we document that children switch to worse schools as measured by school-level learning performance and teachers' qualification. Third, we find that chronic absenteeism has increased significantly. This is important because a broad literature explains that absences are related to short- and long-run consequences, such as lower academic performance (Liu et al., 2021) and criminal activities.

We then investigate the longer-term consequences on labor market outcomes by assessing whether children of winning households have lower labor market participation in the formal labor market when reaching adulthood. Entry into the formal labor market is a suitable indicator, as informality is pervasive in Brazil. The consequences on labor market outcomes are conceptually ambiguous: a worse education environment affects labor outcomes negatively, but since the program promotes a reduction in housing costs because of the subsidies, the extra income may be used to counteract the adverse effects on education. Our lottery-based results indicate that children of winner households have lower labor market participation in the formal labor market when reaching adulthood. Last, we assess the effects on parents' labor market outcomes. Using the same empirical strategy, we show a smaller effect on adults' labor market participation. We provide evidence of adaption measures to counteract the adverse effects of remote locations. However, the negative effects on children suggest that the

[2]We do not find that all children move to new schools because the capacity of nearby schools is not always enough to accommodate the demand of children from recently built projects.

adaption behavior was not enough for compensating the effects on education.

Our paper relates to several strands of the economics literature. We connect to the literature on the effects of housing policies and neighborhood exposure on socioeconomic outcomes (see Chyn and Katz, 2021 for a literature review). We are especially connected to the strand using experimental and lottery-based designs to study the effects of housing policy on human capital accumulation (e.g., Billings et al., 2022; Camacho et al., 2022). This strand has mostly focused on programs inducing people to move out of disadvantaged neighborhoods. While some studies suggest no short-run effects on education (e.g., Jacob, 2004; Sanbonmatsu et al., 2006), papers assessing the long-run outcomes of those children indicate positive impacts, especially on labor market outcomes (e.g., Chetty et al., 2016). More recently, Kumar (2021) studies a housing program in India that does not change the beneficiaries' location and shows that it increases the educational attainment of (adult) lottery winners.

Our setting of a program at scale allows us to revisit the effects on social mobility and make three contributions. First, we provide novel evidence of the impacts of a typical housing program (whose characteristics of building housing in cheaper, remote areas are commonly found in policies in many countries) on children's outcomes. Our findings indicate that children end-up in schools with worse indicators (supply-side factor), present higher school absence (demand-side factor), and present worse labor market outcomes when reaching adulthood. These findings highlight the need to design and target housing policies to stimulate important drivers of social mobility. Second, we add to the distributional debate about the effects of housing programs by performing heterogeneity analyses that are conceptually important. This is only possible due to our detailed administrative data and the setting of a large-sized program (but not possible in the context of smaller-sized interventions). Third, although there is evidence of the impacts of moving households out to better neighborhoods on children's human capital and longer-run labor market performance, there is little evidence of the educational consequences of the opposite phenomenon: relocating households to remote, below-par areas. Since it is unclear whether the socioeconomic effects are symmetrical (e.g., due to behavioral changes), it is relevant to understand the magnitudes of the effects of such housing policies.

More broadly, this paper contributes to a growing literature studying the determinants of social mobility. A more recent and growing strand in economics investigates the role of location in explaining long-term outcomes and life courses of children, focusing mostly on the exposure to historical events and shocks, such as U.S. Civil War (Ager et al., 2021), Great Migration in the U.S. (Derenoncourt, 2022), Apartheid (Carrilo et al., 2021), natural disasters (Nakamura et al., 2022), commodity booms (Sviatschi, 2021), slum clearance (Rojas-Ampuero and Carrera, 2023), and public housing demoli-

tions (Chyn, 2018). The literature has, however, largely overlooked how public policies can also interfere with social mobility or children outcomes. Notable exceptions include Chetty et al. (2016). We contribute by providing a systemic exploration of large-sized policy, whose characteristics are commonly found in policies in many countries. Among this literature, this paper is unique in formally documenting what has been previously suggested anecdotally or more descriptively: that housing programs providing residences in disconnected areas can negatively affect younger generations, creating barriers to social mobility. The extent to which housing programs are able to impact social mobility is policy-relevant in the context of increasing inequality and decreasing social mobility in several countries (Hufe et al., 2021).

This article proceeds as follows. Section 2 details the program. Section 3 describes the data. Section 4 presents the empirical model, while Section 5 reports the results. Section 6 concludes.

2 Background

My House My Life program (In Portuguese, "Programa Minha Casa Minha Vida", henceforth MCMV program) was created in 2009 by the Brazilian national government. The program's goal is twofold: promote access to homeownership for low-income families and stimulate the economy to counteract the adverse effects of the financial crisis of 2007–2008. To be eligible to apply for a housing unit of the program, households must comply with four criteria: monthly income below a threshold, cannot own a residential property, cannot be a beneficiary of another government-run housing program, and have no existing debts with the Brazilian tax authority.

The size of the program's subsidies for homeownership depends on the household income. The lower the income, the greater the subsidy. More specifically, each eligible household is allocated into one of four income brackets (officially called "Faixas") that will determine the amount of subsidy.[3] In this paper, we focus on "Faixa 1" households, the income bracket comprising the poorest households whose monthly income is below R$ 1,800. Subsidies for "Faixa 1" households are massive: they can account for up to 90% of the housing unit construction cost. The residual 10% must be paid in monthly installments, which last up to 120 months. The national public bank "Caixa Econômica Federal" (henceforth CAIXA) provides those installments with below-market interest rates—and in case of default, forecloses on the real estate assets.

This study focuses on "Faixa 1" households due to three factors. First, this group represents the majority of the program's beneficiaries: the income range of the "Faixa

[3]The income brackets are officially called "Faixa 1", "Faixa 1.5", "Faixa 2," and "Faixa 3".

1" group entails households up to the 70th percentile of the income distribution.[4] Second, for reasons that will become clear momentarily, we only have education data for children in households whose monthly income lies inside that income bracket. Last, rules governing the program states that housing lotteries only happen for units in which "Faixa 1" households can apply.

According to the Ministry of Cities' Ordinance n. 140 from April 2010, local governments must select beneficiaries for "Faixa 1" housing projects through housing lotteries if there is oversubscription (i.e., in case there is excess demand for a particular housing project). The local government must also publish a "lottery notice" stating when, how, and where lotteries will occur. Lotteries are widely publicized, and applications are free of charge. Municipalities are responsible for carrying out each lottery to select beneficiaries.[5] CAIXA bank's officials audit the lottery during a ceremony open to the public, where the winners' names are disclosed.[6] According to the legislation, for each housing project, municipalities must use the lottery to create a list of winners (whose number corresponds to the number of units in the housing project), a random waiting list whose participants can eventually receive a housing unit (and whose number of people corresponds to 30% of the number of housing units in the housing project), and a list of participant that do not receive a housing offer.

The lottery result must be published in the Municipal Official Gazette ("diários oficiais municipais"). To apply for a mortgage contract with CAIXA, winners must submit documents to prove their eligibility. Winners cannot sell the property or rent it before paying all installments.

The national government purchases—through a public fund—housing projects built by developers. Those units are then offered to lottery winners. The national government and the CAIXA bank set engineering specifications for those recently built housing units. Alongside technical specifications, the national government set a price cap (of R$ 96,000) for those housing units sold by the developers, which influences the housing projects' feasibility, size, and location. In municipalities where land is more expensive, developers tend to build high-density housing projects located in remote areas. Apart from being physically distanced from the job opportunities and better public services, these areas usually present heavy congestion. MCMV housing units have sanitation, electricity, and other basic urban services. Their minimum size is 39 m^2. Figure 1 shows typical projects of the MCMV program.

Housing policies that specifically focus on affordability and upward mobility are

[4]Data from PNAD Contínua Survey, the National Household Sample Survey conducted by the Brazilian Bureau of Statistics (IBGE).

[5]Municipalities are autonomous entities equivalent to counties in the United States.

[6]CAIXA bank has extensive experience conducting lotteries because it has carried out prize lotteries in Brazil as a monopolist since the 1960s.

Figure 1: MCMV program: Examples of Housing Units

(a) Horizontal project



(b) Vertical project



Notes. The figure shows examples of housing units in vertical and horizontal projects of the program "Minha Casa Minha Vida". Source: Caixa Econômica Federal.

relatively rare, especially in the context of less developed countries. However, even though MCMV does not state social mobility as an official goal, the program rules indicate that housing projects must have schools in the nearby area. According to the main legislation governing the MCMV program (Law n. 11,977 from 2009), if there are no schools near the housing projects, the local government must provide them to the program's beneficiaries.[7] Local government should also work toward allocating beneficiary children in schools near housing projects.

Anecdotal evidence suggests that the schooling provision in MCMV projects is a concern in several cities. Residents, politicians, and other actors regularly complain about schooling provision near housing developments. For instance, in 2015, Senator Angela Portela stated that many beneficiaries could not find free schools to enroll their children near the program's housing projects.[8] In addition, survey data suggest that MCMV beneficiaries present low satisfaction with the proximity of schools to housing units (Ministério das Cidades and Ipea, 2014). Moreover, interviews indicate that in some housing projects with a school nearby, the number of children in the project is greater than the capacity of the school—so a subgroup of children must enroll in schools farther from the project (Biderman, 2019). Below, we provide systematic evidence on the location of schools and variation in school quality.[9]

[7] See MCMV legislation.

[8] See www12.senado.leg.br.

[9] Several studies point out the lack of services surrounding MCMV projects (e.g., Rolnik et al., 2015; Carvalho and Stephan, 2016; Arrigoitia, 2017)—even though they do not focus mainly on schools. However, the lack of services is not observed in every project (e.g., Nisida et al., 2015).

3 Data

We use comprehensive data to assess the effects of the housing program on education and labor market outcomes.

3.1 Administrative data

We work with three individual-level administrative registries. The first registry is the *CadÚnico* registry (Unified Household Registry), which has detailed information of 100 million individuals who are beneficiaries of the government's social programs. Importantly, the *CadÚnico* registry provides family links so that we are able to obtain the family members of each household. From *CadÚnico*, we obtain socioeconomic characteristics of the children (sex and age) and their family members (age and educational attainment).

The second dataset is the *Condicionalidades* registry, which has individual-level information on school attendance for a large set of students in Brazil—for whom attendance was tracked as a condition to receive a nation-wide cash transfer program (see more details below). From *Condicionalidades*, we can track the exact school in which the child is enrolled—this school information is recorded at *Condicionalidades* every two months. Another key information in *Condicionalidades* is the percentage of classes that each student has attended every two months. We create an absenteeism indicator variable that equals one if the school absenteeism is above an official target of 15% of class absence. Therefore, our absenteeism indicator is related to chronic absenteeism.[10]

The third registry provides data on labor market participation: RAIS ("Relação Anual de Informações Sociais"), a matched employee-employer dataset from Brazil's Ministry of Labor. To assess whether there were labor market consequences, we include all children who were at least 18 years old at the time their employment status is measured. RAIS registry has information on the universe of formal labor market contracts, which alleviates concerns about attrition.

We complement the individual-level data with school-level information. We use data from Brazil's Ministry of Education School Census dataset that cover the universe of schools in the country. School quality is measured by the Ideb index (Basic Education Development Index), Brazil's official and primary measure of education quality. The Ideb index considers (i) learning performance and (ii) progress of students through elementary and secondary education. The learning performance stems

[10]The program requires school attendance of at least 85% for children and adolescents aged 6 to 15 years, and 75% for young people aged 16 and 17. See Katie Eklund and McCollom (2022) for a meta-analysis on school absenteeism.

from test scores on Math and Portuguese.[11] Brasil's School Census provides data on pass rates, which are used as the proxy for students' progress. Ideb index ranges from zero to ten, with higher values indicating better school quality, i.e., better grades and pass rates.

Brasil's School Census also provides additional data that we use in our analysis, such as teachers' education (share with tertiary degree) and pass rates. We also obtain the geographic coordinates of each school and link the locations of the geocoded schools and the geocoded housing projects.

3.2 Lotteries and sample

We collect data on ten MCMV lotteries from six municipalities: Rio de Janeiro, Campinas, Guarulhos, São José do Rio Preto, São Gonçalo do Amarante, and Ibiporã. These municipalities made the list of applicants and winners publicly available. The ten lotteries for which we have data happened between 2011 and 2014. Using information of the ten lottery notices, we collect the address of each housing project, from which we generate the geographic coordinates.

Figure 2 details how we built our sample of children of winner and nonwinner households. First, we obtain the list of adult winners and nonwinners and merge with the *CadÚnico* registry. From this step, we find the family members and children of a subset of adults (approximately 50%). To obtain educational outcomes, we follow these children in the *Condicionalidades* registry. More precisely, we work with the subset of children in which the *Condicionalidades* provide educational outcomes (exact school and bi-monthly attendance).

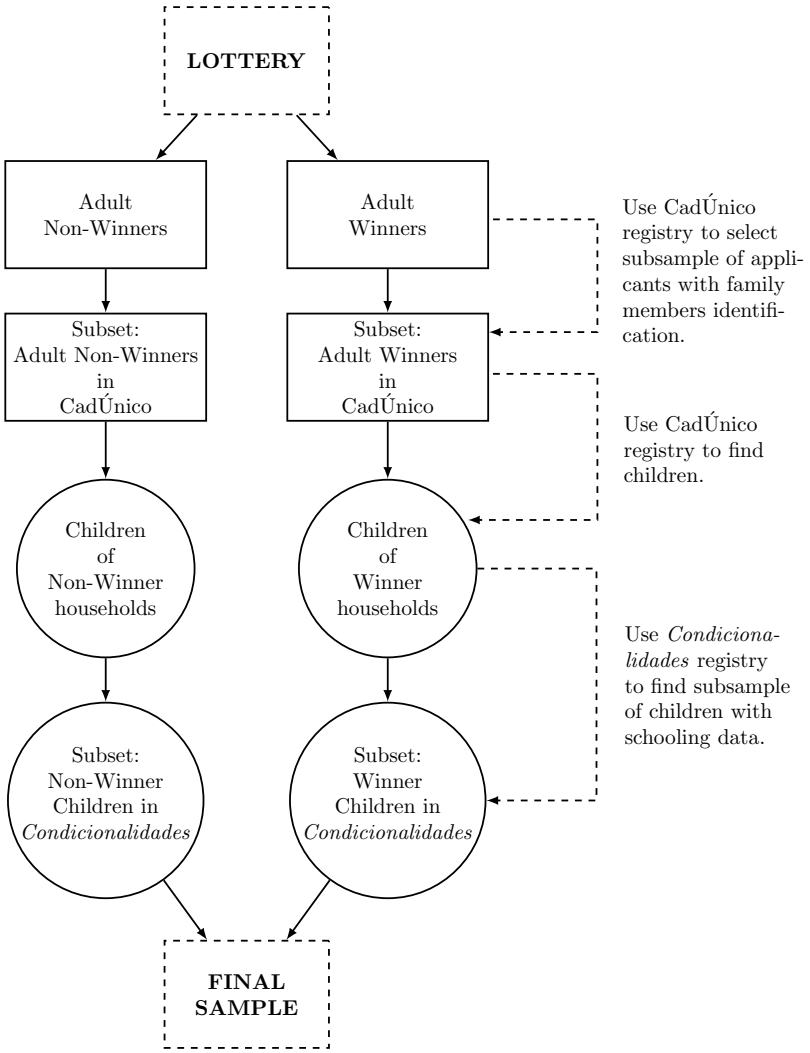
Recall the *Condicionalidades* registry has information for a subset of students in Brazil. This subset consists of children whose parents are beneficiary of a nationwide conditional cash-transfer program: Bolsa Família. Brazil's Bolsa Família is a conditional cash-transfer program focusing on families living in poverty and extreme poverty in Brazil.[12] The program's eligibility is based on an income threshold, and families with or without children (or teenagers) can enter the program. For families with children or teenagers, the main conditionality of the program—which is required from families in order to continue receiving payments—is school attendance. The benefit is suspended, blocked, or canceled if there is no compliance with the targeted school attendance, and this feature makes the registry suitable to obtain education outcomes. Every two months, public schools must register the attendance of those students in a

[11] The test score comes from Saeb ("Sistema de Avaliação da Educação Básica"—National System of Evaluation of Basic Education) exam, is conducted by the National Institute of Educational Studies and Research Anísio Teixeira (Inep), an institute linked to the Ministry of Education. Test scores from Saeb stem from 2nd, 5th and 9th grades of elementary school and the 3rd grade of high school.

[12] Every beneficiary of Bolsa Família is also registered at the "CadÚnico" registry.

government-managed system. These data comprise the *Condicionalidades* registry.

Figure 2: Administrative Registries and Final Sample



Notes. The figure shows how the administrative registries were used to construct the final sample of the paper.

Our final sample comprises 8,881 children of winner families and 306,811 children of nonwinner families. Appendix Table A.3 details the lotteries we use. The final dataset is de-identified. The merged dataset allows us to follow the individuals of our sample over time, minimizing concerns about attrition.

3.3 Stylized fact

In this subsection, we present a stylized fact on how school quality varies by distance to MCMV program's projects. Are schools near housing projects of higher or lower

quality? For the six municipalities for which we have data, we use the geographic coordinates of schools and housing projects to calculate the distance in kilometers between each school-project pair.

We estimate the following cross-section specification:

$$y_{sm} = \alpha + \beta dist_{spm} + \mu_m + \varepsilon_{sm} \quad , \tag{1}$$

where y_{sm} is an educational outcome of school s in municipality m. We use five dependent variables: The Ideb index and four of its components of learning performance (Portuguese and Math scores in the 5th and 9th year of the primary school). $dist_{spm}$ is the distance in kilometers from school s to the nearest MCMV project p in municipality m. μ_m is a municipality fixed effect. The error term is clustered at the municipal-level.

Table 1: Correlation between school quality and distance to MCMV housing projects

Dependent variables:	
IDEB Primary School	0.009***
	(0.003)
SAEB Portuguese: 5th year of primary school	0.499***
	(0.074)
SAEB Math: 5th year of primary school	0.429***
	(0.083)
SAEB Portuguese: 9th year of primary school	0.879***
	(0.103)
SAEB Math: 9th year of primary school	0.919***
	(0.114)
# of Schools	1,626

Notes. The table reports the correlation between school-level quality indicators and the distance to MCMV housing projects. Each cell corresponds to coefficient from Equation 1. Standard errors are clustered at the municipal level.
*** p<0.01, ** p<0.05, * p<0.1

We estimate the empirical model for the year 2011, which is prior to all projects to avoid any influence from composition effect that may stem from the influx of students. We find a strong correlation between the school quality and distance to the MCMV building. More precisely, Table 1 shows that the greater the distance to MCMV projects, the better the average educational outcomes. Results are similar when we run the regressions for the year 2009—see Appendix Table A.1.

The stylized fact suggests a strong correlation pointing out that the schools near MCMV project present on average worse outcomes. In the next section, we detail our

empirical strategy to assess the causal impacts of the program.

4 Empirical Strategy

In the research design, we leverage the random allocation of the housing lotteries to investigate the effects of *moving* to a public housing project. According to rules governing the lotteries, applicants can be partitioned into three groups: (i) "initial-offer" winners (those who were ranked up to the number of vacant housing units), (ii) "replacement" group (individuals randomly allocated who eventually get a housing unit offered if a winner give up a offer), and (iii) "never-offer" group (individuals never offered a housing unit). In this paper, we work with the initial-offer winners and assemble the replacement and never-offer groups together as the "nonwinner" group. According to the program's implementers, initial-offer results were widely publicized and people knew whether they were selected.

Let Z_{ip} be the initial-offer indicator variable, which equals one for applicant i getting an initial offer from the housing lottery p and zero for nonwinners. And let D_{ip} be the moving indicator variable, which equals one if individual i moved to a housing project p and zero otherwise.

We assume the following cross-sectional specification:

$$Y_{ip} = \beta D_{ip} + X'_{ip}\psi + \lambda_p + \upsilon_{ip} \quad , \tag{2}$$

where Y_{ip} is the outcome (education, labor market) for individual i who participated in lottery p. Our dependent variables are at the school and individual levels. We include the lottery fixed effects λ_p to compare winners and nonwinners within the same lottery. X_{ip} is the vector of baseline characteristics (included to improve the precision of the estimates) and υ_{ip} is the error term. If the program has positive impacts, the post-lottery coefficients should be positive and statistically significant.

We instrument for *moving into a housing unit* D_{ip} by using the random variation results of the first housing lottery they applied (Z_{ip}). More precisely, the first-stage equation is as follows:

$$D_{ip} = \eta_1 Z_{ip} + X'_i\eta_2 + \mu_p + e_{ip} \quad . \tag{3}$$

where the parameter η_1 in Equation (3) will show the (differential) compliance rate.

We aim to recover a Local Average Treatment Effect (LATE) due to some implementation constraints. Since some winners do not sign the mortgage contract, non-compliance occurs in the initial-offer group. Besides, a small share of nonwinners end-up winning lotteries in later years—applicants can reapply for lotteries in later years and thus few nonwinners end up winning subsequent housing lotteries. In addi-

tion, to counteract the fact the participants can apply to more than one lottery, we only consider the first lottery in which each individual participates. Therefore, in the empirical implementation, we partition the applicants into groups of "first lottery" they applied for and use the result of the "first lottery" as the instrumental variable for *moving to a housing unit*.[13]

In the robustness exercise, we perform the analysis without the vector of baseline characteristics. To perform heterogeneity analysis, we explore each lottery individually by using variation on pre-lottery school quality.

4.1 Take-Up Rates and Compliers Characterization

Table 2 presents the first-stage results. The initial-offer indicator variable highly predicts the housing-moving indicator variable. The table also shows that the (differential) take-up rate is approximately 42% (i.e., comply with the lottery result by moving to a housing project). The average compliance rate among initial-offer individuals is relatively low compared to housing lotteries studied in other papers of the literature. For instance, in the Moving to Opportunity, the experimental group present a compliance rate of about 60%. Table A.2 in online Appendix A points out that the compliance rate varied considerably among the lotteries in our sample.

Table 2: First-Stage Results

	Moving Indicator Variable	Moving Indicator Variable
Lottery Indicator Variable	0.4930***	0.4922***
	(0.0053)	(0.0053)
Observations	315,692	315,692
F-statistics	5,521	1,572
Strata fixed effects	Yes	Yes
Control: Children Age	No	Yes

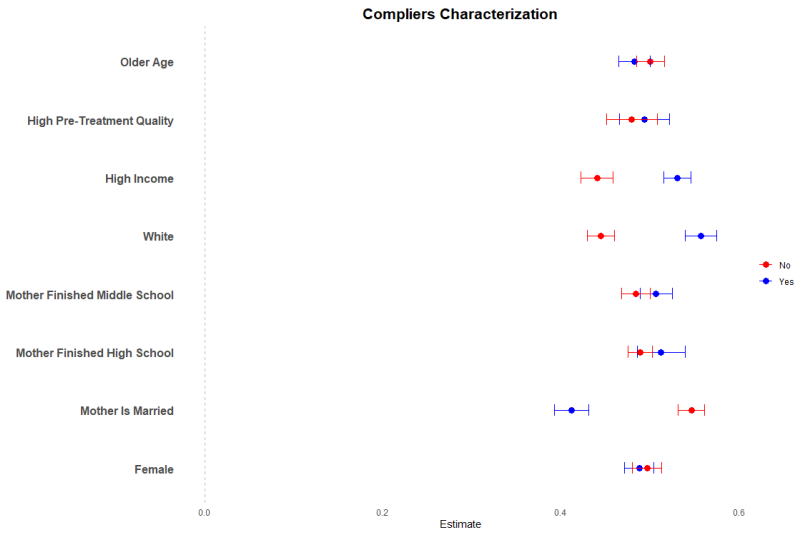
Notes. The table presents the first-stage results. The initial-offer indicator variable equals one for the applicant getting an initial offer at the time of the lottery. The moving indicator variable equals one if the children live in a family who moved to a housing project (after being selected by the MCMV lotteries). Controls include age, gender, race and parents' educational attainment. Robust standard errors (in parentheses) are clustered at the family level. *** p<0.01, ** p<0.05, * p<0.1

We now characterize the families who comply with the lottery results in Figure 3.

[13]For example, for the second lottery of a given municipality, we consider only participants in which this second lottery is their first lottery attempt.

To characterize these families, we show the first-stage coefficients by groups, i.e., by splitting the sample according to families' characteristics. Figure 3 points out that more educated are those complying more with the lottery. This suggests that our results are likely to be upper bound effect, i.e., the negative results we find could be even more negative if more vulnerable families were the compliers instead.

Figure 3: Compliers Characterization



Notes. The figure shows regressions for groups of compliers.

4.2 Balancing

We now assess whether the randomization produced balanced assigned-to-treatment and control groups. Table A.4 shows the balancing between initial-offer winners and other participants. Data for balancing come from *CadÚnico* and *Condicionalidades* registries. We run the following cross-section specification:

$$y_i = \alpha + \rho Z_{ip} + \gamma_p + \varepsilon_i \quad , \tag{4}$$

where y_i is a baseline characteristic of individual i, and Z_{ip} is the initial-offer indicator variable. We include the lottery fixed effects γ_p, and ε_i is the idiosyncratic error term. Consistent with the randomized design, Table A.4 displays that the winners and non-winners of this subgroup are comparable when it comes to observable characteristics. Notice that the difference in age between groups is statistically significant, but small in magnitudes (equivalent to 1 month difference in children age between groups).

Table 3: Lottery balancing

	IO Winners	Nonwinners	Diff. between Winners and Nonwinners	p-value
	(I)	(II)	(III)	(IV)
Age	8.797	9.011	0.015	0.781
	(4.598)	(4.666)	(0.055)	
Female	0.487	0.491	-0.006	0.348
	(0.500)	(0.500)	(0.006)	
White	0.467	0.331	-0.006	0.304
	(0.499)	(0.470)	(0.006)	
Number of observations	6,965	248,981	–	–

Notes. This table shows the balancing tests for 255,946 children of applicants, 9,956 of whom are in the initial-offer (IO) lottery winner group. Column (I) shows the mean and standard deviation (in parentheses) of baseline characteristics for the IO winners (including replacement group). Column (II) presents the mean and standard deviation (in parentheses) of baseline characteristics of nonwinners applicants. Column (III) reports the coefficients estimated from Equation (4) and the last column the corresponding p-value. *** p<0.01, ** p<0.05, * p<0.1

5 Results

We divide the results into three parts. We first present the results for children's education. Then we show the findings for children's future labor market outcomes. Finally, we show the results for the parent's labor market outcomes. To investigate the the effects, we present the results estimating cross-section specification (using Equation 2).

5.1 Results: Education

We start by showing the results on the probability of school switch. Table 4 displays that there is an increase in the probability of switching schools after the lotteries. Notice that it takes time between winning a lottery, signing a mortgage contract, and finally moving to live at the development project. Therefore, the results are consistent with the lag between the lottery and the actual moving. More specifically, we obtain significant coefficient estimates of 11–12 percentage points in the likelihood of changing schools. We do not find that all children move to new schools because the capacity of nearby schools is not always enough to accommodate the demand of children from recently built projects. Besides, some parents may anticipate that school quality is worse nearby the projects and thus refrain from changing their children's school.

Analyzing the quality of schools, Table 4 reports that there is a strong negative effect in average school quality. In addition, the magnitude of the estimates is a decrease of up to 0.16 points in the index, compared to a control group mean of 4.3 points. This provides additional evidence that the program's effects only appear after the actual moving of the beneficiaries.

We also show in Table 4 that the results for school quality are robust for alternative measures: teachers' qualification. The percentage of teachers with college degree is lower in school attended by children of beneficiary families.

Beyond quality, we assess the effects on possible schooling disruptions as measured by a chronic-absenteeism indicator variable (that equals one if the school absenteeism is above an official target). Table 4 shows the results. Consistently, the likelihood of school absence is again statistically significant (and the effects are stronger). Moreover, the effects are substantial in magnitude: an increase of 3.7 percentage points compared to 8.8% of the control group with absence is above an official target.

Table 4: Treatment Effect on Education Outcomes

	IV		ITT		Control Group Mean
Changed Schools	0.118***	0.110***	0.058***	0.053***	0.571
	(0.017)	(0.016)	(0.008)	(0.008)	(0.495)
School Quality	-0.165***	-0.170***	-0.083***	-0.085***	4.335
	(0.023)	(0.022)	(0.012)	(0.011)	(0.688)
Teachers Have College Degree	-1.727***	-1.525***	-0.860***	-0.758***	88.039
	(0.320)	(0.325)	(0.159)	(0.162)	(13.279)
School Absence	0.037***	0.036***	0.018***	0.018***	0.088
	(0.005)	(0.005)	(0.002)	(0.002)	(0.161)
Controls	No	Yes	No	Yes	

Note:
Controls include age, gender, race and mother's educational outcomes. All standard errors are heteroskedasticity-robust and clustered at the family level.All outcomes are post-lottery averages.

Intention-to-Treat. Columns (III) and (IV) of Table 4 show the results for the intention-to-treat analysis and results are consistent.

Robustness. Column (II) of Table 4 reports that the results are highly robust after adding controls.

Heterogenous effects. (TBD) We also assess the impacts of the program for students of different age. This is important because may generate unintended adverse impacts,

which may differ by age. For instance, younger students would suffer more in terms of learning, while older students could additional be exposed to criminality. We also assess the impacts by school quality. Finally, we explore each lottery individually by using variation on pre-lottery school quality.

5.2 Labor Market Outcomes

In this subsection, we assess the impacts of the program on labor market outcomes. We aim to investigate whether the program affects employment outcomes when entering the formal labor market as young adults. We focus on formal labor market outcomes, as our data do not allow us to study informal labor markets. Formal workers as those with an employment contract registered at the Labor and Social Security booklet ("registered wage-earner"). In addition to their wage, formal workers are eligible for benefits such as social security, unemployment insurance, and severance payment. Informal workers do not have access to such benefits and typically receive lower wages.

The consequences on labor market outcomes are conceptually ambiguous: the worse education environment generated by the program affects labor outcomes negatively, but since the program promotes a reduction in housing costs because of the subsidies, the extra income may be used to counteract the adverse effects on education.

Results in Table 5 indicate that children of winner households have lower labor market participation when reaching adulthood. We work with three labor market outcomes measured when the child reaches 18 years old or more: Labor market participation, an intensive margin outcome (number of months worked in the calendar year) and earnings.

Table 5: Program Effects on Labor Market Outcomes

	Sample: Full sample			
	IV		ITT	
	No controls	All controls	No controls	All controls
Labor Market Participation	-0.049***	-0.042**	-0.025***	-0.022**
	(0.019)	(0.019)	(0.010)	(0.010)
Months Worked 2019	-0.372**	-0.327*	-0.192**	-0.169*
	(0.177)	(0.176)	(0.091)	(0.091)
Avg. Wage 2019	-37.567	-32.615	-19.371	-16.795
	(24.932)	(24.856)	(12.866)	(12.810)

Note: Controls include age, gender, race and mother's educational outcomes. All standard errors are heteroskedasticity-robust and clustered at the family level. Only individuals from Condicionalidades who were 16 or older in 2018 were included.*** p < 0.01, ** p < 0.05, * p < 0.1

5.3 Parents: Effects on the Adults' Labor Market Outcomes and Adaption Measures

Using the same identification strategy, we assess the effects on the parents' labor market outcomes. Data for analyzing the labor market participation of adults come is again RAIS. Table 6 shows that labor market impacts are smaller in magnitude.

Table 6: Parents: Effects on Adults' Labor Market Participation

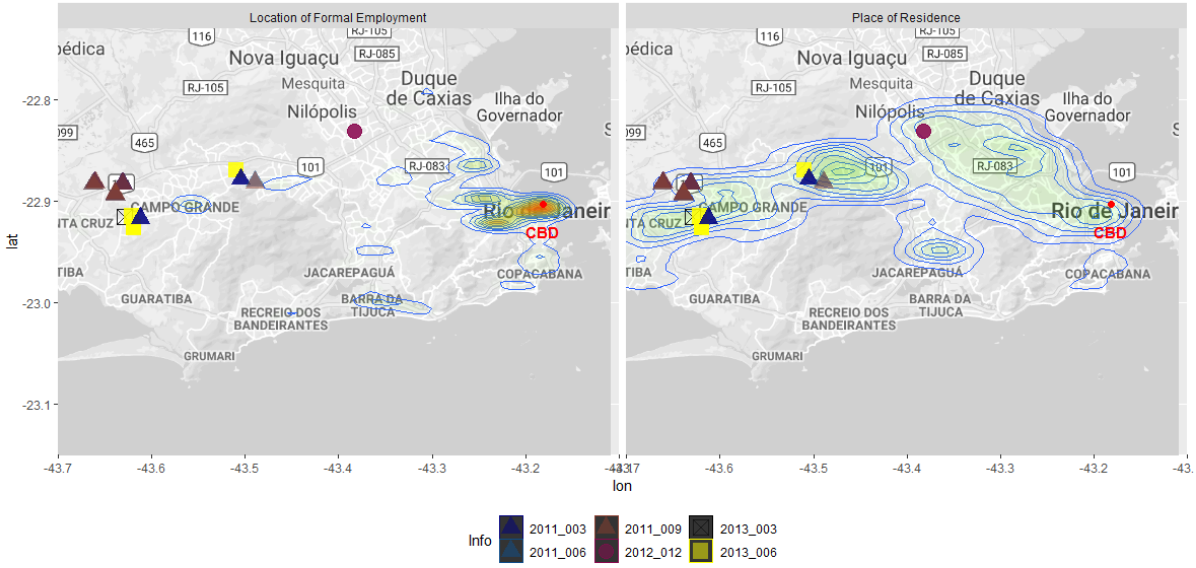
	Labor Market Participation		
Lottery dummy	-0.0192	-0.0269	-0.0125
	(0.0123)	(0.0224)	(0.0122)
Fixed effects	No	Yes	Yes
Controls	No	No	Yes
Control Group Mean	0.451	0.451	0.451
# of persons		707,081	
# of treated pers.		35,305	
# of months		36	

Notes. The table presents the results for the parents (adults' labor market participation). *** p<0.01, ** p<0.05, * p<0.1

To explain the smaller effects on parents, we present evidence on three adaptation measures. The first evidence is the low adherence to lottery results. Recall that the take-up rate was approximately 40% according to Table 2.

Second, winners who moved to projects used to live in nearby areas. Figure 4 describes the location of work and place of residence for the lottery winners in the municipality of Rio de Janeiro.[14] On one hand, the work location is mainly within the central business district boundaries of each of our five municipalities. On the other hand, the place of residence before the lottery varies widely, and many mortgage takers used to live in areas near the program's housing projects. These figures thus suggest lateral moves: only residents who previously lived in remote areas have accepted entering a PMCMV project and signing the mortgage contract.

Figure 4: Place of Work and Place of Residence of Mortgage Takers Before Lotteries in Rio de Janeiro



Notes. Notes. The picture shows the heat map regarding the place of work and residence location of mortgage takers (a subgroup of winners) of Rio de Janeiro's lottery before winning. The color scale goes from light green (very low concentration) to dark red (very high concentration).

Third, we show impacts on vehicle ownership: negative on cars and positive on motorcycles. We use an additional registry for this analysis: Renach-Renavam. The Renach-Renavam dataset provides information on driving licenses and vehicle ownership (cars, motorcycles, trucks). We use this registry to test whether winners purchase cheaper vehicles to compensate for the costs associated with the suburban location of housing projects. The periods for which we have data are 2012 (April and December),

[14]The information on the address is from the Cadastro Único dataset. According to legislation, winners must report their address before the lottery to be able to sign the mortgage contract. The location of work comes from the RAIS dataset.

2013 (November), 2015 (June), and 2016 (March, August and December). Table 7 shows that adult winners sell cars and buy motorcycles, which may be interpreted as a behavior to save on transportation costs.

Table 7: Effects on Vehicle Ownership

	Indicator Variables		
	Car	Motorcycle	Driver's license
Lottery	-0.0068***	0.0125***	-0.0011
	(0.0019)	(0.0012)	(0.0021)
Fixed effects	Yes	Yes	Yes
Controls	Yes	Yes	Yes
# of persons		707,081	
# of treated pers.		35,305	
# of months		7	

Notes. The table presents the results for vehicle ownership. *** p<0.01, ** p<0.05, * p<0.1

6 Concluding Remarks

In many large cities, low-income families tend to be concentrated and isolated in specific regions, leading to fewer opportunities and difficulty accessing public services, including higher-quality schools. This spatial concentration in large cities creates a cycle of poverty. This paper assesses the effects of one of the world's largest housing programs: Brazil's My House My Life. The program heavily subsidized housing units in the outskirts of the country. Using housing lotteries to estimate the causal effects, we document that children of lottery-winner households move to worse schools as measured by various indicators. Moreover, school absences increase significantly. While children present worse labor market outcomes (when they become adults), their parents are able to partially offset adverse effects by using adaptation measures.

Our findings have far-reaching implications, highlighting the need to design and target housing policies to promote social mobility. The rapid urbanization in many low- and middle-income countries requires the provision of social housing. Housing is a relevant distributive policy that usually receives a large amount of public funds. Given the restricted fiscal capacity in several low- and middle-income countries, providing social housing in cheaper, remote locations might be a feasible policy choice. Our findings can illuminate how location in remote areas can adversely affect short- and longer-term socioeconomic outcomes.

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Online Appendix to "Housing Policies and Social Mobility"

Daniel Da Mata and Lucas Mation

March 21, 2025

A Extra Tables and Figures **A-2**

A Extra Tables and Figures

Table A.1: Correlation between school quality and distance to MCMV housing projects: Year 2009

Dependent variables:	
IDEB Primary School	0.013***
	(0.003)
SAEB Portuguese: 5th year of primary school	0.487***
	(0.077)
SAEB Math: 5th year of primary school	0.516***
	(0.083)
SAEB Portuguese: 9th year of primary school	0.557***
	(0.101)
SAEB Math: 9th year of primary school	0.683***
	(0.105)
# of Schools	1,626

Notes. The table reports the correlation between school-level quality indicators and the distance to MCMV housing projects. Each cell corresponds to coefficient from Equation 1. Standard errors are clustered at the municipal level.
*** p<0.01, ** p<0.05, * p<0.1

Table A.2: First-Stage Results by Lottery

Municipality	Lottery	Dependent Variable: Housing-Moving Dummy
Campinas	2012	0.3793***
		(0.0903)
Ibiporã	2014	0.875***
		(0.1211)
Rio de Janeiro	2011 (1st)	0.2185***
		(0.0422)
Rio de Janeiro	2011 (2nd)	0.2185***
		(0.0422)
Rio de Janeiro	2012	0.1875***
		(0.0437)
Rio de Janeiro	2013 (1st)	0.2272***
		(0.0516)
São José do Rio Preto	2013	0.700***
		(0.0485)

Notes. The table presents the first-stage results. The initial-offer dummy equals one for the applicant getting an initial offer at the time of the lottery. The moving dummy equals one if the children live in a family who moved to a housing project (after being selected by the MCMV lotteries). Robust standard errors (in parentheses). The information is for ten lotteries we analyze in the paper. The lotteries took place in five cities in Brazil between 2011 and 2014. *** p<0.01, ** p<0.05, * p<0.1

Table A.3: Information and Statistics for each Lottery

Summary Statistics by Lottery - All					
Lottery	Year	City	N	Winners	Nonwinners
All Lotteries	-	-	315692	8881	306811
Campinas 2012	2012	Campinas	25332	2910	22422
Ibipora 2014	2014	Ibipora	1131	431	700
Rio de Janeiro 2011 N1	2011	Rio de Janeiro	57026	508	56518
Rio de Janeiro 2013 N1	2013	Rio de Janeiro	50125	53	50072
Rio de Janeiro 2013 N2	2013	Rio de Janeiro	12038	74	11964
Rio de Janeiro 2011 N3	2011	Rio de Janeiro	16191	665	15526
Rio de Janeiro 2012 N1	2012	Rio de Janeiro	73921	68	73853
Guarulhos 2014	2014	Guarulhos	59612	372	59240
Sao Jose do Rio Preto 2013	2013	Sao Jose do Rio Preto	9496	3143	6353
Sao Goncalo do Amarante 2014	2014	Sao Goncalo do Amarante	1588	657	931

Note:
Control includes both waitlist and not selected.

Table A.4: Lottery balancing

	IO Winners	Nonwinners	Diff. between Winners and Nonwinners	p-value
	(I)	(II)	(III)	(IV)
Age	9.322	9.601	-0.116	0.046
	(4.363)	(4.376)	(0.058)	
Female	0.485	0.490	-0.008	0.247
	(0.500)	(0.500)	(0.006)	
White	0.439	0.316	0.003	0.646
	(0.496)	(0.465)	(0.006)	
% Absenteeism pre-treatment	0.089	0.070	0.012	0.003
	(0.285)	(0.255)	(0.004)	
School quality pre-treatment	4.121	4.020	-0.088	0.003
	(0.685)	(0.732)	(0.017)	
Number of observations	6,965	248,981	–	–

Notes. This table shows the balancing tests for 255,946 children of applicants, 9,956 of whom are in the initial-offer (IO) lottery winner group. Column (I) shows the mean and standard deviation (in parentheses) of baseline characteristics for the IO winners (including replacement group). Column (II) presents the mean and standard deviation (in parentheses) of baseline characteristics of nonwinners applicants. Column (III) reports the coefficients estimated from Equation (4) and the last column the corresponding p-value. *** p<0.01, ** p<0.05, * p<0.1