

Winning the Housing Lottery in Rio de Janeiro: Curse or Cure?

By

Jonathan Hoagland Leape

B.S. in Engineering  
Cornell University (2011)

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Author \_\_\_\_\_  
Department of Urban Studies and Planning  
May 20, 2020

Certified by \_\_\_\_\_  
Professor P. Christopher Zegras  
Department of Urban Studies and Planning  
Thesis Supervisor

Accepted by \_\_\_\_\_  
Professor of the Practice, Caesar McDowell  
Chair, MCP Committee  
Department of Urban Studies and Planning

Accepted by \_\_\_\_\_  
P. Christopher Zegras  
Professor  
Chair, Graduate Program Committee



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## **Abstract**

In the wake of the 2008 financial crisis, the Brazilian federal government launched My House, My Life (PMCMV), an ambitious program to build subsidized housing for over five million low-income families. While the program has been praised for its scale, early evidence suggests that its beneficiaries may be struggling. Complaints of high utility bills, militia exploitation and intolerable commutes have surfaced alongside studies showing that beneficiaries may be unable to hold a formal job upon moving.

In Rio de Janeiro, many housing units are awarded via random lottery, creating a rare opportunity to infer the causal impacts of the program. In this thesis, I track the employment activity and earnings of over 28,000 participants, half of whom were awarded 90%-subsidized units, between 2011 and 2017. Contradicting most theory and evidence, I find that moving to a PMCMV unit increased earnings by 13% and the likelihood of employment by 2% after four years. Since beneficiaries generally sacrifice both safety and access to jobs in moving, other factors, such as residential stability or the need to cover higher living costs, may explain the increase in labor market activity.

Outcomes vary significantly among types of participants and project locations, revealing opportunities for the government to target follow-up assistance and improve project locations. The types of lottery winners most likely to move differ from those who are most likely to see their formal incomes increase. Men, non-whites, favela residents and the college educated are less likely to move, even though they are at least as likely to benefit. Furthermore, participants are more likely to move to projects far from downtown even though such projects generate weaker income benefits. Participants also revealed a preference for nearby PMCMV units, but those who moved far experienced the same income benefits. These findings indicate that lottery winners are either misinformed about how moving might impact their potential earnings or make their decision to move based on other factors.

Thesis Supervisor: Chris Zegras  
Title: Head, Dept. of Urban Studies and Planning



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## GLOSSARY

Beneficiary – an individual who has won a Tier 1 PMCMV housing lottery and moved to a unit.

R\$ – Brazilian Real, the official currency of Brazil. I convert values to U.S. Dollars (US\$) based on the 2017 PPP exchange rate of 2.013.

CATE – Conditional Average Treatment Effect, the mean causal impact of treatment conditional on the value of a moderator variable.

Compliance – deciding to move to a Tier 1 PMCMV unit after having won the lottery.

Non-complier - a winner of a Tier 1 PMCMV housing lottery who has decided not to move.

Heterogeneity - the quality or state of being diverse in character or content. – Oxford

IBGE – *Instituto Brasileiro de Geografia e Estatística* (Brazilian Institute of Geography and Statistics), analogous to the U.S. Census Bureau.

ITT – Intention-to-Treat, a conservative method for measuring causal impacts that ignores non-compliance.

LATE – Local Average Treatment Effect, the mean causal impact of treatment on those who actually complied. It is estimated using instrumental variables in two-stage regression.

PMCMV – *Programa Minha Casa Minha Vida*, the national public housing program in Brazil, initiated in 2009.

Tier 1 – the lowest income bracket of the PMCMV targeting those who earn less than 1.5 times the minimum wage

Treatment – a Tier 1 PMCMV housing lottery winner's move to a PMCMV unit.

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# 1. INTRODUCTION

The quest to provide formal housing in Rio de Janeiro has been notoriously challenging. In the 1960s, the government cleared urban slums, known as *favelas*, and relocated residents to *Cidade de Deus* (City of God), a purely-residential public housing development located inconveniently behind a mountain. Decades later, one of Brazil's most famous movies portrayed how the neighborhood's desperately isolated residents turned to violent crime (Meirelles and Lund 2002). Then the blockbuster *Tropa de Elite* and its sequel laid bare the lethal drug war that continues to rage in Rio's remaining favelas (Padilha 2007, 2010). Rio's perpetual housing crisis, it seems, is an establishment in popular culture.

When the 2008 financial crisis hit Brazil, though, President Lula launched *Programa Minha Casa Minha Vida* (My House, My Life) (PMCMV), an ambitious program that is putting a dent in the nation's housing deficit. Having built over 4 million units with another 1.5 million contracted (Lis 2019), the program is even larger than its predecessor, *Banco Nacional de Habitação* (BNH), that built *Cidade de Deus*. By letting private developers choose cheap project sites in urban peripheries, though, PMVMC seems to be repeating the BNH's fundamental mistake. A series of studies have shown that PMCMV beneficiaries are already showing symptoms of exclusion from the city's formal labor market. My thesis unpacks where, when and for whom the program is failing, and points to practical steps to address it.

## 1.1 MOTIVATION

As the PMCMV reaches its final phases under a new federal government that is interested in a different approach to housing assistance (Doca 2019), it may seem futile to try to improve it. Recent trends indicate, though, that Brazil will continue to require economic stimulus and investment in housing. Brazil's economy has been weak since 2013 and the COVID-19 pandemic is expected to shrink it by 5.5% this year (Economist Intelligence Unit 2020). The coronavirus may also render much of Rio de Janeiro unfit for habitation if it spreads rapidly in favelas, which are typically dense and often lack basic sanitation infrastructure (Cancian 2020; Riley, Raphael, and Snyder 2020; Rosenthal 2020). Whether through an extension of PMCMV or the birth of a new program, some type of housing assistance could help stimulate the economy and rehouse residents in the highest-risk areas. This thesis provides insights as to how Brazil's new administration can improve upon the PMCMV in order to ensure that the cure is not worse than the disease.

My thesis could also guide the government in reengaging existing beneficiaries who might be struggling to maintain formal jobs. Less than a year after the first PMCMV beneficiaries moved into their units, the government did reach out with a satisfaction survey (MCidades 2014). But recent studies in the U.S. (Briggs, Popkin, and Goering 2010; Chetty, Hendren, and Katz 2016) and Rio (Carneiro 2019; Pacheco 2018) have found, however, that beneficiary experiences can evolve dramatically over time. For example, beneficiaries initially thrilled about the quality of

their new homes may become increasingly dissatisfied years later as their health and productivity suffer. My thesis helps identify who tends to struggle when, so that program officials could target efforts to reengage them.

Finally, evaluating the PMCMV can also inform policy in other countries. China, Thailand, Kenya, Nigeria and India (Barnhardt, Field, and Pande 2017) have all launched similar housing programs. With different political-economic contexts and program designs, each country could expect different outcomes than those I found in Rio. But my research questions and methods could provide policymakers with intuition that helps guide how they design, implement and evaluate their programs.

## 1.2 OVERVIEW

My thesis consists of the following chapters:

- Chapter 2 provides some background on the relevant history, demography and urban form of Rio de Janeiro.
- Chapter 3 reviews existing theory and evidence about how housing programs impact their beneficiaries, and then summarizes my research questions and hypotheses.
- Chapter 4 introduces the methods of causal inference I used to test my hypotheses and describes how I prepared panel data to apply those methods.
- Chapter 5 presents the distributions of variables in the dataset and compares the sample with the overall pool of PMCMV participants.
- Chapter 6 presents a series of models I estimated to test my hypotheses.
- Chapter 7 concludes with a summary of findings, recommendations, limitations and opportunities for future research.

## 2. RIO DE JANEIRO CONTEXT

This chapter highlights features of the Rio de Janeiro context that could potentially influence how the PMCMV affects its beneficiaries. Beginning with a summary of the political economy, I zoom in to point out key features of the city's urban form and offer a glimpse at initial reactions to PMCMV in Rio.

### 2.1 POLITICAL HISTORY

#### 2.1.1 BRAZIL

The *Partido dos Trabalhadores* (Worker's Party) (PT), which created the PMCMV, led Brazil through a decade of increasing prosperity from 2003 to 2013. The economy grew at about 4% per year and was only briefly affected by the 2008 financial crisis (The World Bank 2020). The country was among only a few in the world that reduced inequality during that period (Winter 2017). In 2012, 92% of citizens felt neutral or positive toward President Dilma Rousseff and the likelihood of continued economic growth (Datafolha 2012). With newfound economic confidence, Brazil successfully bid to host three consecutive mega-events: the FIFA Confederations Cup in 2013, the FIFA World Cup in 2014, and the Olympic Games in Rio de Janeiro in 2016. The government invested heavily in stadiums, infrastructure and pacifying crime-ridden neighborhoods.

Catching politicians off-guard, protests broke out in São Paulo when the government announced regular public transit fare increases in June of 2013. In what was dubbed the "Tropical Spring" in reference to concurrent social movements in the Middle East, the protests quickly spread to other cities. As the movement attracted new constituents, though, its focus shifted from bus fares to corruption, police violence, underfunded public services, and excessive spending on the mega-events (Saad-Filho 2013; Winter 2017). Discontent with the PT only worsened as the economy began to decline and the *Lava Jato* (Car Wash) corruption investigations embarrassed many members of the party (Winter 2017). Brazilian's elected Jair Bolsonaro in 2018, marking the end of 16 years under PT governance. The new, conservative administration will likely adopt a different approach to housing assistance, although details remain unclear.

#### 2.1.2 RIO DE JANEIRO

Rio de Janeiro, or more commonly just "Rio", was Brazil's capital until the government built a new one, Brasília, in the interior of the country in 1960. Around the same time, São Paulo overtook Rio as the country's economic center. Nonetheless, Rio de Janeiro remains the nation's cultural capital and a significant economic center.

The tensions that surfaced across the nation in 2013 manifested acutely in Rio. At least 300,000 protestors hit the streets of Rio during the Tropical Spring (Watts and Phillips 2013). Demonstrators were successful in convincing the city to reverse bus fare increases, but the mayor, Eduardo Paes, continued to steam ahead with bold investments and interventions for the mega-events. Although he was a vocal critic of the PT, Paes ultimately relied heavily on the

party's PMCMV to house people he displaced to make way for new BRT corridors and other facilities for the 2016 Olympics (Watts 2016). Desperate to slow the spread of COVID-19 (Klein 2020), Rio's current mayor might also rely on the PMCMV to house residents in neighborhoods vulnerable to infection.

## 2.2 PEOPLE AND ECONOMY

Rio de Janeiro is home to over 6.7 million people (IBGE 2019) who often refer to themselves as *Cariocas*. With significant manufacturing, printing and tourism sectors, and many public sector agencies which never moved to Brasília, Rio has the second largest economy after São Paulo. In 2017, GDP per capita in Rio was US\$ 15,632, almost double the national average. Higher incomes are likely part of the reason that Rio attracts so many immigrants. As many as 18% of Rio's residents migrated from other states (Faunce and Peace 2020).

Although Rio ranks among the top 0.5% of municipalities for average income, the municipality does not rate as well in terms of education, health or inequality. Over 3% of children aged 6 to 14 are not in school, a portion higher than 67% of municipalities in the country (IBGE 2019). Among all residents in 2010, only 71% completed primary school, 57% completed secondary school and 20% earned bachelor's degrees (IBGE 2010). Rio falls to the 49<sup>th</sup> percentile for infant mortality, with over 11 per 1000 births, and to the 15<sup>th</sup> percentile for hospitalizations due to diarrhea (IBGE 2019). In 2010, 31.4% of residents had incomes less than half of the minimum wage (IBGE 2010).

## 2.3 URBAN FORM

With colonial buildings abutting vibrant beaches and hillsides flowing with informal settlements, Rio de Janeiro features a dramatic landscape that has profound impacts on the livelihoods of its residents. This section discusses some general patterns of Rio's urban form that guided much of my thinking in this study.

### 2.3.1 PLANNING ZONES

The City of Rio divides the municipality into the planning regions shown in Figure 1.



**Figure 1: Rio de Janeiro Planning Zones** (PrefeituraRio 2020a)

Downtown is located in the *Centro* (Center) zone, and the most well-known beaches and wealthy neighborhoods are located in *Zona Sul* (South Zone). *Zona Norte* is heavily populated and industrial, but most of the city's recent growth has occurred in the western half of the municipality (SETRANS 2014).

Former Mayor Paes invested heavily in Olympic venues in *Barra da Tijuca* and connected the area to *Zona Sul* and downtown with two rapid transit corridors. *Barra da Tijuca* has become an increasingly affluent part of the city (Watts 2016), while the *Zona Oeste*, where most Tier 1 PMCMV projects have been built, has seen more growth in low-income residents (Vetter, Beltrão, and Massena 2014).

### 2.3.2 GEOGRAPHY

Rio de Janeiro nestles between tropical forests and mountains spilling into the Guanabara Bay and Atlantic Ocean.



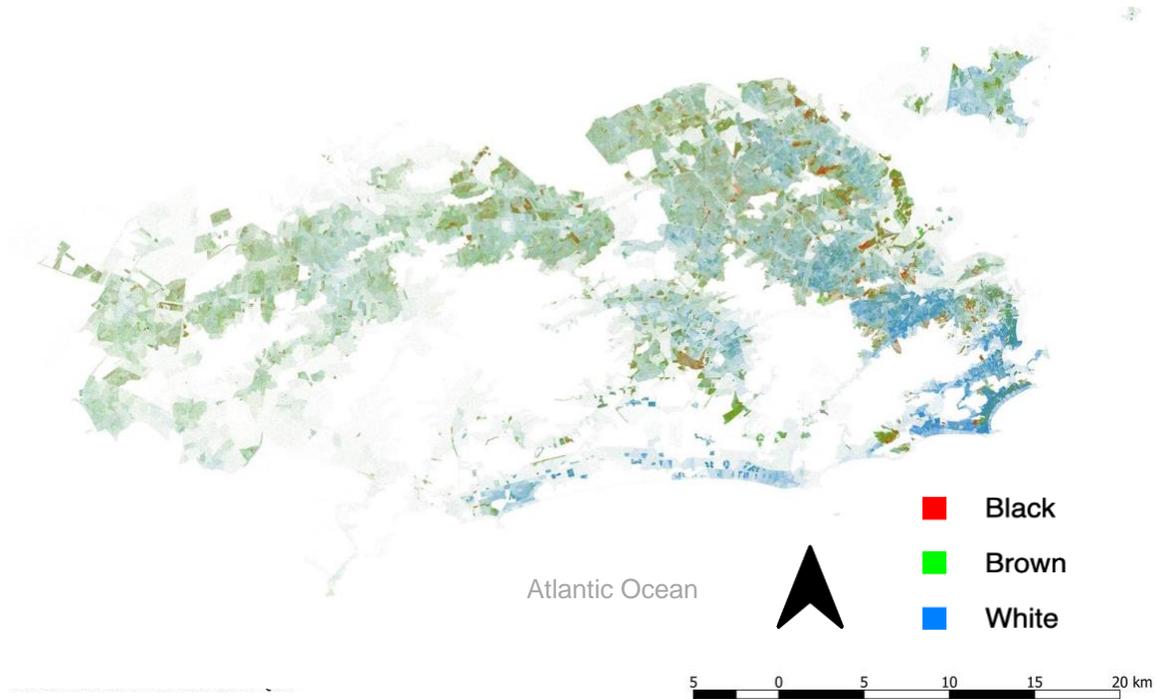
**Figure 2: Sugar Loaf Mountain in Rio de Janeiro (Creative Commons)**

The city's most beautiful locations, such as the *Pão de Açúcar* (Sugar Loaf) mountain and beaches, are located near downtown, in the historically prosperous *Zona Sul*, or in the increasingly affluent *Barra da Tijuca* zones. These “anchor” sites, whose attractiveness is embedded in the landscape and thus constant over time, are likely to remain wealthier areas (Lee and Lin 2017).

### 2.3.3 SEGREGATION

Rio de Janeiro's anchor sites in the *Zona Sul* and *Barra da Tijuca* zones are not only predominantly wealthy, they are also primarily white. The *Instituto Brasileiro de Geografia e Estatística* (Brazilian Institute of Geography and Statistics) asks residents to identify with one of the following racial categories: *branco* (white) (caucasian), *pardo* (brown) (mixed-race), *preto* (black) (African descent), *amarelo* (yellow) (Asian descent), and *indígena* (native). In 2010, 51.2% of residents identified as white, followed by 36.5% as brown, 11.5% as black; less than 1% identified as yellow or native (IBGE 2010).

Figure 3 shows how the primary racial groups are spatially distributed in the municipality.



**Figure 3: Racial Segregation in Rio de Janeiro (2010)** (Barbosa 2015)

One study calculated an Urban Health Index based on a variety of illnesses and revealed similar patterns; non-white, low-income neighborhoods fared worse (Bortz 2015).

While the *Centro*, *Zona Sul* and *Barra da Tijuca* zones are clearly predominantly white, closer examination reveals some pockets with other racial compositions. Many of these are informal favelas, which I discuss in the next section.

#### 2.3.4 FAVELAS

Rio de Janeiro's urban fabric is interrupted by steep, forested hills that are precarious to build on. Sacrificing their own safety to gain access to the city, many low-income immigrants settle on these hillsides and form informal neighborhoods called *favelas*. While many favelas have been razed, others continue to grow in size and prosperity (Cummings 2015). In 2010, 15% of residents in the metropolitan area of Rio lived in favelas, up from 12% in 2000. In fact, the only residential growth to occur within 15 km of downtown has been within favelas. On average in 2010, favela residents lived 5.6 km closer to the city center than non-favela residents (Cotelo and Rodrigues 2016).



**Figure 4: Favela in Rio de Janeiro (Creative Commons)**

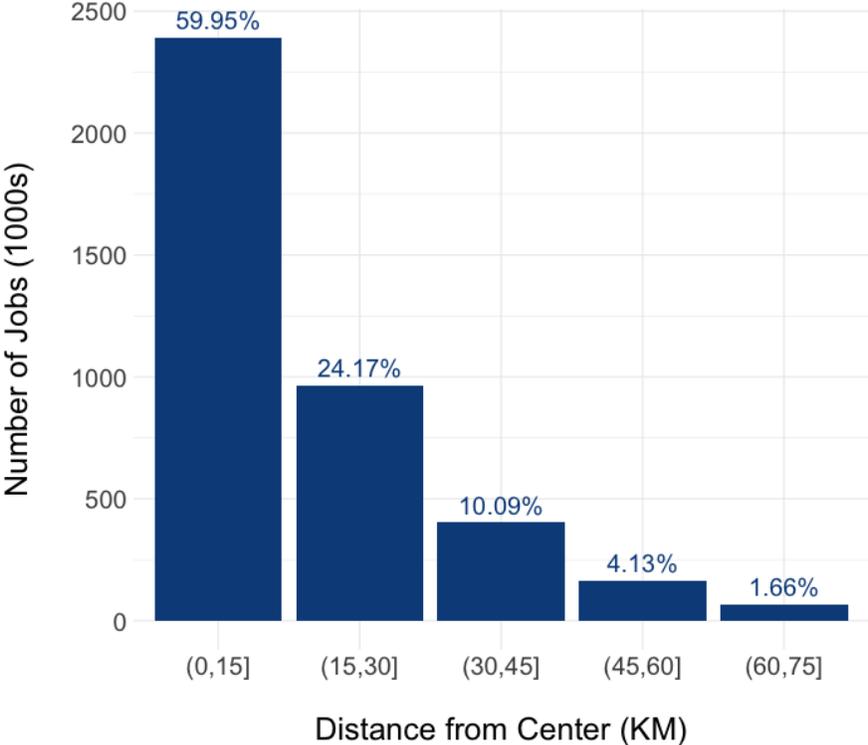
Many favelas suffer high rates of violent crime. In anticipation of an influx of tourists for the 2016 Olympics, Mayor Paes attempted to overwhelm favelas dominated by militias with police. In 2018, Marielle Franco, a human rights activist critical of police brutality in favelas, was mysteriously murdered (Miranda 2019). The state reduced its “pacification” efforts and crime began to climb again. With support from the new conservative administration, however, the state of Rio de Janeiro has recently adopted a policy of “confrontation” whereby police can execute any armed suspects. The approach has simultaneously led to a record low rate of reported murders and a record high rate of killings by police in 2019 (BBC News 2020).

With high population densities and uneven access to basic infrastructure, favelas are also vulnerable to infectious disease. In some areas, there is not access to running water or sewage systems, creating an acute risk of a COVID-19 outbreak (Ruge 2020).

### 2.3.5 MONOCENTRICITY

Despite their risks, favelas are attractive in large part due to their proximity to downtown Rio de Janeiro. This section explores how concentrated employment opportunities really are in downtown, and what implications that might have for the PMCMV’s pattern of building housing in the periphery.

While the Rio’s greater metropolitan region has multiple business centers (Vetter, Beltrão, and Massena 2014), the municipality of Rio closely resembles a monocentric city with employment concentrated near the center. Figure 5 shows how formal jobs are distributed according to their roadway distance from *Praça Tiradentes* in downtown. The labels above the columns indicate the share of all jobs in the municipality that fall within the radius bin.



**Figure 5: Monocentric Job Distribution in Rio de Janeiro (RAIS 2017)**

Over 84% of the jobs in the municipality are located within 30 km of downtown. Since Rio de Janeiro has a mostly market-based real estate sector, the concentration of jobs in the center should cause both density and property values to decrease with distance from the center (DiPasquale and Wheaton. 1996). Indeed, studies do find such gradients for density (Cotelo and Rodrigues 2016) and property values (Vetter, Beltrão, and Massena 2014). According to the monocentric city model, land prices at the periphery of such cities can be extremely volatile, dropping dramatically when the property market shrinks (DiPasquale and Wheaton. 1996). In fact, Rio’s property market has been declining since 2015 (Faunce and Peace 2020), so land prices at the periphery have likely dropped.

The fact that the municipality of Rio is generally monocentric does not necessarily imply that residents in the West Zone, where most PMCMV projects have been constructed, must commute to the center to find work. Two studies, however, suggest that few residents in the West Zone are likely to find work nearby in adjacent municipalities. First, a survey of over 265,000 residents of the greater metropolitan area found that only 3% of residents of the municipality of Rio work in

other municipalities (SETRANS 2014). Second, another study found that residents in the neighborhoods where most PMCMV projects are being built tolerate commutes of 60-75 minutes on average (Vetter, Beltrão, and Massena 2014).

### 2.3.6 TRANSPORTATION SYSTEM

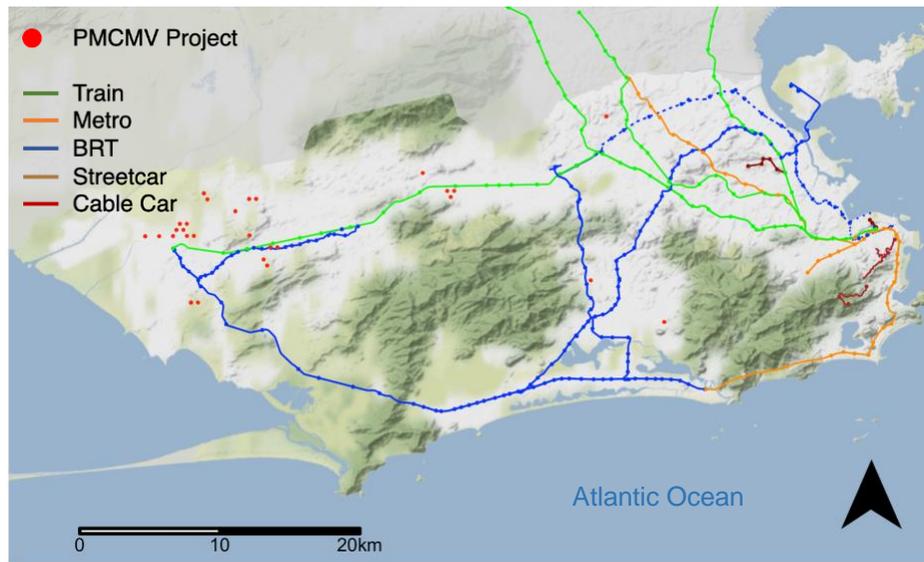
Mayor Paes invested heavily in transportation infrastructure in anticipation of the 2016 Olympic Games, but the projects drew criticism for underserving the city’s low-income population. Table 1 shows the mode split in the metropolitan area in 2012, along with the average annual growth rate since 2003.

**Table 1: Mode Split in Rio de Janeiro Metropolitan Area in 2012 (SETRANS 2014)**

Mode	Share of All Trips	Annual Rate of Growth in Trips
Public Transit	35%	3.4%
Non-motorized	32%	-0.3%
Car	18%	3.0%
Motorcycle	1%	4.9%
Intermunicipal Bus	8%	3.3%
Informal Bus	0%	0.0%
Other	6%	-2.0%

Although there are 300 cars per 1000 residents in Rio (Faunce and Peace 2020), only 18% of trips are made by car. Motorcycle was the fastest growing mode of choice but only accounted for 1% of trips in 2012. Public transit is the most popular mode, and includes traditional buses, Bus Rapid Transit (BRT), commuter rail, metro, light rail and cable cars.

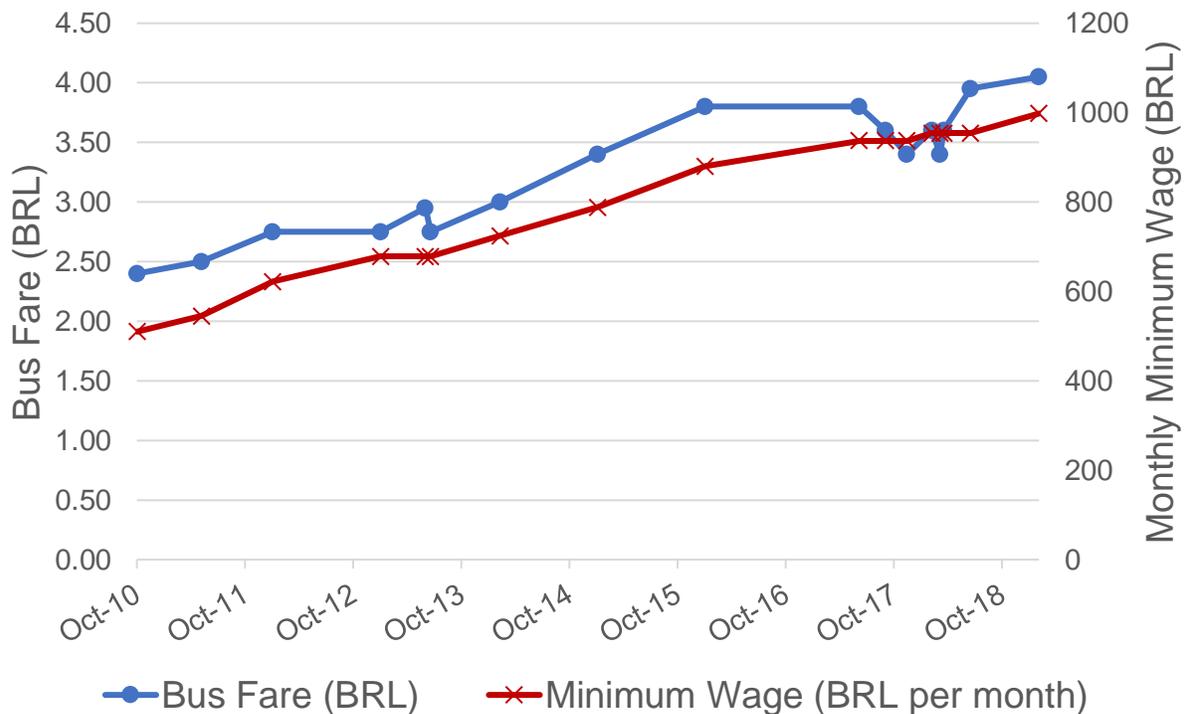
Figure 6 maps all of the city's non-bus transit corridors.



**Figure 6: Terrain and Transit in Rio de Janeiro (2020)** (PrefeituraRio 2020b)

For the 2016 Olympics, Mayor Paes extend the Metro from *Zona Sul* to *Barra da Tijuca* and built most of the BRT system. The TransBrasil BRT corridor, shown in the blue, dashed arc to the north in Figure 6, has yet to be completed. It would have served the traditionally lower-income *Zona Norte*, but the city prioritized projects serving the Olympic venues. The Metro extension and BRT corridors were expensive, so the city subsequently reduced traditional bus service to cut costs. A study found that, between 2014 – 2017, accessibility to jobs by public transit decreased by 4% among all residents. Meanwhile, wealthier areas such as *Barra da Tijuca* and *Zona Sul* saw their accessibility increase thanks to the new transit corridors (Pereira et al. 2017).

Pereira et al. (2017) note that accounting for the affordability of transit service would likely reveal even starker disparities in accessibility. Although the city agreed to reverse transit fare increases after the Tropical Spring demonstrations, Figure 7 shows that fares subsequently continued to increase at roughly the same pace as the minimum wage.



**Figure 7: Bus Fares vs. Minimum Wage in Rio de Janeiro** (MTE 2020; PrefeituraRio 2019)

Furthermore, transit costs are nearly double for commuters who have to transfer between different modes (Pereira 2018). Such transfers are necessary to commute from most PMCMV projects, which are not within walking distance of the train or BRT corridors, to downtown.

## 2.4 MINHA CASA, MINHA VIDA

President Lula da Silva initiated PMCMV in 2009 to build subsidized housing for millions of low-income Brazilians while stimulating the depressed economy. The PMCMV is composed of four tiers, each targeting a different income bracket. Tier 1, the focus of this thesis, offers 90% - subsidized units worth up to R\$ 96,000 (US\$ 48,000) to applicants with salaries up to 1.5 times the minimum wage. In Rio de Janeiro, units are assigned via lotteries, some of which are “general” and do not prioritize local or disabled residents. Lottery winners who accept their units, called “beneficiaries” hereafter, pay the remaining 10% of the unit value over a period of up to 10 years in monthly installments of R\$ 80 – 270 (US\$ 40 – 134) depending on their income. Beneficiaries typically move in to their new units within a year after the lottery (Caixa 2020).

#### 2.4.1 CRITICISMS

The program's first beneficiaries were surprised to see their living costs dramatically increase. In one project, *Jardim da Acácias*, less than half of residents had been paying their monthly bills. "We have to pay for everything here. In the favelas, we didn't pay for electricity, water, or a condominium fee, and many people don't realize they need to pay for these things," one resident explained (Menasce and Dantas 2015). Monthly condo fees can reach R\$ 92 (US\$ 46) (Menasce and Dantas 2015) and electricity bills can be as high R\$ 200 – 300 (US\$ 100 – 150), roughly the tuition of some private schools (Arrigoitia 2017). Adding to those costs, militias that dominate many PMCMV projects charge high fees for security and sometimes even evict beneficiaries from their new homes (Menasce and Dantas 2015).

Residents of *Recanto da Natureza*, one of the Tier 1 PMCMV projects examined in my thesis, also struggle financially due to the lack of access to jobs (Arrigoitia 2017). The Tier 1 projects are primarily located in the western *Zona Oeste* region of the city, over 50 km from the central business district. "Most people started to work at home in small businesses, such as selling cleaning products, beauty products, computer repairs. And their incomes shrank, but expenses increased with bills, fees, and consumer items," Arrigoitia (2017) explained in an interview (Guimarães 2016). One resident lost her job because her employer doubted she would tolerate a daily bus commute with two transfers (Duarte and Benevides 2013). Even though PMCMV projects are not zoned for commercial uses, some residents have converted their units into bars and beauty salons (Menasce and Dantas 2015).

Long commutes and isolation have affected residents' physical and mental health. "Some people cited the physical exhaustion caused by the distance. One woman had a car, but almost died when she crashed the vehicle one day. She quit her job and set up a home business." The peripheral locations have taken a toll on residents' mental health, too. Others described how the disruption and isolation triggered depression (Guimarães 2016).

If not the beneficiaries, other entities are benefitting from the PMCMV in Rio. Arrigoitia (2017) explained that the units are located on the outskirts because land is cheaper so private developers can earn wider profit margins when they sell their units at values that do not properly account for the location (Guimarães 2016). The projects also gave Mayor Paes a place to send as many as 22,000 families he displaced from neighborhoods near Olympic venues or along the new bus corridors between them (Douglas 2015).

#### 2.4.2 FUTURE OF PMCMV

Current President Bolsonaro's administration is eager to reform the PMCMV but has not definitively announced what form its replacement will take. Citing concerns of fraud, the national government decided that cities will no longer manage the selection process to award units and the government will likely require all applicants to register their incomes in a welfare database in order to be eligible (Rittner and Bitencourt 2020b). The federal housing minister discussed reducing subsidies by R\$ 500 million (US\$ 250 million) per year until 2023 (Geralda Doca 2020), but later reports suggest that Tier 1 of the program will continue while the other tiers will move to a voucher program managed at the regional level (Rittner and Bitencourt 2020a).

## 3. THEORY, EVIDENCE AND RESEARCH QUESTIONS

Housing programs appear in many forms and incur a range of direct and indirect impacts beyond securing shelter for their beneficiaries. While scholars have devoted substantial effort to evaluating programs, existing evidence does not point to a one-size-fits-all approach to housing assistance. If any generalization can be made, it is that the impacts of housing assistance are heterogenous across cities, programs and individuals. This chapter introduces the most relevant debates, providing theory and evidence from international examples and Rio de Janeiro.

I begin with an introduction to various forms of housing assistance, highlighting the fundamental design decisions, advantages and drawbacks of each. Section 3.2 introduces a range of causal pathways that can determine the outcomes of such programs and Section 3.3 mentions types of phenomena that present methodological challenges. Section 3.4 consolidates evidence of the impact of housing programs on labor market outcomes. Section 3.5 summarizes how literature shaped my research questions and hypotheses, and how I improved upon recent work on the PMCMV in Rio.

### 3.1 HOUSING ASSISTANCE

Housing assistance includes any government intervention intended to provide beneficiaries with better quality housing than they could otherwise afford. Over the past 60 years, governments have experimented with programs shaped by a few fundamental decisions. Some approaches have proven generally ineffective but there remain several viable options for policymakers to debate over when designing the best housing program for their context. This section elaborates on key debates around program design and then compare cases in four countries to PMCMV.

#### 3.1.1 PROGRAM DESIGN

##### WHAT IS THE GOAL?

The official aim of housing programs is typically to resolve a deficit of quality housing. Whether stated or not, most programs are driven by other motives that can influence their implementation. Housing programs can aim to stimulate the economy, alleviate poverty, incentivize certain family structures, and/or alter the spatial distribution of socio-demographic groups. Studies often present evaluations of public housing programs as either corroborating or contradicting suspicions that programs do not prioritize the welfare of their beneficiaries.

##### WHO BUILDS?

Governments can build public housing themselves or incentivize the private sector to build it. The former approach has succumbed to the latter as neo-liberal movements have encouraged governments to withdraw from productive activities. The degree to which the government interferes in private development varies considerably. At one extreme, the government can merely provide subsidized credit or vouchers that beneficiaries can use to rent or buy a unit of their choosing. More involved programs might specify the architecture and location of projects.

Many programs attempt to strike a balance by setting some basic standards for quality and location while letting private developers design their own projects.

#### TO WHAT STANDARD?

Housing programs face a trade-off between quality and cost. Quality standards protect residents from threats ranging from fires and earthquakes to social stigma. Setting standards too high, though, might render the housing unaffordable to the poorest residents, who might then prefer to settle illegally (Gilbert 2004). Even approaches as minimalistic as “sites and services”, whereby the government installs basic infrastructure before urban migrants arrive and build their own housing, can exemplify this trade-off. In a review of 116 projects led by the World Bank, one study found that *in situ* slum upgrading proved more effective in reducing poverty than sites and services approaches, partly because the latter approach excluded families unable to recover the costs of the infrastructure (Pugh 1994). The ideal balance between quality and affordability thus depends on the ability and willingness to pay of both the government and target beneficiaries.

#### WHERE IS IT?

“There are three things that matter in property,” the saying goes, “*location, location, location.*” The expression has been a motto of the real estate industry for decades (Safire 2009), but has been lost on many housing programs. Housing programs can help reverse segregation by incentivizing units in wealthier neighborhoods, or reinforce it by clustering units in ghettos. Similarly, programs can combat sprawl by encouraging infill or transit-oriented development, or exacerbate sprawl by approving developments in the periphery where land is cheapest. Some cities employ planning instruments such as land banking to reserve good locations for public housing before urban growth or new public transit infrastructure render them unaffordable (Santoro 2019). However, many programs lack the mechanisms or funding necessary to secure better locations and risk compromising their beneficiaries’ access to the city.

#### WHO BENEFITS?

How a society perceives housing within its social contract may affect how a program benefits the most vulnerable populations. Where housing is considered a human right, programs may prioritize applicants according to need. If housing is considered a labor right, access may be linked to formal employment. Where housing is viewed as a privilege, applicants may be required to meet strict credit standards.

Housing programs may also benefit developers and landlords. Some cities require developers to designate some affordable units in all their developments, while others provide compensation and insurance. Some recent programs have taken steps to make the process of constructing and awarding units more transparent and competitive.

#### WHO OWNS?

As with conceptions of housing as a right, sentiments regarding the merits of home ownership versus renting can be similarly deep-seated in social contracts. If beneficiaries rent, they can more easily migrate to pursue better jobs and property owners can more easily redevelop.

Ownership, on the other hand, can grant beneficiaries greater stake in their neighborhoods and relieve the government of maintenance liabilities. Many developing countries have opted to subsidize ownership.

### 3.1.2 CASES

#### UNITED STATES

The federal government began constructing public housing to replace slums and stimulate the economy as part of F.D.R.'s New Deal. For many decades, the government built consolidated public housing projects until they, deservedly or not, gained a reputation as hotbeds of poverty and gang violence (Griffiths and Tita 2014; Schill 1993). Apart from a brief experiment of subsidizing ownership in 1985 (Rohe and Stegman 1992), the U.S. Department of Housing and Urban Development (HUD) has largely focused on rental units.

In 1993, the HOPE VI program began to redevelop distressed housing projects into mixed-income neighborhoods, often providing displaced residents with the option to use rent vouchers in market-rate apartments (HUD 2020). Agencies in the U.S. have largely moved away from building public housing, instead requiring or incentivizing private developers to offer some portion of units below market rate or issuing "Section 8" rent vouchers. Both approaches avoid concentrating vulnerable families.

In the same year that it approved HOPE VI, the U.S. Congress approved the Moving To Opportunity (MTO) experiment (NBER 2020). Low-income families in highly distressed public housing projects were randomly assigned to one of three groups: a group that received a voucher usable only in a low-poverty neighborhood, a group that received a typical Section 8 voucher, and a control group. The families were followed for years afterward in order to gauge how neighborhood quality affected their wellbeing. By awarding units via random lotteries, the PMCMV in Rio also presents a rare opportunity to infer the causal impacts of the program.

The PMCMV is similar to outdated federal projects in the U.S. in that its developments concentrate low-income residents in marginal communities. In the U.S., public housing tended to occupy inner cities while employment and affluent populations shifted to suburbs. As discussed in Section 2.3.5, employment and wealth are largely centralized in Rio, so locating PMCMV projects in the periphery creates a similar spatial mismatch. Unlike any of the aforementioned U.S. programs, though, PMCMV beneficiaries own their units.

#### MEXICO

In Mexico, housing was established as a labor right in the constitution. The two largest programs, FOVI and INFONAVIT, subsidize mortgages for salaried, credit-worthy workers but offer no assistance to unaffiliated residents. While the programs originally specified the architecture and location of units, they were reduced to financial entities during the neoliberal movement in the 1990s (Peralta 2010).

As a financial institution, INFONAVIT has accelerated sprawl and exacerbated excess vacancy in cities across the country. The program's loans tended to favor newer, over-sized and homogeneous developments on the urban periphery (Peralta 2010). While some of these developments remained unoccupied, the successful ones attracted residents from urban centers that were left largely vacant (Monkkonen 2014). These recent side-effects of the INFONAVIT approach highlight the risks of over-stimulating the supply of housing and failing to incentivize infill development.

Designed to serve salaried workers, INFONAVIT has also failed to serve unaffiliated workers for whom housing assistance might be more imperative. Two attempts to broaden access to public housing in Mexico have fallen short. Housing units were historically assigned through negotiations with unions that were vulnerable to corruption. Private intermediary firms now allocate units based on credit screening, an approach that may reduce corruption but lacks a progressive mandate (Peralta and Hofer 2006). In 2001, private lenders called *Sociedades Financieras de Objeto Limitado* (SOFOL) emerged to provide mortgages for unaffiliated workers who did not qualify for INFONAVIT or FOVI. However, SOFOLs all but collapsed during the 2008 financial crisis (Herbert, Belsky, and DuBroff 2012).

The PMCMV is similar to Mexico's programs in facilitating ownership and in having private developers build projects with little oversight. Both programs are stimulating development on the urban periphery, so PMCMV officials would be wise to heed criticism of INFONAVIT's effects on urban form and monitor the program's impact on vacancy rates in the urban core. By prioritizing the poorest residents, though, PMCMV already fulfills a more progressive agenda.

## CHILE

When the military overthrew the government in 1973, the new neo-liberal regime sought a more market-driven approach to carry out the long-held mission to eliminate slums. After its sites and services approaches failed, Chile became the first country to issue vouchers to purchase privately built housing (Gilbert 2004). Chile's voucher program initially targeted slum dwellers but in 1984 it began to allocate vouchers based on a score, that was based on savings, family size, socio-economic situation and how long the applicant had been waiting for assistance (Kast 2009). Between 1992 and 2002, as many as 49% of all housing units constructed were purchased with vouchers, while 22% were constructed directly by the government for low-income residents (Tironi 2009).

In contrast to the INFONAVIT experience, housing subsidized or constructed by the Chilean government has been praised as innovative and high-quality. Studies had criticized recent public housing projects in Chile for prioritizing material conditions over cohesion and neighborhood quality, but surveys showed that residents rate newer projects higher in these respects (Tironi 2009). Through an innovative approach called *Vivienda Progresiva*, Chile has begun to build small units that beneficiaries can easily and safely expand themselves (Kast 2009).

Chile's hands-off voucher program may have some adverse consequences, however. One study found that most of the subsidy is transferred to the property owner, who charges higher prices according to the generosity of the voucher (Antonio et al. 2010). Another argues that, in extending housing assistance to the middle class, the government has overlooked patterns of peripheralization of the poor (Hidalgo Dattwyler, Santana Rivas, and Link 2019).

By aggressively subsidizing ownership for the lowest-income residents, Chile's program was likely a model for PMCMV. While both programs should consider incentivizing better locations for privately developed projects, PMCMV could learn from Chile's innovative ways of balancing cost and quality.

#### OTHER PROGRAMS IN BRAZIL

While housing programs in both the U.S. and Chile shared a goal to eliminate slums, Brazil has recently adopted a more liberal attitude toward informal development. Programs such as *Favela Bairro* and Growth Acceleration Program – Urbanization in Precarious Settlements (PAC-UAP) upgrade favelas with grants for housing, infrastructure and improvements to basic services. Rather than granting ownership, these programs strike a compromise by granting land leases to improve security of tenure (Handzic 2010). While some express doubts over the long-term efficacy of slum-upgrading (Marx, Stoker, and Suri 2013; Werlin 1999), evidence from India suggests that it can improve economic welfare if designed well (Kapoor et al. 2004). Since many PMCMV participants come from favelas, it may be worth evaluating if they would have been better off applying for *Favela Bairro* grants.

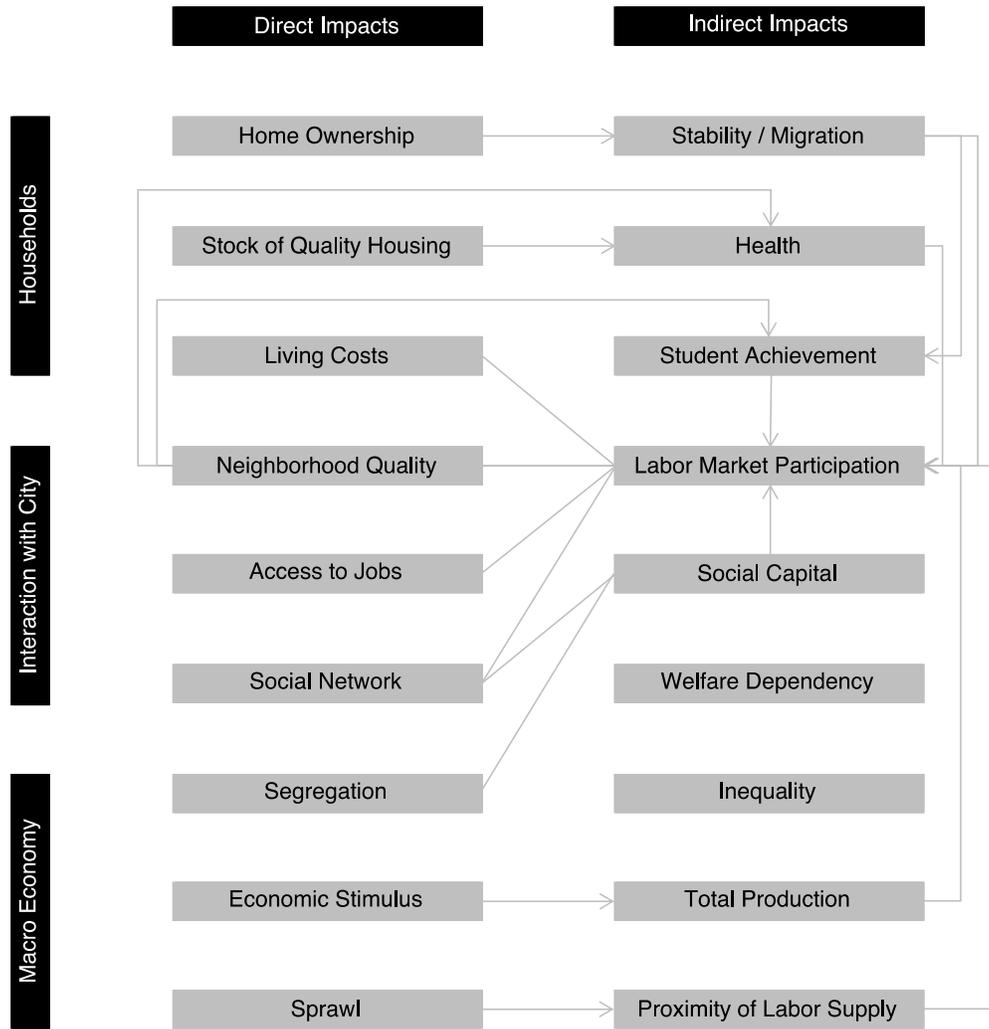
*Minha Casa, Minha Vida – Entidades* (Entities) (MCMV-E) is a small, experimental program within the federal PMCMV to support self-organized public housing projects in partnership with non-governmental organizations. Prospective residents meet with architects to collaboratively design and build their complexes. An organization called *Grupo Esperança* (Hope Group) organized a pilot project in *Colônia Juliano Moreira*, the site of one of the PMCMV projects examined in this study. While offering an interesting alternative, MCMV-E accounts for less than 10% of public housing in Rio de Janeiro (Osborn 2013).

## 3.2 CAUSAL PATHWAYS

Touting the slogan, “More than changing address, it's changing your life” (Caixa 2020), the Brazilian government seems aware that PMCMV can profoundly impact beneficiaries. This section introduces a range of possible outcomes of housing programs and attempts to map out the relationships between them. While not exhaustive, this discussion serves as a reminder that specific findings like those in this study must be considered alongside other outcomes when evaluating the over-all efficacy of a housing program.

Figure 8 organizes the types of potential impacts into a grid. The first column includes the direct impacts of the program and the second includes indirect impacts which occur as a result of other impacts. The first set of three rows describe impacts to beneficiaries, the second set describes

their interaction with others and the third describes macro-economic impacts at the city or national level. The arrows show a few examples of potential causal impact pathways.



**Figure 8: Pathways for First and Second Order Impacts of Housing Programs**

PMCMV relocates beneficiaries to a new neighborhood, directly impacting their neighborhood quality. If the new neighborhood has lower crime, for example, beneficiaries may experience less anxiety. Their improved mental health may enable them to be more productive in the labor market and potentially earn higher wages.

The following subsections systematically explore each direct outcome and the impact pathways that emanate from it. Where available, I provide evidence from international cases. Section 3.4 consolidates evidence of labor market outcomes, which became the focus of this thesis.

### 3.2.1 STOCK OF QUALITY HOUSING

The most direct impact of housing programs is to improve housing quality for beneficiaries. By establishing standards, public housing can guarantee basic services, some degree of protection

from natural disasters, and some minimum amount of space. Studies have shown that better housing quality can lead to greater student achievement among children. Children raised in housing projects in the U.S. were less likely to be held back thanks to reduced overcrowding (Currie and Yelowitz 2000). A study in Chile showed that improving housing quality in precarious neighborhoods increased student achievement (Kast 2009). Housing quality does not seem to drive labor market outcomes, however. A study in Mexico found that workers who moved to higher quality public housing were no more productive (Healy 1971).

If housing programs only add units without clearing precarious ones, they could potentially attract an excess of workers and exacerbate unemployment (Forrester 1969). Even if the PMCMV is not of sufficient scale to unbalance the labor market at the scale of the city, it may exacerbate a spatial mismatch between workers and jobs by locating PMCMV units in the periphery, far from the concentration of jobs downtown.

### 3.2.2 HOME OWNERSHIP

To many beneficiaries, owning a home generates a sense of pride that can be hard to quantify. Several studies, however, have quantified some second-order effects of home ownership. Since home value is tied to neighborhood quality, the theory goes, home owners have an incentive to invest in their community. One study found that home owners are more likely to volunteer, participate in local government, join clubs and engage in other activities that could increase the value of their home (DiPasquale and Glaeser 1998). Home ownership can also increase residential stability, which in turn fosters better student achievement among children (Aaronson 2000; Haurin, Parcel, and Haurin 2002) and reduces teenage pregnancy (Green and White 1997).

When beneficiaries have good reason to move, though, ownership can pose a barrier. Beneficiaries may develop health problems or injuries that make it impossible to access their walk-up units. They could receive an offer for a higher-paying job that would require moving. At a minimum, ownership requires beneficiaries to go through the potentially lengthy and stressful process of selling their houses. In an attempt to avoid abuse, many programs make it even harder to migrate by forbidding beneficiaries from selling their units. If they choose to migrate, they either forfeit their homes or continue to pay mortgage.

A study in Chile found that by prohibiting beneficiaries from selling their units, the public housing program in Chile was preventing migration that would have reduced income inequality (Soto and Torche 2004). In Rio, Carneiro (2019) found that participating in the PMCMV does indeed reduce migration, although the secondary impact on employment is minimal.

### 3.2.3 ECONOMIC STIMULUS

Like many housing programs (Khatiwada 2009; Santoro 2019), the PMCMV was a “counter-cyclic” intervention intended to stimulate an economy shocked by the 2008 financial crisis. The government spending on construction, according to Keynesian economics, generates a multiplier effect that can further increase consumption and eventually increase total production and

employment opportunities. It is difficult to tell if PMCMV can take some credit for Brazil's initial recovery.

### 3.2.4 LIVING COSTS

By subsidizing rent or the capital costs of a home, housing programs are often assumed to lower living costs for their beneficiaries. However, moving may increase the cost of utilities and mobility, or introduce new costs. In the U.S., families from a HOPE VI site chose not to use vouchers over fears of high utility costs (Clampet-Lundquist 2004). High rates of unpaid utility bills and condominium fees in PMCMV projects suggest that similar issues exist in Rio (Vasconcellos 2020). Some of those bills may go unpaid as beneficiaries who originally relied on their social networks to provide childcare suddenly have to pay for it upon moving (Barrett, Geisel, and Johnston 2006).

Beneficiaries who relocated from urban centers to suburbs report dramatic increases in mobility costs. Some participants of the MTO in low-density cities such as Los Angeles exited the program because they could not afford to get around (Briggs, Popkin, and Goering 2010). In a survey of households in several Latin American cities, workers who lived in the periphery spent twice the money commuting as those who lived centrally (Libertun de Duren 2018). PMCMV beneficiaries across Brazilian cities also reported higher mobility costs (MCidades 2014; Souza and Sugai 2018).

In the long-term, housing programs could lower living costs indirectly. For example, beneficiaries might choose to have smaller families, as was found to occur in the U.S. (Susin 2005). Breaking ties with friends and family who frequently solicit financial support could also reduce financial burdens (Briggs, Popkin, and Goering 2010).

Changes in the cost of living can in turn affect other outcomes. If living costs decrease overall, beneficiaries may become less dependent on welfare and more able to study and care for their health. On the other hand, if living costs increase, they may tolerate lower levels of consumption or work longer hours.

### 3.2.5 SOCIAL NETWORK DISRUPTION

Social networks of friends, family, churches, clubs and sports teams provide a variety of services, including emotional support (Briggs, Popkin, and Goering 2010), informal childcare (Barrett, Geisel, and Johnston 2006; Reed 2007; Trudeau 2006), informal insurance (Barnhardt, Field, and Pande 2017) and job referrals (Bayer, Ross, and Topa 2008). Moving as part of a housing program can weaken these social networks and leave beneficiaries less able to work, study or maintain good health.

Disrupting social networks can drive indirect costs through a variety of pathways. With less emotional support, those who move may develop anxiety as they cope with changes and uncertainties. Families who relied on informal childcare from friends and family, for example, may have to pay for it after moving. The increased costs could make them more dependent on

welfare or require them to work more. With fewer friends to turn to in the event of unexpected shocks, such as injuries, beneficiaries might require commercial insurance or simply tolerate greater risk. All of these potential impact pathways may affect some types of beneficiaries more than others. Women, for example, might rely more on social networks for domestic duties and thus be less able to maintain a formal job if uprooted.

Social network disruption has proven difficult to isolate statistically. Since the quality of social networks is not typically recorded in administrative data, some researchers attempt to identify it through variables presumed to be closely related. Looking at monthly formal employment rates in Rio, for example, Carneiro (2019) was unable to detect any short-term disruption effect. Other studies blame disruption to social networks for muffling other expected outcomes. Chetty et al. (2016), for example, suspected that disruption effects prevented teenagers who moved to better neighborhoods as part of the MTO from demonstrating the benefits seen in younger children.

Interview-based research, however, reveals that moving significantly damages social networks. A group of families displaced by HOPE VI redevelopment in the U.S. were unable to rebuild social ties after two years (Clampet-Lundquist 2004). In India, beneficiaries relocated to the periphery felt more isolated from family and caste networks 14 years after moving (Barnhardt, Field, and Pande 2017). The severity of disruption might depend on the moving distance from beneficiaries' original homes to public housing units (Libertun de Duren 2018).

Intriguingly, interviews with MTO participants reveal that breaking social ties can sometimes do more good than harm. Relationships can be taxing, especially if they require more investment – in terms of money, time and emotional energy – than they provide. Housing programs can provide a way out, and it could be that the farther beneficiaries move, the more they are relieved of burdensome relationships (Briggs, Popkin, and Goering 2010).

### 3.2.6 NEIGHBORHOOD QUALITY

Although the precise definition varies between studies, “neighborhood quality” generally refers to some combination of neighborhood attributes presumed to be intercorrelated, such as the quality of local amenities, safety, income levels and even social norms.

Moving from a low to high-quality neighborhood can impact families through several pathways. In the medium-term, access to better schools and reduced distraction from bullying and violence can boost student achievement among children (Briggs, Popkin, and Goering 2010). When those children reach the labor market, they may (Chetty, Hendren, and Katz 2016) or may not (Oreopoulos 2003) earn more. Moving to neighborhoods of the same quality does not generate these benefits (B. A. Jacob 2004).

Neighborhoods with lower levels of violence and pollution, access to open space and recreation, and quality healthcare services can support better mental and physical health outcomes. Adults in the MTO, for example, reported improved mental and physical health 10 – 15 years after moving (Ludwig et al. 2012). A study of families displaced in New York found similar outcomes after

only two years (Fauth, Leventhal, and Brooks-Gunn 2004). There is some evidence that neighborhood quality is associated with health in developing cities as well (Montgomery and Hewett 2005). If beneficiaries from walkable neighborhoods relocate to low-density suburbs where they depend on motorized modes, however, they could struggle with obesity and other negative health outcomes.

Better local resources and lower levels of violence can also foster the formation of social capital (Curley 2010), which in turn drives other important outcomes. As beneficiaries integrate into high quality neighborhoods, they may receive better and more frequent employment referrals (Bayer, Ross, and Topa 2008). Beneficiaries might also become more productive if they adopt certain social norms more prevalent in lower-poverty neighborhoods. Those social norms might be reinforced by social pressure (Festinger, Schachter, and Back 1950), information channels such as schools, or simply by example (Coleman 1988).

It is not obvious whether or not the PMCMV in Rio de Janeiro will provide better neighborhood quality for most beneficiaries. Across Brazilian cities, PMCMV beneficiaries claim that living on the periphery has not compromised their access to quality education and healthcare (MCidades 2014), but no studies have yet measured changes in student achievement or health. The 2020 census will provide data necessary to more accurately assess the quality of PMCMV neighborhoods. However, since the indirect impacts of neighborhood quality take over a decade to manifest, researchers may have to revisit the PMCMV after several years to find significant results.

### 3.2.7 SEGREGATION

When certain socio-demographic groups are spatially segregated, they can experience notably different levels of neighborhood quality. If individual success depends on neighborhood quality, reversing segregation could reduce inequality. Considering impacts on employment, education and single parenthood, one study estimated that reducing segregation by one standard deviation would eliminate one third of inequality between whites and blacks in the U.S. The result would be driven more by benefits to blacks than costs to whites (Cutler and Glaeser 1997). Another U.S. study found that spatial effects, broadly defined, account for 10-40% of observed racial differences in employment. The main driver is social access, indicated by proximity to adults who are employed and either white or affluent (O'Regan and Quigley 1998).

By shuffling populations, housing assistance programs may incur additional social impacts. If beneficiaries are able to integrate into their new communities, their new social ties might build broader trust between ethnic groups or economic classes. There is some direct evidence of these effects. In Ethiopia, for example, beneficiaries reported less vibrant social lives but “reductions in conflict with neighbors and increased willingness to contribute to public goods” (Franklin 2019).

Reversing segregation through housing programs is not, however, straightforward. Even if wealthy families were convinced to welcome new neighbors from troubled areas, housing program participants typically prefer moving to similar neighborhoods (B. A. Jacob 2004) unless they are more educated (Clampet-Lundquist 2004). Housing programs that build housing, rather than provide vouchers, could locate their projects in better neighborhoods as a means of affirmative action. Thus far, though, the PMCMV seems to be reinforcing, not reversing, segregation (Gonçalves 2014; J. C. Rodrigues 2016; L. P. Rodrigues 2015; Santos and Jorge 2014; Silva and Tourinho 2015).

### 3.2.8 ACCESS TO JOBS AND SPRAWL

Beyond the neighborhood, beneficiaries may struggle to participate in the labor market if they cannot access job opportunities within a reasonable time and budget. Gobillon, Selod and Zenou (2007) provide a useful summary of the specific mechanisms through which a spatial mismatch between labor and jobs can affect individual labor market activity:

1. Workers may refuse a job that involves commutes that are too long because commuting to that job would be too costly in view of the proposed wage.
2. Workers' job search efficiency may decrease with distance to jobs. In other words, for a given search effort, workers who live far away from jobs have fewer chances to find a job because, for instance, they get less information on distant job opportunities.
3. Workers residing far away from jobs may not search intensively. For instance, when house prices decrease with distance to jobs, distant workers may feel less pressured to search for a job in order to pay their rent.
4. Workers may incur high search costs that cause them to restrict their spatial search horizon at the vicinity of their neighborhood.
5. Employers may discriminate against residentially segregated workers because of the stigma or prejudice associated with their residential location.
6. Employers may refuse to hire or prefer to pay lower wages to distant workers because commuting long distances makes them less productive (they are more tired or more likely to be absent). (Gobillon, Selod, and Zenou 2007)

Few studies assess the effect of public housing relocation on job accessibility at the individual level. A study in the U.S. found that, although social capital at the neighborhood level is more important, job accessibility is significantly correlated with labor market outcomes for young adults of minority ethnic groups (O'Regan and Quigley 1998). Section 3.2.4 mentions several studies that show how living in peripheral areas can escalate mobility costs.

A broader body of literature examines how public housing can reinforce sprawl. When cities "sprawl" at a low-density, they can reduce access to jobs and social opportunities, particularly for those without access to a car. Recent research has shown that urban sprawl, whether via accessibility or other mechanisms, is detrimental to upward mobility (Ewing et al. 2016).

Resisting sprawl through public housing may be easier than reversing segregation for two reasons. First, sprawl is harmful and costly to everyone, not just vulnerable populations (Real Estate Research Corporation 1974). Second, while potential housing beneficiaries generally resisted moving to demographically different neighborhoods, they generally prefer to live more centrally (Kapoor et al. 2004; MCidades 2014; Prudente and Leiro 2017).

As with segregation, recent evidence suggests that the PMCMV might actually exacerbate sprawl by locating projects in the periphery. One working paper found that Brazilian cities were infilling faster before PMCMV was implemented (Biderman, Hiromoto, and Ramos 2018). In Florianopolis, PMCMV projects are located in peripheral districts with poor transit service (Souza and Sugai 2018). In Porto Alegre, locations are even worse for the most vulnerable beneficiaries in Tier 1 than higher-income tiers of the PMCMV, reflecting a total disregard for the fact that Tier 1 participants are less likely to own a motor vehicle (Lima 2016). In Rio de Janeiro, lottery winners experience a significant decrease in job accessibility (Pacheco 2018).

If officials are more concerned with building more housing at minimal cost, to maximize economic stimulus for example, they will likely continue to locate projects peripherally where land is cheaper. Even in this case, the city could provide access to jobs by improving transit service. Rio de Janeiro enacted Law 12.424, which requires that PMCMV projects be located in urban areas near transportation infrastructure. The law does not guarantee any minimum frequency or level of accessibility, though, and transit service to PMCMV projects has actually declined in recent years (Pacheco 2018; Pereira 2018).

### 3.2.9 LABOR MARKET PARTICIPATION

Thus far, I have discussed the various pathways by which the direct impacts of housing programs can lead to indirect outcomes. This section reviews some additional theory regarding the indirect impacts of housing programs on employment and earnings. These outcomes attract considerable attention for several reasons. First, taxpayers may hope that housing programs improve self-sufficiency among beneficiaries, and eventually reduce the tax burden. Second, labor market data are likely more reliable, detailed and available than data on other outcomes such as health, for example. Third, improvements in labor market outcomes can drive other important benefits. Employment stability, for example, can improve health outcomes (Benach et al. 2014).

Classical economic theory offers three potential mechanisms that could explain labor market outcomes: substitution, income and commodity-subsidy effects. If housing assistance is viewed as a means-tested income supplement, substitution and income effects should reduce labor market participation (Shroder 2002). By the substitution effect, beneficiaries will be discouraged to earn more income because it will reduce their eligibility for welfare benefits. Since the overall subsidy for a PMCMV unit is fixed at 90% of the value, beneficiaries are not incentivized to substitute earned income for more assistance. Under the income effect, housing programs that lower living costs allow beneficiaries to work less while maintaining the same standard of living. The income effect is also unlikely to apply to the PMCMV, since beneficiaries report that

moving has increased their living costs. Finally, if housing assistance is viewed as a commodity subsidy, it could liberate disposable income and stimulate a pattern of high consumption and earnings (Shroder 2002). Again, if beneficiaries actual face increased costs, they will not experience this surplus of disposable income. That said, living on the periphery could motivate the purchase of car and other high-cost items, which might then motivate more work activity.

Section 3.4 summarizes empirical evidence of the causal impact of housing programs on labor market outcomes.

### 3.3 METHODOLOGICAL CHALLENGES

#### 3.3.1 ADAPTATION

When beneficiaries do not have access to formal jobs, they may adapt in ways that are difficult to track with administrative data. The informal economy provides an alternative means of earning income that, while largely invisible to researchers, is important to acknowledge. Data from surveys a decade prior to the PMCMV indicate that 40 – 63% of employment in Brazil is informal (Henley, Arabsheibani, and Carneiro 2009). A 2003 survey by the IBGE and a database of welfare recipients, CADUNICO, contain self-reported informal income. In his review of studies in the U.S., though, Shroder (2002) found that self-reported data can be particularly unreliable and warned against using it in impact studies. Regardless of reliability concerns, even a fusion of these data sources would fail to provide the resolution necessary to assess evolutions in informal labor market activity at the individual level. The outcomes measured in this study are thus not proxies for total employment or earnings, but rather indicators of integration into the formal economy specifically.

Beneficiaries may also adapt to locations with poor access by turning to alternative modes of transportation. Residents in Soacha, a low-income exurb of Bogotá that, until recently, received poor formal transit service to employment centers, turned to informal transit for commuting (Hernandez and Titheridge 2016). The informal transit system in Rio de Janeiro has historically also been extensive (Golub et al. 2009) but a recent travel survey (see Table 1) found that it accounted for less than 1% of trips in the Rio metropolitan region in 2012 (SETRANS 2014). Beneficiaries might also purchase their own vehicle to access jobs. One study found that PMCMV is encouraging motorcycle purchases in several cities (Mata and Mation 2018). Without recent, spatial data on mode choices, though, my thesis cannot account for the effect of vehicle purchases on accessibility. These adaptation mechanisms may soften the real impacts of poor job accessibility for beneficiaries, but also obfuscate my assessment of the importance of transit access in determining labor market outcomes.

#### 3.3.2 HETEROGENOUS EFFECTS

Beneficiaries might hold diverse attitudes and come from a range of situations that could significantly impact their experience with the program. Many studies that focus on average outcomes and forego qualitative techniques fail to expose such heterogeneity. For example, some

couples that moved via the MTO program emphasized in interviews a sense of pride in no longer relying on welfare payments that others did not express (Briggs, Popkin, and Goering 2010). Beneficiaries may also face a range of responsibilities and distractions unrelated to the housing program, such as taking care of sick or elderly family members, that could prevent them from entering the work force (Shroder 2002). Strikingly few studies categorize beneficiaries before measuring impacts. Those that do, such as (Chetty, Hendren, and Katz 2016) and (Carneiro 2019), often find interesting results. For these reasons, I chose to explore heterogeneous effects and developed instruments for field research that could reveal the mechanisms behind them.

### 3.3.3 SELECTION BIAS

Heterogeneity among housing lottery winners may skew outcomes if certain types of people are more likely to move to their units. On one hand, individuals who are more proactive and eager to escape their situations may be more likely to move. On the other, if housing options are particularly unattractive, they might only attract participation from the most desperate individuals who may be unable to work. Even if the decision to move is not based on financial calculus, factors such as family situations (Kleit and Manzo 2006) and safety (Briggs, Popkin, and Goering 2010) could also affect the decision to move and the eventual outcomes. In measuring outcomes of housing programs where potential beneficiaries can opt-out, it is thus essential to account for selection bias (Shroder 2002).

Identifying causal impacts requires some source of variation among the sample that is unrelated to the variables under study. In Chile, for example, Kast (2009) compares applicants with eligibility scores just above and below the cut-off score, which applicants do not know beforehand, in order to create comparable and randomly assigned treatment and control groups for causal inference. Another study used the fact that the magnitude of housing subsidies depend on the gender of the children in the family as an exogenous source of variation in treatment (Currie and Yelowitz 2000). Random housing lotteries like those used in Rio, however, provide possibly the best source of exogenous variation for causal inference (Rubin 1974).

### 3.3.4 OUTCOMES OVER TIME

Whether due to data limitations or equilibrium assumptions, the vast majority of quantitative studies measure the impacts of housing programs as a single difference in outcomes before and after treatment. A few studies, though, found that outcomes evolve over time (Briggs, Popkin, and Goering 2010; Chetty, Hendren, and Katz 2016). Surveys show that PMCMV beneficiaries tend to become less satisfied over time (MCidades 2014), perhaps reflecting growing frustration with neighborhood quality or long commutes. In order to capture such trends, I measure treatment effects across time throughout this study.

### 3.3.5 HETEROGENEOUS CONTEXTS

Regardless of how a housing program is designed, the nature of the political economy in which it operates will inevitably influence outcomes. For example, relocating families from inner-cities to suburbs generally improves neighborhood quality and opportunities for beneficiaries in the U.S.,

but may do the opposite in contexts where the most affluent live centrally. In his study of the PMCMV in Rio, Carneiro (2019) hypothesizes that labor market outcomes will be less observable in Brazil than in the U.S. because employment tends to be more rigid in Brazil. Cultural norms may affect how feasibly female beneficiaries could enter the labor force. Countries with less severe housing deficits may attract participation from more vulnerable citizens less capable of working. The potential disparities in context are too numerous to discuss exhaustively here. It is up to the reader to think critically before directly comparing evidence between cities.

## 3.4 EVIDENCE OF LABOR MARKET OUTCOMES

For the many nuances discussed in this chapter, any evidence that housing programs affect labor market participation should be interpreted with care. Details of the program design and implementation, the political-economic context in which it operates, and the types of beneficiaries in the sample can all affect outcomes. This section summarizes evidence from the studies that are most similar in scope and methods.

### 3.4.1 UNITED STATES

Both HOPE VI and the MTO programs in the U.S. exogenously relocated families, creating an opportunity to infer causal impacts. Nonetheless, early studies were fraught with methodological issues, including poor handling of selection bias and over-reliance on self-reported data. Among empirical studies before 2002 with valid methods and reliable data, Shroder (2002) found that housing programs in the U.S. had zero significant impact on labor market participation.

Later studies, however, consistently found negative impacts among adults. Drawing on survey and administrative data in the U.S. from 1996-1999, Susin (2005) found that those who received housing assistance earned 15% less after three years than their matches in the control group, although he attributed much of the impact to reduced household sizes (Susin 2005). Another U.S. study found an overall decrease in work activity across housing assistance programs, but a lesser effect for voucher users (Olsen et al. 2005). Drawing on data from a Chicago housing voucher lottery, Jacob et al. (2012) found that voucher use reduced labor market participation by 6% and earnings by 10%, and increased the receipt of other welfare by 15%.

Early studies were unable to identify the mechanisms behind the observed labor market outcomes. Using a structural model, one study did find correlations between public housing and neighborhood disadvantages, but could not demonstrate causal linkages with labor market outcomes (Reingold, Van Ryzin, and Ronda 2001). Goetz (2010) found that families uniformly displaced into better neighborhoods by HOPE VI redevelopment showed no increase in labor market activity; he suspected that social network disruption may have undermined any neighborhood effects. Jacob et al. (2012), who did find negative causal outcomes, found no evidence that neighborhood quality or residential stability could explain them. However, Chetty

et al. (2016) found that children who moved to better neighborhoods before the age of 13 as part of the MTO experiment earned 31% more in their twenties.

Overall, U.S. evidence suggests that adult beneficiaries tend to withdraw from the labor market, perhaps due to income and substitution effects. Young children ultimately benefit from neighborhood effects, although it is unclear whether local resources, social capital or other components of neighborhood quality explain the results.

### 3.4.2 OTHER INTERNATIONAL CASES

A study in Denmark found that, correcting for endogeneity, home ownership creates a barrier to switching jobs. As a result, owning a home increases the risk of unemployment. However, home ownership did have a positive impact on wages (Munch, Rosholm, and Svarer 2008).

Cases from countries less wealthy with housing lotteries offer potentially more relevant evidence. Nearly half of the winners of a housing lottery in Ethiopia decided to move, even though they were given the option to rent out their awarded units. Moving to public housing had no significant impact on their employment status or income, however (Franklin 2019).

A study in India also found no significant labor market impacts, although the result was presented in a negative light. Approximately a third of lottery winners forewent their units, and another third eventually abandoned their units. No gains in human capital, measured in terms of health and school attendance among children, or income were identified (Barnhardt, Field, and Pande 2017).

### 3.4.3 RIO DE JANEIRO

Four studies of the PMCMV in Rio de Janeiro found significant but inconsistent labor market impacts. The first study, which included some other Brazilian cities, found that the PMCMV caused unemployment and had no impact on entrepreneurship (Mata and Mation 2018). The second study, which only considered participants who have at some point held a formal job, also found decreased employment and increased welfare dependency among beneficiaries, and no impact on wages (Rocha 2018).

Pacheco (2018) studied the same lotteries as Rocha (2018), but added three more from 2015 and did not remove participants who had never been formally employed from her sample. She also added a year of employment data and analyzed outcomes on a monthly basis in order to observe changes over time in greater detail. Pacheco (2018) found two lotteries in which winners became less likely to be formally employed, although the differential disappeared within three years. Because the impact was temporary, Pacheco (2018) pointed to Mata and Mation (2018)'s study and suspected that beneficiaries might be adapting to poor locations by purchasing motorcycles.

Interested in neighborhood and location effects, Carneiro (2019) examined a subset of participants whose addresses had been recorded in a database of welfare recipients. He found that moving increased formal employment and earnings, and reduced dependency on social

programs. Carneiro (2019) then segmented his sample to see how outcomes varied between participants and PMCMV projects. He found that treatment increased the employment probability for men by 7.8% three years after move-in, but had no significant effect on that of women. He was unable to demonstrate that disruption, neighborhood quality or displacement distance affected outcomes. He did find, however, a negative correlation between employment probability three years after moving and the distance from the PMCMV unit to the beneficiary’s original workplace (Carneiro 2019). Carneiro (2019)’s work suggests that further exploration of heterogenous effects might reveal other significant outcomes.

### 3.4.4 SUMMARY

Many studies have examined the overall impact of public housing on individual labor market participation; Table 2 summarizes those which point to specific underlying mechanisms.

**Table 2: Summary of Mechanisms that Can Drive Labor Market Outcomes**

Mechanism	Description	Literature
Income	Subsidizing housing costs reduces need to work.	(Shroder 2002)
Substitution	Means-tested assistance undermines incentive to work.	(Shroder 2002)
Commodity Subsidy	Subsidizing housing encourages greater overall consumption, requiring more income.	(Shroder 2002)
Migration	Home ownership can impede migration to better job opportunities.	(Carneiro 2019; Munch, Rosholm, and Svarer 2008; Soto and Torche 2004)
Neighborhood Quality	Moving to neighborhoods with better resources and social capital can improve professional network and productivity.	(Bayer, Ross, and Topa 2008; Chetty, Hendren, and Katz 2016; Cutler and Glaeser 1997; O’Regan and Quigley 1998; Oreopoulos 2003)
Accessibility	Improving access to jobs can reduce mobility costs, increase productivity and improve job matching.	(Ewing et al. 2016; O’Regan and Quigley 1998; Pacheco 2018)
Social Network Disruption	Relocation weakens social ties, reducing availability of informal services that enable productivity.	(Barnhardt, Field, and Pande 2017; Bayer, Ross, and Topa 2008; Briggs, Popkin, and Goering 2010; Carneiro 2019; Goetz 2010)

Because the PMCMV does not vary the size of the subsidy for beneficiaries within the same income bracket, there is not a clear opportunity to statistically test for the first three mechanisms in Table 2. On the other hand, since the PMCMV does not allow beneficiaries to rent out or immediately sell their units, the migration effect could be relevant. Since Carneiro (2019) rigorously examined migration, however, I opted to focus my research on the remaining three mechanisms: neighborhood quality, accessibility, and social network disruption.

## 3.5 RESEARCH QUESTIONS AND HYPOTHESES

The network of causal impact pathways is complex but the literature I reviewed demonstrates that well-designed analysis can sometimes reveal causal impacts, specific mechanisms and

heterogenous effects. Empirical results, even for the same impact pathway, vary between contexts, programs and subject types. Hence, there is good reason to examine the PMCMV in Rio de Janeiro in more detail. This section summarizes my research questions and hypotheses, and outlines the specific ways that I improve upon previous studies. Table 3 directly associates my hypotheses with the literature that informed them.

**Table 3: Research Questions and Hypotheses**

ID	Research Question	Hypothesis	Literature	
1	Does moving to a PMCMV unit increase individual labor market participation?	Moving to a PMCMV house will not increase individual labor market participation.	(Barnhardt, Field, and Pande 2017; Franklin 2019; B. Jacob et al. 2012; Olsen et al. 2005; Susin 2005)	
2	Does the impact of moving to a PMCMV unit on formal income depend on pre-treatment attributes of the beneficiary?			
2a	Age	Treatment effect does not vary by the age.		
2b		Gender	Males benefit more.	(Carneiro 2019)
2c		Race	Non-whites benefit more.	(Cutler and Glaeser 1997; O'Regan and Quigley 1998)
2d		Education Level	More educated benefit more.	(Clampet-Lundquist 2004)
2e		From Favela	Former favela residents benefit more.	(O'Regan and Quigley 1998)
2f		Original Proximity to Downtown	Participants who already lived far from downtown benefit more.	(Ewing et al. 2016)
3	Does the impact of moving to a PMCMV unit on formal income depend on the unit's location?			
3a	Proximity to Downtown	Beneficiaries who move to more central area benefit more.	(Ewing et al. 2016)	
3b		Job Accessibility	Beneficiaries who move to areas with better job accessibility benefit more.	(Ewing et al. 2016)
3c		Murder Rate	Beneficiaries who move to safer areas benefit more.	(Curley 2010)
3d		Moving Distance	Moving distance will not affect the benefits.	(Carneiro 2019)
4	Which lottery winners are more likely to move?	Lottery winners are more likely to move if they: identify as brown, are more educated, or are residents of a peripheral area.	(Clampet-Lundquist 2004; B. A. Jacob 2004; Kapoor et al. 2004; MCidades 2014)	
5	Which PMCMV project locations are attractive?	Projects that are: closer to downtown, closer to original homes, or in safer areas are more attractive to lottery winners.	(Barnhardt, Field, and Pande 2017; Briggs, Popkin, and Goering 2010; Kapoor et al. 2004; MCidades 2014)	
6	Are the lottery winners who are more likely to benefit more likely to move?	Lottery winners who are more likely to benefit are more likely to move.	(Shroder 2002)	
7	Are projects in better locations more attractive to lottery winners?	Projects in better locations are more attractive to lottery winners.	(Shroder 2002)	

In most cases, I directly derived my hypotheses from the evidence identified in the associated literature. In a few cases, however, my hypotheses reflect some judgement about how the causal mechanisms from the literature apply to the PMCMV context.

Since I investigated mechanisms that depend on participants' original locations, my sample was most similar to that which Carneiro (2019) studied. I thus expected to find comparable results for Questions 1 and 2b, even though literature provides counter evidence from other contexts. Although Chetty et al (2016) found that treatment effects depend significantly on age for children, I did not find evidence of such heterogeneous effects among adults in the literature. I thus hypothesize no significant heterogeneous effects for Question 2a. For Question 2b, I suspect that moving will be more disruptive to women, who may depend more on social networks in order to balance domestic duties with formal jobs. Since I found that whites generally live in the zones of the city with higher incomes, better health indices, and better infrastructure, I expect that moving to a PMCMV project would reduce their neighborhood quality and thus reduce their ability to work. For Question 2d, I hypothesize that more educated lottery winners will be more likely to seize the opportunity to move if the PMCMV unit offers a better neighborhood (Clampet-Lundquist 2004), which could then drive better outcomes.

Question 2e invokes two competing mechanisms; accessibility and neighborhood quality. As described in Chapter 2, favela residents typically live more centrally than others of similar economic status, and thus are more likely to suffer a decrease in proximity to downtown by moving to a PMCMV unit. Furthermore, since the municipality of Rio de Janeiro is monocentric, the decreased proximity to downtown would reduce job accessibility. However, O'Regan and Quigley (1998) found that neighborhood quality is a stronger driver of individual labor market outcomes. Favelas are often associated with violence and a lack of basic services, but some are more affluent and vibrant (Cummings 2015; Maloney 2004). It would thus be unwise to analogize American inner-city ghettos to favelas (Peattie 1987; Roy 2017). As a starting point, though, I hypothesized that favela residents will generally experience an improvement in neighborhood quality by moving to a PMCMV unit, and thus benefit more.

Hypothesis 3d considers the moving distance from beneficiaries' original homes to the PMCMV unit as a potential proxy for the degree to which beneficiaries experience a social network disruption effect. Moving is inevitably disruptive but whether or not the disruption is ultimately harmful is hard to predict. For example, Briggs et al. (2010) interviewed some MTO beneficiaries that were relieved to move far away from some burdensome friends and family. Other beneficiaries quickly moved back to their original neighborhoods. In Rio de Janeiro, Carneiro (2019) found no evidence that the moving distance affects outcomes. Without clear theory or local evidence to indicate otherwise, I expect to corroborate Carneiro (2019)'s finding.

For Question 4, I offer three distinct hypotheses. Based on Jacob (2004) and Kapoor, Lall and Lundberg (2004)'s findings that displaced families preferred to move to demographically similar neighborhoods, I expect that lottery winners who identify as brown will be more likely to move because PMCMV projects are located in areas where most residents identify as brown. Clampet and Lundquist (2004) found that more educated voucher recipients were more likely to move to better neighborhoods. If more educated lottery winners are more likely to move where PMCMV units offer an improvement in neighborhood quality, that may increase the group's likelihood of

moving overall. Finally, since participants in developing countries have expressed a general preference to live near downtown (Kapoor et al. 2004; MCidades 2014), I expect that lottery winners would be reluctant to sacrifice their proximity to downtown if they already have it. In Hypothesis 5, I expect that PMCMV lottery winners will reveal the same preferences reported in other studies, including the national survey of PMCMV beneficiaries.

For Questions 6 and 7, I did not find studies that directly compare the factors that make households more likely to move with factors associated with better labor market outcomes. However, Shroder (2002) argued that when participants can choose whether or where to move, they can make the decision according to their potential to benefit. If lottery winners generally desire to increase their participation in the formal labor market, then the factors correlated with that outcome among beneficiaries should align with the factors that make lottery winners more likely to decide to move.

In testing these hypotheses, I introduce several improvements to methods from recent studies of the PMCMV in Rio de Janeiro. First, I incorporate 2017 formal labor market data, which could potentially reveal lagged outcomes. Second, I also integrate all 19 random housing lotteries into a single data panel to expand the sample size. Third, I introduce several techniques to better clean input data and more carefully match lottery winners and losers. Finally, in Appendix C, I propose a field study to gather information about participant motivations, experiences, reflections, adaptation mechanisms and social networks.

## 4. METHODS AND DATA

This chapter describes the methods and data I used to test the hypotheses in Table 3. The first section introduces three methods for inferring causal impacts, followed by a brief description of how I modeled the likelihood of moving. The second section documents how I drew on various data sources to construct the panel necessary to apply the causal inference methods. The final section summarizes the key limitations in the dataset.

### 4.1 METHODS

In order to infer the causal impact of the PMCMV on its beneficiaries, I draw from methods widely used in randomized control trials (RCTs). While commonly used to test the effectiveness of medical treatments, RCTs are increasingly used in social science to evaluate programs and projects. In this case, the PMCMV lottery randomly assigned applicants into “treatment” (lottery winner) and control (non-winner) groups. A challenge in this case, also common in other RCTs, is “non-compliance” with the treatment. Individuals who win the housing lottery can decide not to “comply” with treatment and forego their units. Non-compliance can bias results if the outcomes of interest are related to the likelihood of compliance.

This section introduces several approaches to causal inference that rely on the PMCMV’s resemblance to an RCT experiment and address non-compliance. I first describe two techniques, Intention-to-Treat (ITT) and Local Average Treatment Effect (LATE), to measure average impacts across the sample. Section 4.1.3 introduces the Conditional Average Treatment Effect (CATE) method, a generalization of the LATE approach useful in observing how treatment effects vary according to attributes of the participants and PMCMV projects. Finally, Section 4.1.4 explains how I used logistic regression to indicate how lottery winners decide whether or not to move to PMCMV units.

The methods in this section require awareness of the variable types summarized in Table 4.

**Table 4: Variable Types and Examples**

Type	Description	Examples
Dependent	Outcome of interest to be predicted	Employment, Income
Exogenous	Independent of the other variables in the system	Gender, Race, Pre-treatment Income
Endogenous	Affected by the system and correlated with error terms	Treatment Compliance, Residential Location
Instrumental	Relates to the outcome of interest only through treatment, used to address endogeneity	Housing Lottery
Moderator	Affects the relationship between another independent variable, such as treatment, and the outcome	Gender, Race

The dependent variables represent the outcomes of interest, which all describe labor market participation in this study. The independent variables that are not affected by other variables in the system, such as gender and race, are considered exogenous. Some variables, such as education level, are exogenous when measured before treatment, but then become endogenous after treatment.

Endogenous variables are intuitively problematic covariates that may be affected by treatment or correlated with other excluded variables that drive outcomes. Deciding to move to a PMCMV unit is endogenous because participants who are more driven to increase their income, for example, may be more likely to decide to move. Variables describing participants' residential location are also endogenous since moving changes their location.

An instrumental variable (IV) is a proxy for an endogenous variable that does not exhibit the same correlation with unspecified factors. IVs are used to address issues with including endogenous variables in a regression model. Since the PMCMV housing lottery is randomized, it serves as an IV for becoming a beneficiary. Section 4.1.2 explains in more detail how using IVs in two-stage regression helps correct for the selection bias.

Moderator variables can affect how an independent variable, such as treatment, affects outcomes. The variables listed under Research Questions 2 and 3 are all moderators that I suspect influence the effect of treatment on labor market participation.

#### 4.1.1 INTENTION TO TREAT

To test whether moving to a PMCMV lottery increases individual labor market participation (Hypothesis 1 in Table 3), I first estimate the average treatment effect using a conservative technique called Intention-to-treat (ITT). ITT relies only on the lottery to categorize subjects into treatment and control groups, and ignores whether or not the subjects actually complied with

treatment by moving to a PMCMV unit and staying there throughout the study period. The technique prevents issues like non-compliance from biasing estimates of treatment effects, but also tends to reduce the magnitude of the result.

To estimate the impact of treatment assignment (T) on outcome (Y) using the ITT technique, I specify and estimate the following general model:

$$Y = \beta_0 + \beta_1 T + \beta_2 \cdot X + \varepsilon \quad \text{Eq. 1}$$

Note that exogenous variables (X) can also be included to control for variables that may not be balanced between the treatment and control groups if treatment assignment is not perfectly random. For this study, I define the variables as follows:

Y = the individual's participation in the formal labor market

T = years since move-in date for lottery winners

X = vector of pre-treatment attributes and dummies for each month and lottery

In an experimental setting where we could completely preserve the randomized treatment assignment, it would be unnecessary to control for pre-treatment variables in X. In this study, though, I included pre-treatment controls to help correct for cases where the process of eliminating subjects with incomplete data created imbalances between the treatment and control groups.

#### 4.1.2 LOCAL AVERAGE TREATMENT EFFECT

To address non-compliance while avoiding the dilution of treatment effects, I also estimate the Local Average Treatment Effect (LATE). Rather than estimate the impact of receiving randomized treatment, in this case winning the housing lottery, the LATE estimates the effect of complying with treatment, in this case moving to a PMCMV unit.

To estimate the LATE, I use two-staged least squares (2SLS) regression with an instrumental variable (IV) (Angrist, Imbens, and Rubin 1996). The first stage predicts who will comply with treatment (T) based on the IV (Z) and exogenous variables (X):

$$T = \beta_0 + \beta_1 Z + \beta_2 \cdot X + \varepsilon \quad \text{Eq. 2}$$

In the second stage, the estimated probability of treatment from the first stage ( $\hat{T}$ ) becomes a covariate alongside the same exogenous variables (X) to estimate the outcome of interest (Y):

$$Y = \gamma_0 + \gamma_1 \hat{T} + \gamma_2 \cdot X + \varepsilon \quad \text{Eq. 3}$$

Note that the same exogenous variables, X, from the first stage reappear in the second.

The IV should satisfy the following conditions (Angrist and Pischke 2009):

1. Independence: the IV is unrelated to potential outcomes
2. Exclusion: the IV only affects outcome through treatment
3. First-stage: the IV affects treatment
4. Monotonicity: the IV's effect on treatment is weakly positive or weakly negative

For this study, the result of the housing lottery serves as a suitable IV. Since the lottery is random, we can assume that it only affects potential labor market outcomes by enabling treatment, moving to a PMCMV unit. It therefore satisfies conditions 1 and 2. Since winning the lottery is a prerequisite for treatment, it will generate a non-zero first-stage monotonically and satisfy conditions 3 and 4.

When using 2SLS, I define the variables from Eq. 2 and Eq. 3 as follows:

T = years since move-in date for beneficiaries

Z = years since units become available for lottery winners

X = vector of pre-treatment attributes and dummies for each month and lottery

Y = dependent variable representing participation in the formal labor market

If Eq. 3 includes additional endogenous variables besides T, it is necessary to define an IV for each one. Furthermore, each endogenous variable must be estimated by a separate first stage regression.

Note that X does not include “fixed-effects” dummy variables to control for all time-invariant attributes of participants. Since the panel here consists of random treatment and control groups, it is not necessary to apply such controls. In fact, doing so would eliminate the statistical power to model compliance with treatment, since that decision occurs at only one point in time. These models do, however, include temporal dummy variables that control for differences in formal labor market conditions between lotteries.

#### 4.1.3 CONDITIONAL AVERAGE TREATMENT EFFECT

To test Hypotheses 2a-f and 3a-d in Table 3 that treatment effects depend on attributes of participants and PMCMV projects, I estimate the Conditional Average Treatment Effect (CATE) for each of those attributes. The CATE technique involves interacting the treatment and instrumental variables in Eq. 2 and Eq. 3 with a “moderator” variable that represents the attribute hypothesized to influence the treatment effect.

Where the moderator is continuous, I discretized it into bins that each interact with treatment separately (Carneiro 2019; Hainmueller, Mummolo, and Xu 2019; Malesky, Schuler, and Tran 2012). I then specify and estimate a model of the following form:

$$Y = \gamma_0 + \sum_{i=1}^n \gamma_{1,i} \widehat{T * b_i} + \sum_{j=1}^{n-1} \gamma_{2,j} b_j + \gamma_3 \cdot X + \varepsilon \quad \text{Eq. 4}$$

Where:

$b$  = vector of  $n$  indicator variables for all bins

and all other variables are as defined previously.

Each interaction term  $\widehat{T * b_i}$  is estimated in a separate first-stage regression. The first stage includes IVs of the form  $Z * b_i$  for each bin. Note that a reference level is only dropped from  $b$  in the term where it does not interact with treatment,  $T$ , in order to avoid perfect multi-collinearity. Coefficient  $\gamma_{1,i}$  represents the CATE for bin  $i$ .

Eq. 4 differs from the traditional specification to estimate the CATE<sub>1</sub>, which includes all “constitutive” terms,  $\widehat{T}$  and  $b$ , but drops a reference level from  $b$  in the interaction term (Brambor, Clark, and Golder 2006). The specification in Eq. 4 is valid, however, as long as all datapoints are assigned to a bin and all bins interact with treatment,  $T$ . I prefer this specification because it provides an estimate of variance for all of the moderator bins, whereas the traditional formulation does not provide confidence intervals for the dropped reference level.

#### 4.1.4 DECISION TO MOVE

To test Hypotheses 5 and 6 in Table 3 regarding the factors that predict the likelihood of moving, I estimate a model that closely resembles the first stage regression in Eq. 2 used to estimate the LATE. I do, however, make three modifications. First, I define  $T$  as a binary variable indicating simply whether the lottery winner did (1) or did not (0) move to a PMCMV unit. Since  $T$  is discrete, I estimate the model with logistic regression. Second, I eliminate participants who did not win the lottery, since they do not have the option of moving. Third, I introduce variables that describe the mean location attributes of the projects offered in a given lottery. I exponentiate the resulting coefficients to determine how each factor affects the likelihood of deciding to move to a PMCMV unit.

$$Y = \gamma_0 + \gamma_1 \widehat{T} + \gamma_2 b + \gamma_3 \widehat{T * b} + \gamma_4 \cdot X + \varepsilon$$

where  $b$  is a binary moderator

$$CATE = \begin{cases} \gamma_1 & \text{where } b = 0 \\ \gamma_1 + \gamma_3 & \text{where } b = 1 \end{cases}$$

## 4.2 KEY DATA SOURCES

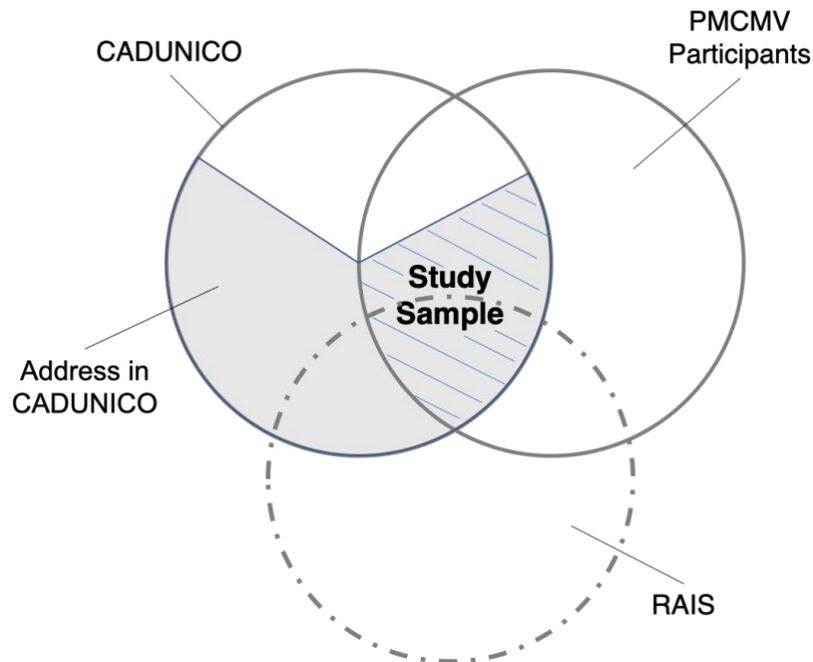
Since this study involves following a large pool of subjects over time, a panel is a natural form in which to organize the relevant data. While Pacheco (2018) considered each housing lottery individually using a repeated cross-section method, Rocha (2018) and Carneiro (2019) constructed panels in order to analyze multiple lotteries simultaneously and derive more general results. This section describes how I constructed the panel that served as the basis for all of the causal impact analysis in my study.

As in the aforementioned studies of the PMCMV in Rio, the dataset here is fundamentally a fusion of three ingredients:

1. Housing lottery results from the City of Rio website and lists of beneficiaries from *Caixa Econômica Federal* (Federal Savings Bank) (CEF) and *Banco do Brasil* (Bank of Brazil) (BB)
2. Monthly employment status and earnings by individual from the *Relação Anual de Informações Sociais* (Annual Social Information Report) (RAIS) database maintained by the *Ministério do Trabalho* (Department of Labor)
3. Demographic variables and original addresses from a database of beneficiaries of social programs called *Cadastro Único para Programas Sociais do Governo Federal* (Single Registry for Social Programs of the Federal Government) (CADUNICO) maintained by the *Ministério do Desenvolvimento Social* (Department of Social Development)

Each of the previous studies in Rio combines these data sources in different ways. Pacheco (2018) kept all participants in her dataset, even if they did not appear in either CADUNICO or RAIS. Rocha (2018) removed participants who never appeared in RAIS in order to use demographic variables from RAIS to estimate the LATE. Carneiro (2019) kept participants who never appeared in RAIS but removed those who did not have their original address registered in CADUNICO in order to use location variables in his models. Also interested in location effects to test Hypotheses 3 through 6 in Table 3, I use the same filtering approach as Carneiro (2019).

Figure 9 shows how my sample relates to the three main data sources.



**Figure 9: Key Database Joins for Panel Data**

Even after this filtering, my sample provided ample statistical power to answer my research questions. However, the filtering limits the external validity of all my findings. My population of interest thus consists of residents of Rio de Janeiro who have benefitted from a federal social program and signed up for the Tier 1 PMCMV housing lottery.

I made two further decisions that affect the size of the panel. Theoretically, the panel could include all participants of the housing lottery that survive the various filters described in this chapter. In order to keep the sample size manageable, though, I matched each lottery winner with only one lottery loser. With fewer subjects, I was able to incorporate monthly labor market data without the panel becoming unmanageably large.

Taking advantage of the residential addresses from CADUNICO, I drew on a variety of sources to append location attributes to the panel. Figure 10 summarizes the key steps in constructing the panel.

1. Left join lottery results with beneficiary lists
2. Remove beneficiaries from previous lottery lists
3. Remove winners from future lottery lists
4. Left join with RAIS, zero missing values
5. Fill missing values in CADUNICO with most recent record
6. Inner join with CADUNICO
7. Delete records without original postal code
8. Separate winners and losers
9. For each lottery, match winners with losers according to pre-treatment attributes
10. Spatial join panel with location data

#### **Figure 10: Key Steps in Panel Construction**

The following sections describe in more detail how calculated each variable in the panel. Appendix A provides a comprehensive description of the data sources.

##### **4.2.1 PMCMV DATA**

All of the data regarding the PMCMV lotteries, projects and participants are published online. The official website of the City of Rio publishes documents with the rules of each lottery, specifying key dates and the PMCMV projects awarding units. The city also publishes the unique personal identifier from the *Cadastro de Pessoas Físicas* (CPF), an ID analogous to a Social Security Number in the U.S., of all applicants and winners of each lottery (Prefeitura 2020c). CPFs are constructed according to several rules regarding the values of certain digits. I eliminated a small (<0.1%) portion of CPFs from the lottery lists that did not follow the specification.

The lists of lottery winners who ultimately moved to a PMCMV house, called “beneficiaries” hereafter, are available from the *Caixa Econômica Federal* (CEF) and *Banco do Brasil* (BB), the largest state-owned banks in Brazil. These databases provide the name of the PMCMV project and the year in which the individual moved, but do not specify through which lottery the individual was awarded the unit. This is problematic because many participants win several lotteries before finally accepting a PMCMV unit. I therefore assumed that the enabling lottery was the most recent one for the same project before or during the move-in year. I eliminated 490 participants who were beneficiaries of PMCMV projects whose units were not awarded by the lotteries considered here.

When participants lose a lottery or win and forego a PMCMV unit, they are automatically entered into subsequent lotteries. As a result, most individuals appear several times in the

participant lists. Individuals who never win the lottery are not problematic, and they can appear repeatedly in the panel. However, I remove individuals who eventually became PMCMV beneficiaries from the loser pools of previous lotteries, since they no longer properly represent the control group. I also eliminate non-compliers from any future lotteries in the panel where they may have won the lottery again. These individuals may be ineligible for the Tier 1 program, may not have the correct contact information registered with the city, or may simply possess traits that distinguish them from typical winners.

Information about the PMCMV projects, such as the opening dates, number of units and location, is not as consolidated. The City of Rio's open data portal includes partial data on most developments (Prefeitura 2020), but I gathered much of the data from independent news outlets. Pacheco (2018) shared all of the data from these sources that she had digitized and organized for her study. As I expanded the sample to include all general lotteries, I referred to the same sources to retrieve the missing data.

#### 4.2.2 LABOR MARKET

The dependent variables in this study, which indicate an individual's participation in the formal labor market, come from the RAIS database. While the database is proprietary, *Fundação Getúlio Vargas* (FGV) provided access to records from 2010 to 2017. As of April, 2020, data for 2018 still had not been released. Of the 743,011 participants of general lotteries, 525,274 (71%) appear in RAIS at some point between 2010 – 2017.

Each year of RAIS includes, for each individual, a record for every employee contract. The records specify start and end dates, contracted hours per week and monthly salary. RAIS also has fields for absenteeism and industry code, which were not considered here. I standardized and combined each year of data into a single long table in order to properly treat employment contracts that span the new year. I then grouped the data by CPF and by month, summing income and weekly hours contracted, and taking the maximum employment status. The resulting table includes total income, total weekly hours contracted and employment status for each individual at each month.

Since the nominal minimum wage (MW) nearly doubled over the study period from R\$ 540 (US\$ 270) in 2011 to R\$ 937 (US\$ 465) in 2017 (MTE 2020), I opted to measure income in terms of multiples of MW. The processed RAIS table includes, for each individual and month: total nominal monthly income, total real income in terms of multiples of the minimum wage, total weekly contracted work hours, and a dummy variable indicating formal employment status.

The PMCMV is “means-tested”; in order to be eligible for a PMCMV tier 1 unit, you must demonstrate monthly household income below a certain threshold, approximately twice the minimum wage (MW), that ranged from R\$ 1395 (US\$ 690) in 2011 to R\$ 1800 (US\$ 894) in 2018. The city only verifies income for lottery winners, however, which creates the possibility that many winners were denied their PMCMV unit because they could not demonstrate

eligibility. RAIS data indicate that, while enforcement is not complete, income eligibility may indeed affect compliance. While 33% of lottery losers exceeded the income limit, only 9% of beneficiaries did. The maximum original income was 103 MW among lottery losers, but only 13 MW among beneficiaries.

Since my population of interest consists of individuals who are eligible for the Tier 1 program, I discarded all individuals who reported more work activity and income than the maximum values found among beneficiaries: 88 weekly contracted hours and formal incomes of 13 MW the year before the lottery. Even after this filtering, these RAIS variables occupy a large range and could follow different distributions between lottery winners and losers. Section 4.2.4 explains how I include pre-treatment RAIS variables in the matching process to preserve balance between the treatment and control groups. When estimating models, I also controlled for pre-treatment RAIS variables corresponding with the dependent variable.

#### 4.2.3 ORIGINAL ADDRESS

Questions 2e, 2f, 3d, 4 and 5 in Table 3 all involve the participants' original locations. This information is actually recorded for all participants in the *Banco Cadastral de Demanda* (Demand Registry), but the city of Rio rejected requests to share the postal codes under a non-disclosure agreement. The next best option is to use the CADUNICO database, which includes records for all welfare recipients, as an alternative source of participant addresses. Access to CADUNICO was also made available through my partnership with FGV.

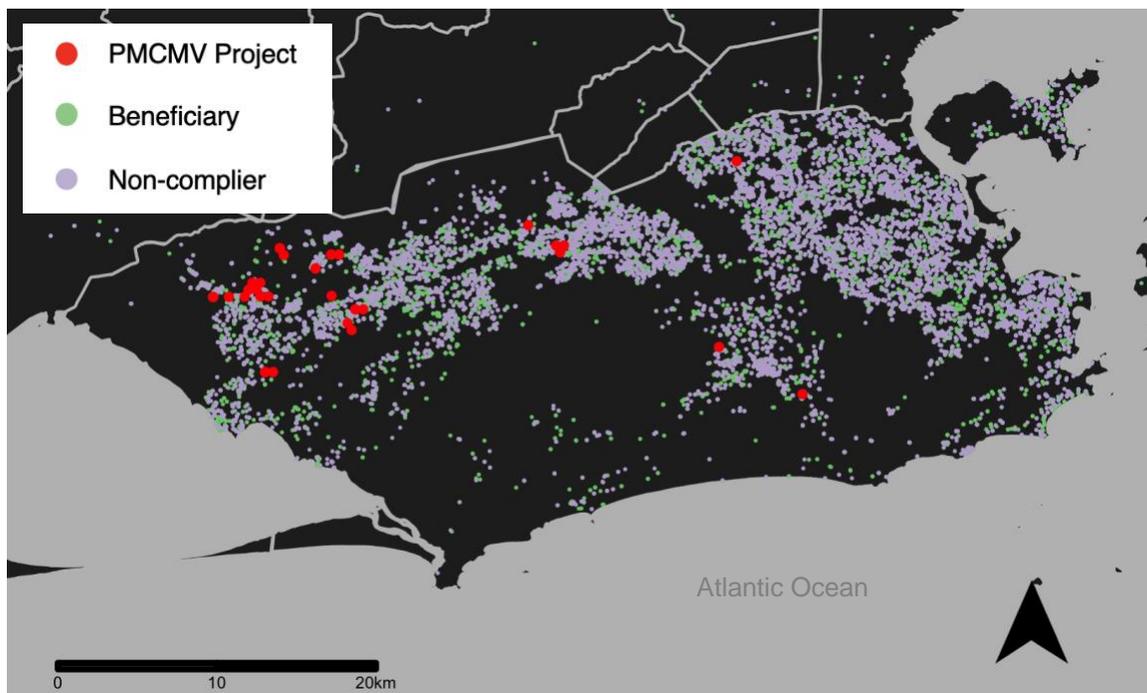
CADUNICO contains a wealth of interesting variables, listed in Appendix A, many of which could be used in future research. Rocha (2018) used the receipt of public benefits as a dependent variable and Carneiro (2019) combined informal employment from CADUNICO with formal employment from RAIS. This study only draws on CADUNICO for independent variables. I use gender, age, race and educational attainment, as recorded the year before the move-in date, as exogenous variables. I also use the CEP (postal code) to calculate various location variables, such as the distance from the participant's home to downtown Rio de Janeiro and PMCMV projects.

CADUNICO comes with several critical limitations. First, the database only includes original addresses for a fraction of PMCMV participants. Second, for the individuals it does include, records are infrequent and often incomplete. To avoid excessive attrition, I imputed relevant variables using the most recent information to fill any gaps<sup>2</sup>. Third, data are only available from 2012 through 2018, although several large lotteries took place in 2011. In order to include those lotteries, I extrapolated CADUNICO back to 2011, copying all variables except age, which I

<sup>2</sup> For variables that do not change predictably over time, I imputed by simply copying the most recent values for later years. For age, however, I used linear interpolation to fill the gaps.

adjusted by a year. I then filtered out PMCMV beneficiaries whose record had already been updated in 2012 with the PMCMV unit address.

Figure 11 shows the original location of all lottery winners, distinguishing those who became beneficiaries with those who did not comply with treatment.



**Figure 11: Origins of Lottery Winners: Beneficiaries vs. Non-compliers in Rio de Janeiro**

Non-compliers and beneficiaries come from all parts of the city, although fewer come from the more affluent *Zona Sul* and *Barra da Tijuca* regions in the South of the city. The map does not immediately suggest that participants who live closer to PMCMV projects are more likely to become beneficiaries. I examine the second point more carefully when testing Hypotheses 5 and 6 from Table 3.

#### 4.2.4 BALANCING AND ATTRITION

Rocha (2018), Pacheco (2018) and Carneiro (2019) all verified that the winners and losers in the lotteries they studied featured similar characteristics, and thus were likely to have been truly randomized. Since I consider additional general lotteries, I repeated balance tests although using a different approach. Instead of conducting t-tests for each variable, I conducted joint test of orthogonality for each lottery that determine the degree of imbalance among all variables simultaneously (Bruhn and McKenzie 2008). I also calculated the normalized differences for the balance variables, since the magnitude of any disparities is often more important than the significance of the disparities (Imbens and Rubin 2015).

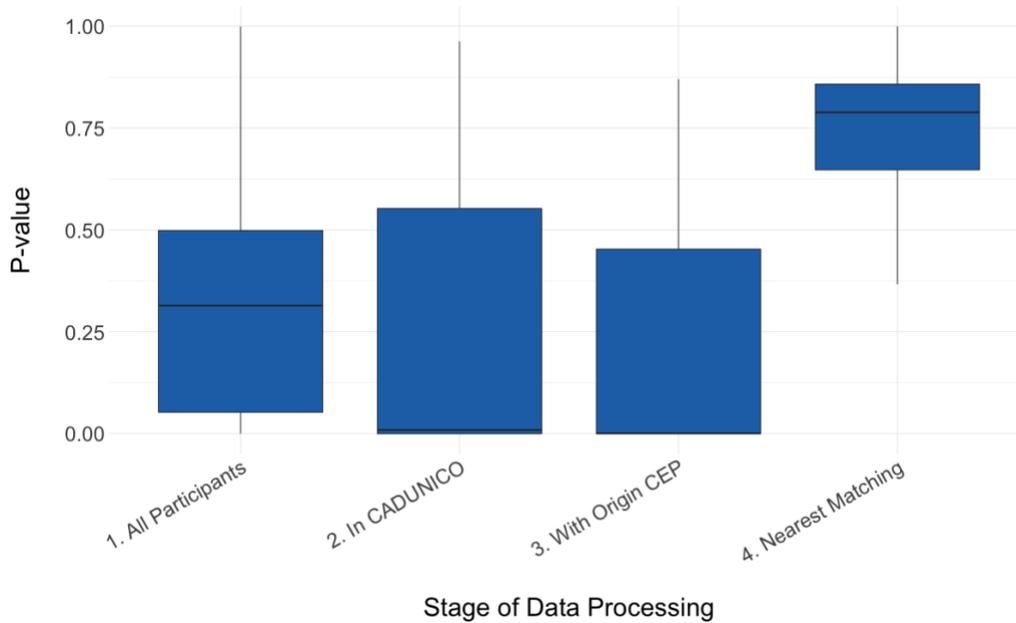
I found that Lottery #26 of 2015 was significantly unbalanced. While the lottery notice claims it was random, perhaps it was announced through other outlets that the lottery would actually prioritize nearby residents or the disabled. Regardless of the explanation, I removed it from the panel.

Confident that the remaining housing lotteries were indeed randomized, I then repeated those balance tests with my sample at key steps during the construction of the panel. The balance between treatment and control groups changed significantly between the following steps:

1. All lottery participants (Step 1 in Figure 10)
2. Inner join with CADUNICO database (Step 6 in Figure 10)
3. Elimination of individuals without pre-lottery postal code (Step 7 in Figure 10)
4. Match lottery winners and losers (Step 9 in Figure 10)

To balance the treatment and control groups in step 4, I matched lottery winners with losers from the same lottery using a propensity-score method (Imbens and Rubin 2015). Propensity scores, estimated via logistic regression, weight the balancing variables according to how strongly they determine the likelihood of treatment. I implemented this approach using the MatchIt R package (Imai et al. 2018).

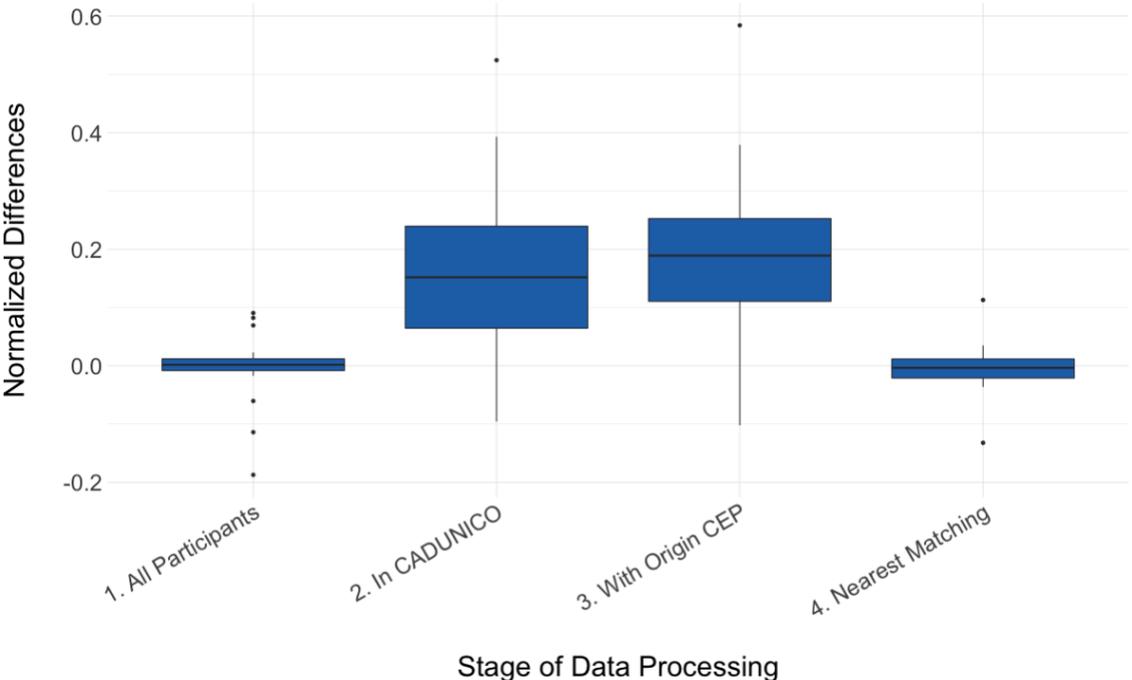
Figure 12 shows how the P-values from the joint test of orthogonality, which indicate the probability that any imbalances are due to chance, evolved over the four major data-processing steps.



**Figure 12: F-test P-values from Joint Orthogonality Balance Tests**

While Carneiro (2019) reported that eliminating participants without original addresses in CADUNICO (steps 2 and 3) did not unbalance his sample, it significantly unbalanced mine. However, matching the lottery winners with losers based on pre-treatment attributes in step 4 effectively rebalanced the treatment and control groups in all lotteries, at least in terms of RAIS labor market variables.

Figure 13 illustrates how mean formal income differed between lottery winners and losers.



**Figure 13: Normalized Differences in Income Between Lottery Winners and Losers**

Figure 13 tells a similar story as Figure 12 regarding balancing, but also reveals that the filtering caused the mean income lottery winners to consistently exceed that of losers in the sample. The matching process in step 4 effectively corrected this disparity.

In addition to altering the balance between treatment groups, the data processing also significantly reduced the size of the sample. Table 5 shows the number of lottery winners and losers at each step where I eliminated subjects.

**Table 5: Attrition of Participants from Sample during Data Processing**

Data Processing Step	Lottery Winners	Lottery Losers
All participants (Step 1 in Figure 10)	38,128	734,964
Eliminate beneficiaries from previous lotteries (Step 2 in Figure 10)	38,070	723,827
Eliminate participants without valid original postal code in CADUNICO (Step 7 in Figure 10)	14,852	179,737
Eliminate participants reporting income greater than 13 MW and more than 88 weekly hours contracted.	14,842	179,687
Match lottery winners with most similar losers (Step 9 in Figure 10)	14,842	14,060

The same step that disrupted the balance of the treatment groups, eliminating participants without postal codes in CADUNICO, eliminated more than half of the sample. Chapter 5 examines how the resulting sample compares to the overall pool of participants.

Note that there are fewer lottery losers than winners in the panel. In order to use the closest match for each lottery winner, I permit lottery losers to appear in multiple lotteries within the panel.

#### 4.2.5 LOCATION VARIABLES

The balanced panel as described so far provides enough information to estimate the causal impacts of the PMCMV on participation in the formal labor market and test Hypotheses 1 and 2a-d in Table 3. In order to explore the remaining questions, however, I needed to append my panel with variables describing the locations of participants' original homes and the PMCMV projects.

#### HEX GRID

The location of all homes, PMCMV projects and workplaces in this study are identified by CEP (postal codes) that Pacheco (2018) already georeferenced. It would be possible, but inefficient, to calculate location variables using CEPs, because it would require repeating calculations for neighboring locations that return the same values. Instead, I follow Pacheco (2018) and Pereira (2018)'s approach and divide the study area into a raster grid of 5,544 hexagonal cells with a 500 m radius. I then calculate location variables for all cells in the grid and spatially join them with the postal codes for original homes and PMCMV projects.

### MOVING DISTANCE

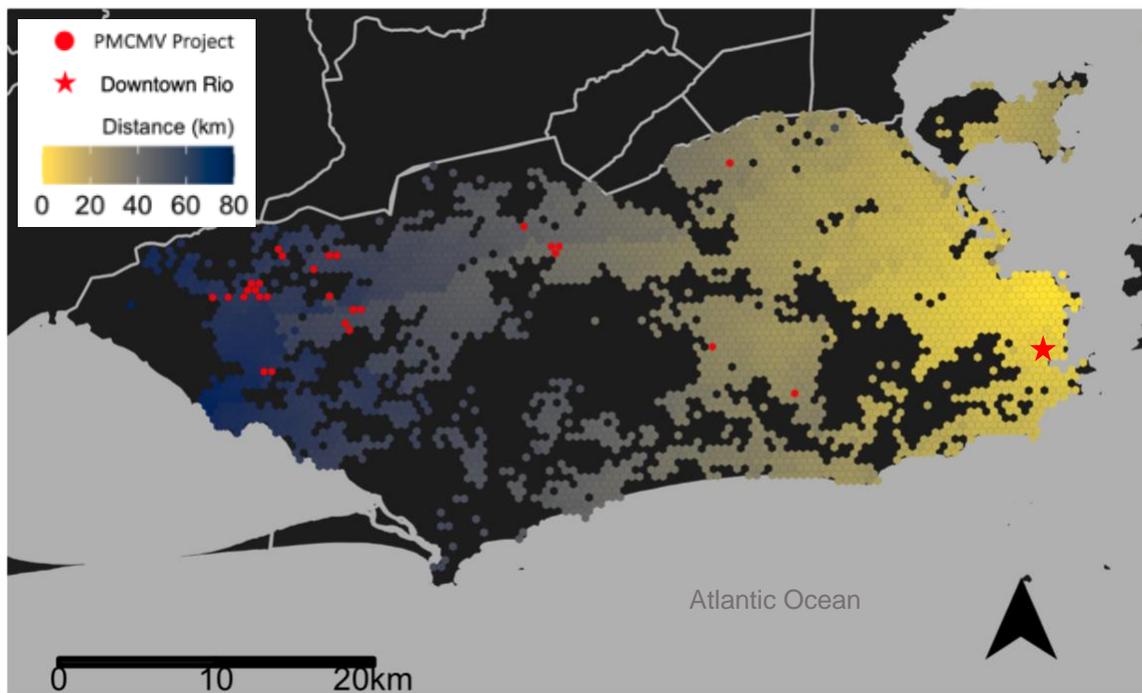
I define Moving Distance as the driving distance in kilometers between a participant's original address and a PMCMV project to which he/she could potentially move. To calculate Moving Distance, I used Open Source Routing Machine (OSRM) to calculate the shortest-path driving distances along the Open Street Map road network between every pair a hexagonal cells in the grid (Luxen and Vetter 2011).<sup>3</sup> Then I spatially joined the CEPs of participants' original addresses with the origin hexagon and the CEPs of their potential PMCMV project location with the destination hexagon to retrieve the potential Moving Distance for each participant.

### PROXIMITY TO DOWNTOWN

I define Proximity to Downtown as the travel distance in kilometers along public roads from a given location to *Praça Tiradentes*, a plaza in downtown Rio de Janeiro. Since formal jobs within the municipality of Rio de Janeiro are largely concentrated near the center, Proximity to Downtown serves as a proxy for access to jobs. Using roadway distance from the aforementioned OSRM matrix, rather than Euclidian distance, accounts for the many geographical irregularities that impede access to downtown Rio.

<sup>3</sup> I first used the OpenTripPlanner routing engine, which is designed for transit routing, with the travel mode set to "CAR"; however, comparing a random selection of results with Google Maps showed significant disparities.

Figure 14 illustrates how the roadway Proximity to Downtown varies across the municipality of Rio de Janeiro.



**Figure 14: Roadway Distance to Downtown Rio de Janeiro (km)**

The map reveals how highway infrastructure improves access to downtown along the southern coast and a corridor heading west from the center. Twenty two of the 29 PMCMV projects are located over 50 km from downtown by roadway.

#### JOB ACCESSIBILITY

Proximity to Downtown has two shortcomings as an indicator of access to jobs. First, while the municipality is mostly monocentric, there are still many jobs outside the center that could be more easily accessed from peripheral locations. Second, as shown in Table 1, most motorized trips in Rio are made by transit, which likely incurs travel times that are not directly proportional to commute distance over the road network. To account for both of these shortcomings, I defined an index, Job Accessibility, as the percentage of all formal jobs in the municipality that were accessible within 90 minutes by formal transit at 7:30 AM on Thursday, October 19, 2017.

To calculate Job Accessibility for each cell of the hexagonal grid, I adapted code and procedures from Pacheco (2018) and Pereira et al. (2019) based on the following formula:

$$Job\ Accessibility_i = \frac{\sum_{j=1}^n Jobs_j * Accessible_{ij}}{Total\ Jobs} \quad \text{Eq. 5}$$

Where:

i = index of the origin hexagonal cell

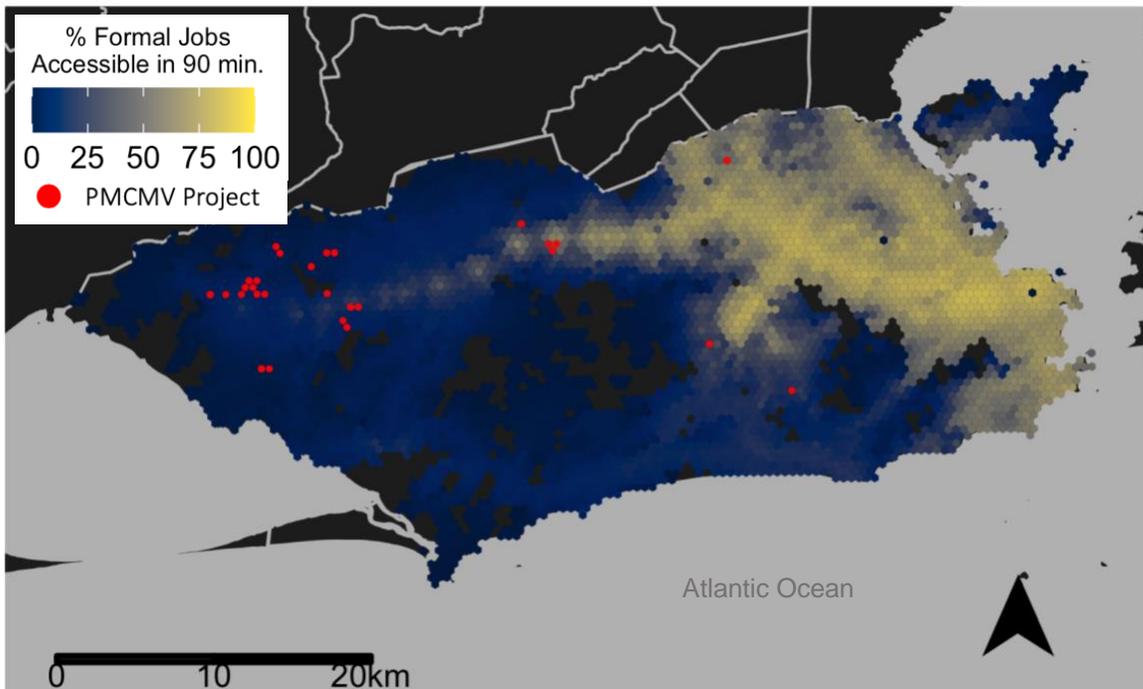
j = index of the destination hexagonal cell

n = number of hexagon cells in Rio municipality

Accessible = 1 if travel time by transit is less than 90 minutes, 0 otherwise

Total Jobs = number of formal jobs in the Rio municipality

Appendix A provides a more detailed description of methods. The choropleth map in Figure 15 illustrates how Job Accessibility varied spatially across the municipality of Rio in 2017.



**Figure 15: Cumulative Opportunities within 90 min. by transit in 2017 in Rio de Janeiro**

As with Proximity to Downtown (Figure 14), PMCMV projects are poorly located in terms of Job Accessibility. More than half of the Tier 1 PMCMV projects completed within my study period have Job Accessibility indices below 10%.

#### 4.2.6 NEIGHBORHOOD ATTRIBUTES

This section presents the variables representing neighborhood quality. Chapter 3 discussed how the MTO program in the U.S., for example, demonstrated that extracting families from low-income, high-crime neighborhoods can benefit their health and earnings in the long-term (Chetty, Hendren, and Katz 2016). In this section, I add three variables to the panel in order to test if neighborhood quality and location also affect outcomes among PMCMV participants.

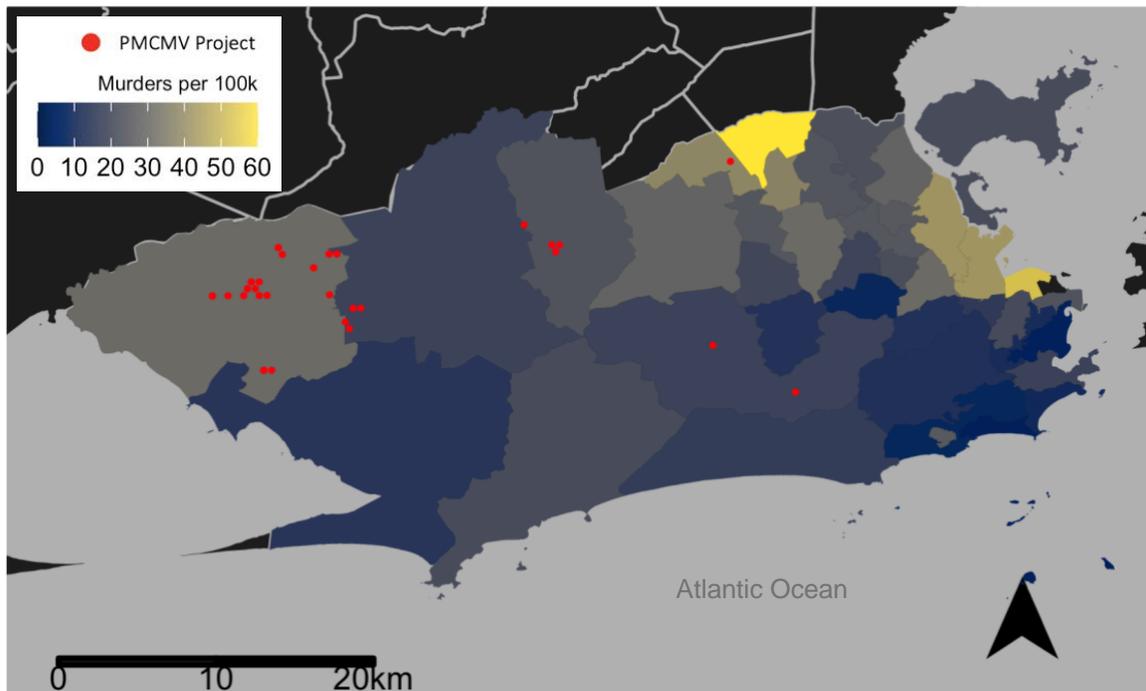
##### MURDER RATE

I use the annual murder rate as an indicator of neighborhood safety. Of course, many other factors, such as rates of bullying, muggings or domestic abuse, can contribute to safety concerns and associated health risks. Furthermore, studies have found that homicide counts in Rio de Janeiro may be particularly unreliable due to underreporting and shifting classifications of violent crimes (Cerqueira 2012; Zdun 2011). Nonetheless, the official murder rate served as a suitable starting point.

The *Instituto de Segurança Pública* (ISP) maintains microdata of criminal incidents available by petition. I requested records on incidents of murder, rape, violent theft and non-violent theft, which ISP provided by month and by police jurisdiction zone (*Circunscrição Integrada de Segurança Pública*, CISP). I aggregated the incidents by type, year and CISP, and joined them with a polygon layer of CISP zones (Prefeitura 2020a). I then divided the sums of incidents by the population of each CISP (ISP Dados 2020) and multiplied by 100,000.

Since rape and theft variables proved insignificant in the models I estimate in Chapter 6, I only consider murder rate hereafter.

Figure 16 is a choropleth map of the murder rate by CISP zone in 2017.



**Figure 16: Murders per 100k Residents in 2017 in Rio de Janeiro**

Because downtown is primarily commercial, dividing by the low residential population gives a high rate of 118 murders per 100k residents. In order to illustrate the heterogeneity among other, more residential CISP zones, I exclude it from the map. The map shows that PMCMV projects tend to be located in areas with moderate murder rates, which could represent either an improvement or deterioration for potential beneficiaries, depending on their original location.

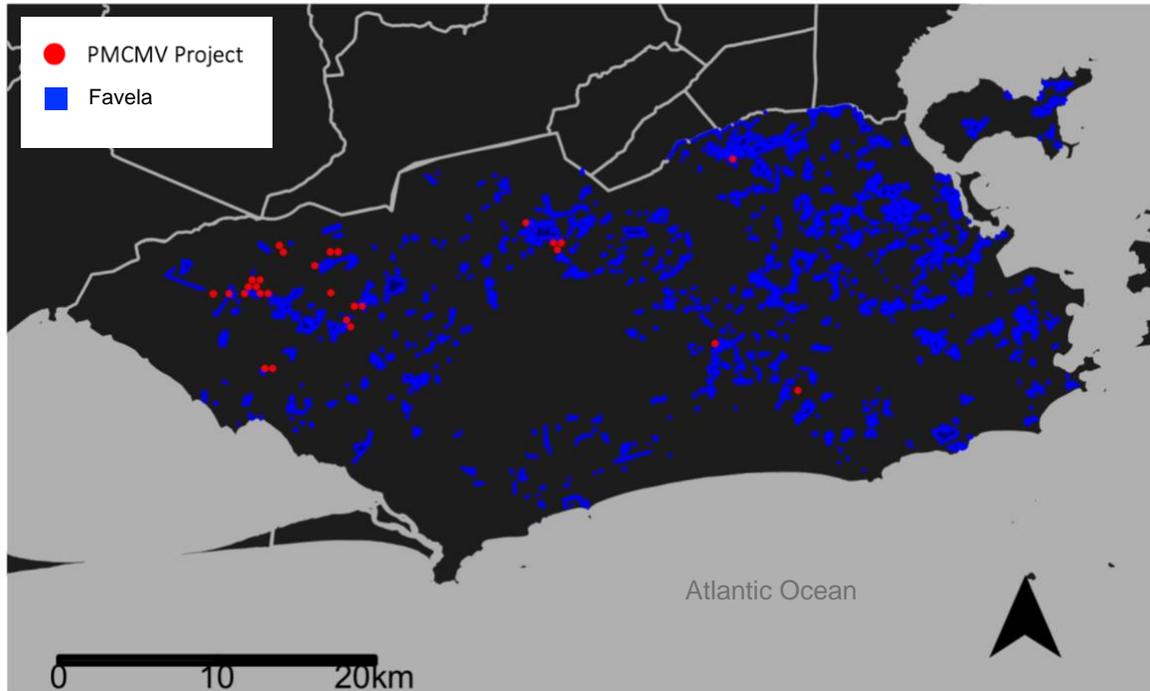
#### **SOCIAL DEVELOPMENT INDEX**

The *Instituto Brasileiro de Geografia e Estatística* (IBGE), responsible for the decadal census, reports the Índice de Desenvolvimento Social (Social Development Index) (IDS) that combines ratings of basic infrastructure provision, household income and literacy rates (SIURB 2020).

Several PMCMV projects are located on newly developed land that did not receive an IDS score in 2010. I therefore opted to exclude this indicator from my analysis, although it may be interesting to consider after the 2020 census. I provide a choropleth map of the 10,142 tracts with an IDS score in Figure 29 in Appendix D.

## FAVELA RESIDENCE

As described in Section 2.3.4, favelas are informal settlements that may lack the infrastructure and basic quality of housing that PMCMV projects guarantee. While many favelas have been pacified with overwhelming military police presence, others are dominated by armed gangs. Favelas remain attractive to many, though, in part because they are more centrally located than formal neighborhoods with comparable rents. In order to identify which PMCMV participants originally lived in favelas, I spatially joined their postal codes with a layer of favela boundaries published by the City of Rio (Prefeitura 2019) and shown in Figure 17.



**Figure 17: Favela Boundaries as of 2017 in Rio de Janeiro**

Since Favelas are scattered throughout the municipality, Favela Residence likely adds richness to the set of neighborhood quality indicators.

#### 4.2.7 SUMMARY OF DATA SOURCES

The final panel includes 28,259 participants over 84 months from January, 2011 to December, 2017. Figure 18 summarizes the structure of the panel and the sources of each of its components.

Panel Data						
Month	Lottery Results	Treatment Status	Pre-treatment Variables	Participant Location Variables	Project Location Variables	Labor Market Outcomes
Jan 2011 to Dec 2017	CPF, Lottery, Lottery Date, Participants, Winners, PMCMV Projects (City of Rio)	Beneficiaries, PMCMV Projects, Move-in Year (CEF, BB)	Demographics (CADUNICO) Labor Market Participation (RAIS)	Proximity to Downtown (OSM) Moving Distance (City of Rio, OSM) Murder Rate (ISP) Favela Residence (City of Rio) Participant postal codes (CADUNICO)	Proximity to Downtown (OSM) Job Accessibility (GTFS, RAIS) Murder Rate (ISP) Project postal codes (City of Rio)	Monthly Income, Weekly Hours Contracted, Employment Status (RAIS)

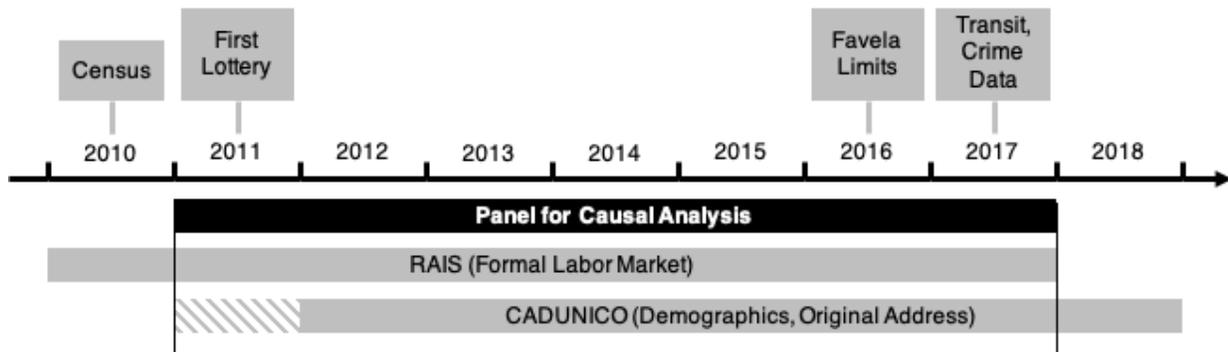
**Figure 18: Summary of Panel Data Sources**

### 4.3 DATA LIMITATIONS

Housing lotteries in Rio de Janeiro have been the subject of several studies in part because of how easily lists of participants can be joined with rich datasets such as RAIS and CADUNICO using the CPF unique identifier. Nonetheless, data availability and quality did significantly limit the scope of this work.

The most serious limitation is the short period of analysis, limited by the delayed release of 2018 and 2019 RAIS data. I only have a few years of post-treatment data for beneficiaries of the large lotteries in 2015, so the direct impact of moving on their labor market activity may not yet be visible. Since many of the indirect and inter-generational impacts discussed in Section 3.2 could take a decade or more to fully manifest, my study period is too short to observe these outcomes among even the earliest PMCMV beneficiaries.

Figure 19 summarizes the timeline of data availability.



**Figure 19: Timeline of Key Data Availability**

Further limiting the analysis is the absence of data describing the informal labor market. With the formal employment rate among participants in the panel dropping below 30% in 2017, it is important to remember that many participants may work in the informal sector. Carneiro (2019) estimated informal employment from the CADUNICO database, but I chose not to do so given how infrequently the database is updated.

There are also several limitations among independent variables in the panel. With only aggregate travel mode shares, I do not know for which participants Proximity to Downtown, which is based on roadway distance, or Job Accessibility, which is based on the transit system, are relevant. While I found in Section 2.3.6 that trips by motorcycles and informal transit are generally rare, those modes may provide PMCMV beneficiaries with better accessibility than my indicators suggest. The Social Development Index, derived from the 2010 census proved too outdated for me to include. Finally, the murder rate is a narrow proxy for safety, and may be unreliable.

## 5. DESCRIPTIVE STATISTICS

This chapter describes how the variables included in the regression models that test my hypotheses are distributed and interrelated. Section 5.1 provides cross-sectional summary statistics of participants measured a year before their potential move-in date and at the end of the study period. Section 5.2 illustrates the variation among PMCMV projects and housing lotteries. Section 5.3 compares labor market statistics between the entire pool of participants and my sample over time to indicate the external validity of my results. Finally, Section 5.4 presents a correlation matrix to identify pairs of variables that may be problematic to include simultaneously in regressions.

### 5.1 CROSS-SECTIONS

This section provides basic statistics of the variables in my panel at two points in time: the year before the move-in date and the end of the study period. Table 6 provides descriptive statistics of the continuous variables and Table 7 shows mean values of all variables among all participants in the panel and by treatment group. Both are measured pre-treatment.

**Table 6: Descriptive Statistics of Continuous Pre-treatment Attributes**

<b>Variable</b>	<b>Mean</b>	<b>Std. Deviation</b>	<b>Minimum</b>	<b>Maximum</b>
<b>Weekly Work Hours</b>	15.5	19.2	0	88
<b>Monthly Income (MW)</b>	0.633	0.958	0	12.6
<b>Proximity to Downtown (km)</b>	29.9	17.5	0.538	71.9
<b>Job Accessibility (% of jobs)</b>	43.5	26.4	0	83.6
<b>Murder Rate (per 100k)</b>	25.2	11.4	0	118
<b>Age</b>	42.1	12.9	17	90

**Table 7: Mean Pre-Treatment Attributes by Treatment Group**

<b>Variable</b>	<b>All Participants</b>	<b>Beneficiaries</b>	<b>Non-compliers</b>	<b>Losers</b>
<b>Employed</b>	0.361	0.362	0.361	0.362
<b>Weekly Work Hours</b>	15.5	15.5	15.5	15.6
<b>Monthly Income (MW)</b>	0.633	0.576	0.633	0.689
<b>Proximity to Downtown (km)</b>	29.9	31.9	29.4	28.8
<b>Job Accessibility (% of jobs)</b>	43.5	41.3	44.1	44.7
<b>Murder Rate (per 100k)</b>	25.2	24.9	25.2	25.5
<b>From Favela</b>	0.117	0.0975	0.124	0.122
<b>Female</b>	0.686	0.749	0.682	0.631
<b>Age</b>	42.1	41.2	42.2	42.7
<b>Race: Black</b>	0.214	0.204	0.222	0.207
<b>Race: Brown</b>	0.464	0.431	0.485	0.456
<b>Race: White</b>	0.317	0.36	0.288	0.332
<b>Race: Other</b>	0.00519	0.00467	0.00546	0.00517
<b>Illiterate</b>	0.0145	0.0125	0.0161	0.0132
<b>Primary School</b>	0.858	0.872	0.858	0.845
<b>Secondary School</b>	0.577	0.593	0.578	0.56
<b>Higher Education</b>	0.0525	0.0539	0.0532	0.0494

Table 8 and Table 9 provide analogous statistics measured at the end of the study period in December, 2017. I exclude from Table 9 the variables that do not change over time.

**Table 8: Descriptive Statistics of Continuous Attributes at End of Study Period (Dec. 2017)**

<b>Variable</b>	<b>Mean</b>	<b>Std. Deviation</b>	<b>Minimum</b>	<b>Maximum</b>
<b>Weekly Work Hours</b>	12.6	19.8	0	100
<b>Monthly Income (MW)</b>	0.548	1.05	0	18.6
<b>Proximity to Downtown (km)</b>	35.1	18.9	0.538	71.9
<b>Job Accessibility (% of jobs)</b>	36.6	27.1	0	83.2
<b>Murder Rate (per 100k)</b>	25.5	10.2	4.35	118
<b>Moving Distance (km)</b>	7.16	14.9	0	87.9

**Table 9: Mean Attributes at End of Study Period (Dec. 2017)**

<b>Variable</b>	<b>All Participants</b>	<b>Beneficiaries</b>	<b>Non-compliers</b>	<b>Losers</b>
<b>Employed</b>	0.294	0.306	0.284	0.303
<b>Weekly Work Hours</b>	12.6	13	12.1	13.1
<b>Monthly Income (MW)</b>	0.548	0.54	0.52	0.615
<b>Proximity to Downtown (km)</b>	35.1	52.7	29.4	28.8
<b>Job Accessibility (% of jobs)</b>	36.6	13.9	44.1	44.6
<b>Murder Rate (per 100k)</b>	25.5	26.1	25.2	25.5
<b>Moving Distance (km)</b>	7.16	28.4	0	0

Comparing mean attributes of beneficiaries before move-in and at the end of the study period offers some insight into their experience with the program. While their labor market activity decreased, it decreased by a larger magnitude for non-compliers and losers. Those results came despite the fact that Job Accessibility, Proximity to Downtown and the Murder Rate all worsened for this group.

## 5.2 PROJECTS AND LOTTERIES

Appendix D provides mean attributes by project and lottery. Table 15 shows the mean characteristics of panel beneficiaries in each project measure a year prior to move-in. Table 16

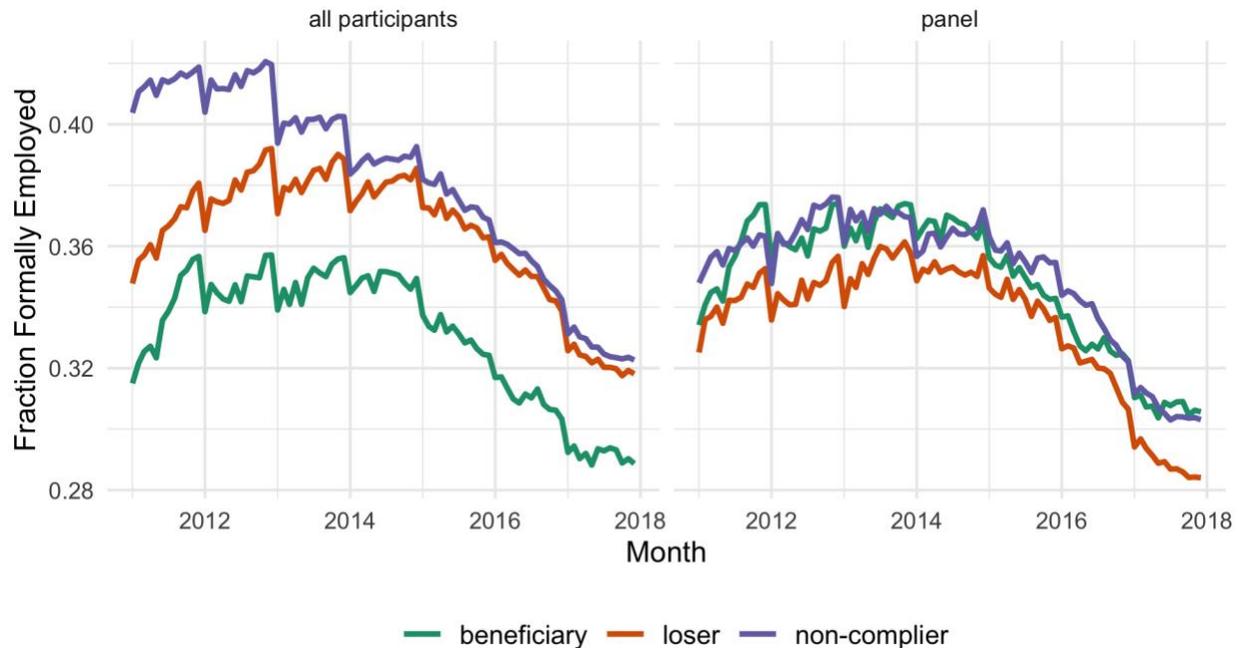
shows means by project at the end of the study period for those attributes that vary over time. While educational attainment does vary notably between projects, beneficiaries do not seem to advance much on average in terms of education between the year prior to move-in and the end of the study period.

I also calculated mean formal income and employment rates at the end of the study period for each project. Average income ranges from R\$ 69 (US\$ 34) in *Park Topázio* to (US\$ 372) in *Vivenda dos Colibris* and employment rates range from 7% in *Park Topázio* to 46% in *Park Jade*. In Table 3, I hypothesized that the location of projects may affect labor market outcomes. Thematic maps in Figure 30 and Figure 31 do not reveal such a relationship, but I explore the question at the individual level in Section 6.3.

A single lottery often awards units in multiple PMCMV projects. Since participants that do not win the lottery or win but do not move are not assigned to specific PMCMV projects, it was sometimes necessary to use the mean location attributes across all projects within a given lottery as IVs and moderators in my models. Table 17 and Table 18 juxtapose the project location attributes with the mean values for each lottery. The tables reveal significant heterogeneity among the average location attributes offered to winners in each lottery, especially Job Accessibility.

### 5.3 TEMPORAL TRENDS

The labor market variables are particularly volatile, so I visualize how they evolve over time for each treatment group in Figure 20 here, and Figure 32 and Figure 33 in Appendix D.



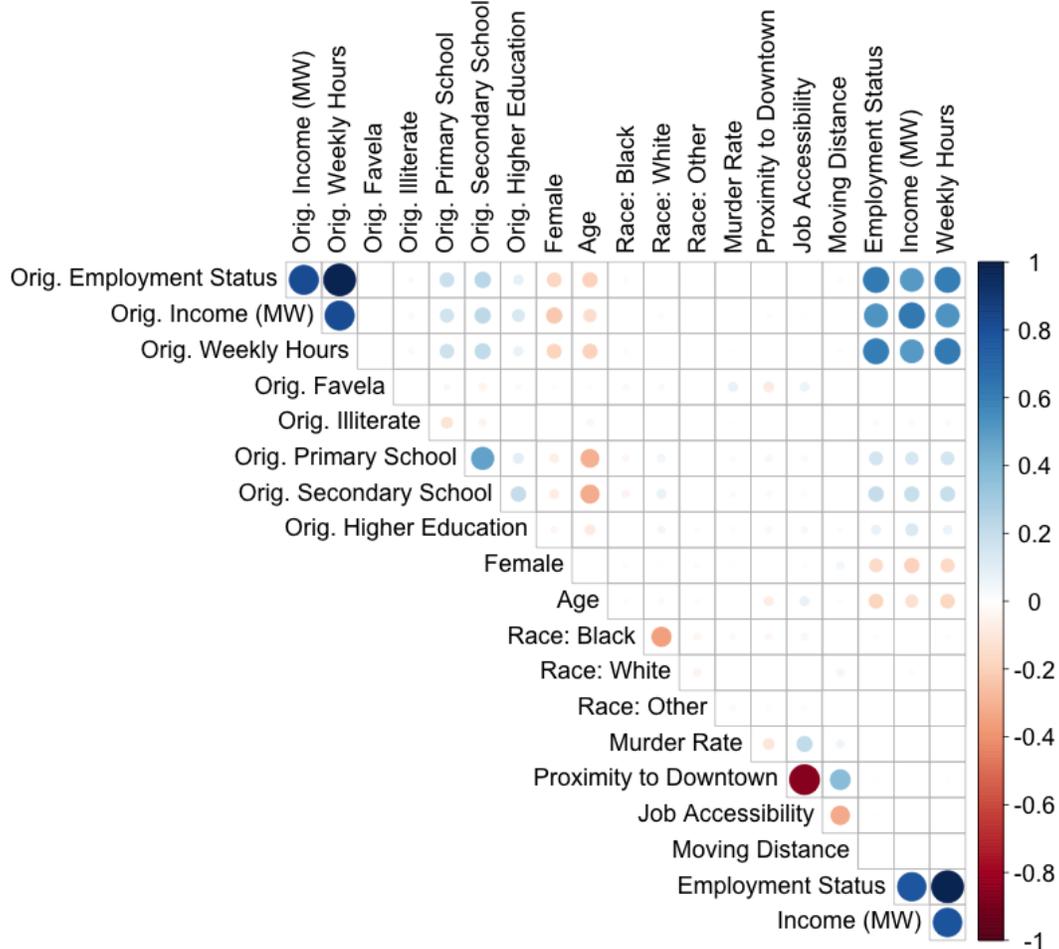
**Figure 20: Sample Comparison - Employment Rate by Treatment Group over Time**

The graphs illustrate two main phenomena. First, the panel significantly reduces heterogeneity between the treatment groups, likely due to my matching process. Because my sample only includes participants who had received social assistance, I expected my sample’s mean labor market participation to be lower than the overall pool of participants. Figure 20 shows that beneficiaries in my sample are actually slightly more likely to be formally employed.

Second, formal employment declines dramatically between 2013 – 2017 among all participants and within my sample, reflecting broader trends in Brazil’s economy described in Chapter 2. Since the panel combines lotteries that occurred at different times, I included dummy variables for each month in all models to control for these trends.

## 5.4 CORRELATION MATRIX

Linear regression assumes that the independent variables in the model are not correlated with each other. The correlation matrix in Figure 21 highlights which variables are collinear, and thus could not be simultaneously included in the regression models presented in Chapter 6. The original participant attributes measured pre-treatment are prefixed with “Orig.”.



**Figure 21: Matrix of Correlation among Panel Variables**

The three labor market variables measured pre-treatment are highly correlated, so I never include more than one of them in the same model. Since those variables are moderately correlated with labor market outcomes, though, it is important to include one of them as a covariate to control for differing advantages among participants. Proximity to Downtown is highly correlated with Job Accessibility, so I also avoid including them simultaneously. Their correlation also suggests that Proximity to Downtown serves as a reasonable proxy for Job Accessibility.

Independent variables that are correlated with outcomes are important to keep balanced between treatment and control groups. Observing that pre-treatment labor market variables, education status and age correlate at least somewhat with the dependent variables, I re-matched lottery winners and losers in the panel using propensity scores based on only these variables.

## 6. RESULTS

This chapter presents the models I estimated to test my hypotheses outlined in Chapter 3. Section 6.1 compares the average treatment effects estimated with the ITT and LATE approaches. Then I show how the treatment effect varies according to pre-treatment attributes in Section 6.2 and according to PMCMV project location attributes in 6.3. Finally, Section 6.4 presents a model of the decision to move among lottery winners.

Before I begin, though, it is worth elaborating on how the treatment variables are specified in the subsequent models. Table 10 illustrates how the treatment variables count the months after the move-in dates. Months Since Can Move remains zero for lottery losers. Months Since Move remains zero for lottery losers and lottery winners who decided not to move to a PMCMV unit.

**Table 10: Illustration of Treatment Variable Definitions**

		Lottery		Move-in			
Variable	Result	Jan, 2013	Feb, 2013	Mar, 2013	Apr, 2013	May, 2013	Jun, 2013
Months Since Can Move	Beneficiary	0	0	0	1	2	3
	Non-complier	0	0	0	1	2	3
	Loser	0	0	0	0	0	0
Months Since Move	Beneficiary	0	0	0	1	2	3
	Non-complier	0	0	0	0	0	0
	Loser	0	0	0	0	0	0

I use Months Since Can Move as a treatment variable when using the ITT approach. Months Since Move serves as the treatment variable with the LATE approach but, since it is endogenous, I instrument it in the first stage with Months Since Can Move. In this Chapter, I estimate treatment effects where these treatment and instrumental variables are multiples of 12, marking years since the move-in date.

### 6.1 CAUSAL IMPACTS OF PMCMV

*Hypothesis 1: Moving to a PMCMV house will not increase individual labor market participation.*

To test Hypothesis 1, I first followed the ITT approach and estimated a model as specified in Eq. 1 to identify the causal impact of winning the lottery on labor market participation. Then I used 2SLS regression according to Eq. 2 and Eq. 3 to estimate the LATE, the causal impact of moving

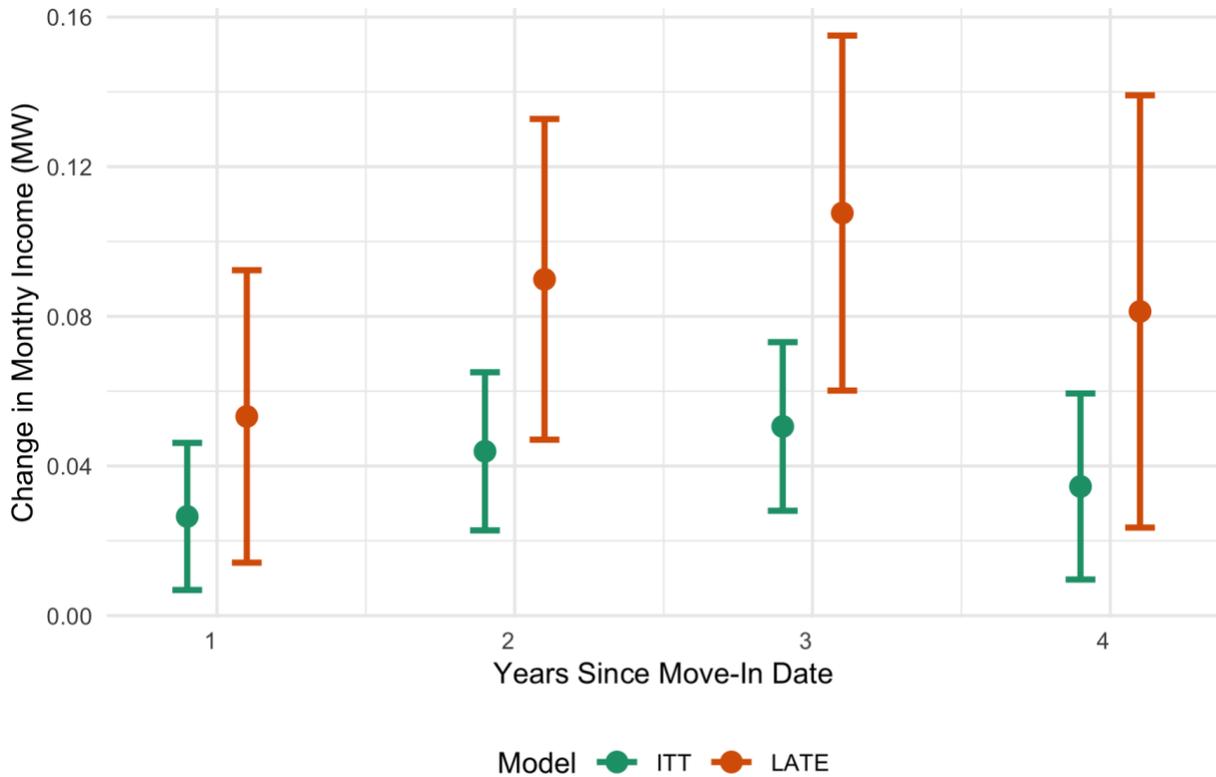
to a PMCMV unit on labor market participation. Table 11 presents the average treatment effects on formal income as a fraction of the minimum wage.

**Table 11: Treatment Effect on Income (ITT vs. LATE)**

Term	ITT				LATE			
	Est.	C.I. low	C.I. high	p-value	Est.	C.I. low	C.I. high	p-value
Year 1	0.0265	0.00684	0.0462	0.027	0.0532	0.0142	0.0923	0.025
Year 2	0.0439	0.0228	0.0651	0.001	0.0899	0.047	0.133	0.001
Year 3	0.0506	0.028	0.0731	0.000	0.108	0.0602	0.155	0.000
Year 4	0.0345	0.00965	0.0594	0.022	0.0813	0.0235	0.139	0.021
Orig. Income (MW)	0.642	0.637	0.648	0.000	0.643	0.637	0.648	0.000
Orig. Favela	0.0174	0.00266	0.0322	0.052	0.0193	0.00447	0.034	0.032
Orig. Proximity to Downtown (km)	0.0000152	-0.00026	0.00029	0.927	-0.0000677	-0.000344	0.000209	0.687
Female	-0.172	-0.183	-0.162	0.000	-0.176	-0.187	-0.166	0.000
Age	-0.000342	-0.00262	0.00194	0.805	-0.000144	-0.00243	0.00214	0.917
Sq. of Age	-0.0000475	-0.0000719	-0.0000231	0.001	-0.0000489	-0.0000733	-0.0000244	0.001
Race: Black	-0.00882	-0.0212	0.00361	0.243	-0.00958	-0.022	0.00286	0.205
Race: White	-0.0104	-0.0213	0.000645	0.122	-0.0121	-0.0231	-0.00104	0.072
Race: Other	0.0388	-0.0279	0.105	0.339	0.0408	-0.0259	0.108	0.314
Orig. Illiterate	-0.00847	-0.0488	0.0319	0.730	-0.00792	-0.0483	0.0325	0.747
Orig. Primary School	0.0152	-0.000576	0.031	0.113	0.0149	-0.00091	0.0307	0.121
Orig. Secondary School	0.107	0.0953	0.118	0.000	0.107	0.0955	0.119	0.000
Orig. Higher Education	0.29	0.268	0.312	0.000	0.289	0.267	0.311	0.000

<sup>a</sup> Sample: 28259 participants, 2011 - 2017

In both models, coefficients for all but two of the racial indicator variables were statistically significant. To illustrate how the treatment effect evolves over time, I plot the coefficients in Figure 22. The error bars in this and all subsequent plots of treatment effects denote 90% confidence intervals. Note that clustered standard errors, which were too computationally intensive to calculate for this sample, would likely reveal greater uncertainty than suggested here (Cameron and Miller 2015).



**Figure 22: Treatment Effect on Income (ITT vs. LATE)**

The ITT model indicates that winning the housing lottery boosts earnings by 0.03 MW (5%) after four years. By overcoming dilution from non-compliance, the LATE technique reveals a stronger treatment effect. Moving to a PMCMV unit increases earnings by 0.08 MW (13%) at Year 4. The impact is comparable to that of completing secondary school.

I found smaller impacts on employment. Using the LATE approach, treatment increases the likelihood of employment by 2% and weekly contracted hours by 1.2 hours per week (8%). Appendix D provides full results in Table 19, Table 20, Figure 34 and Figure 35.

The treatment effects estimated for all three labor market outcomes contradict my hypothesis and most recent evidence. The outcome is especially surprising given the fact that, as described in

Section 5.1, moving to a PMCMV unit represents a sacrifice in safety and access to jobs for most beneficiaries. My results do, however, corroborate Carneiro (2019)'s estimated treatment effect on employment of 2% for the same population.

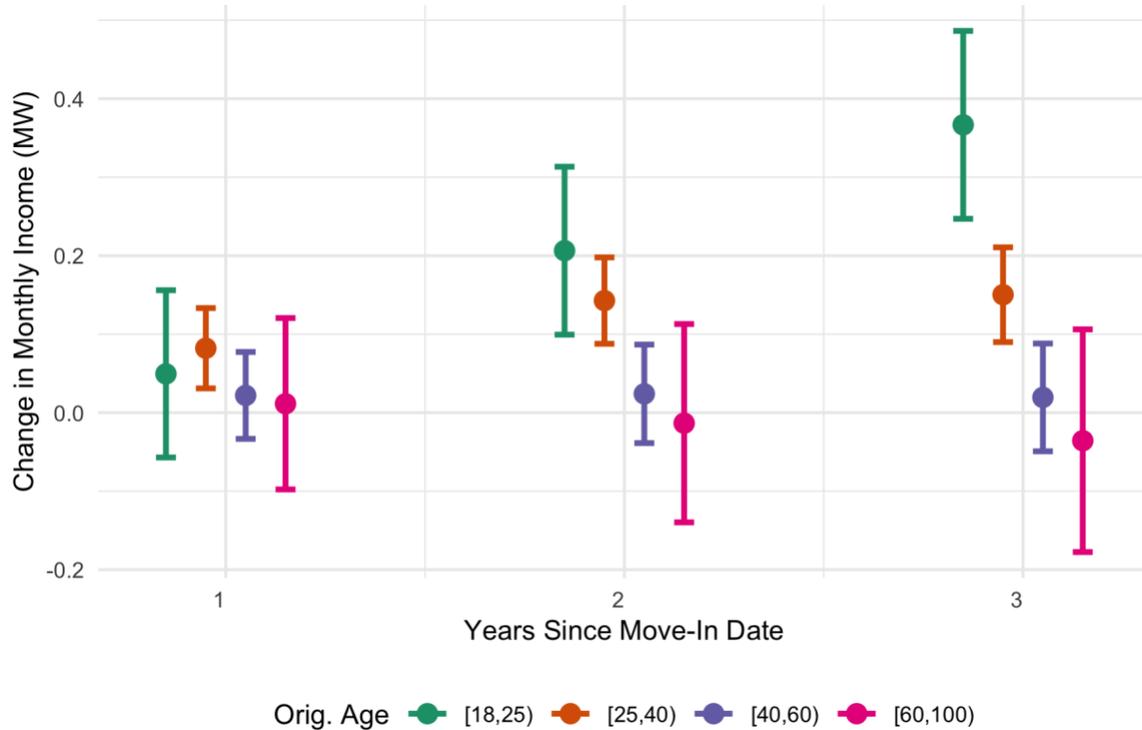
The coefficients on the pre-treatment participant attributes in Table 11 deserve some brief discussion. The large negative coefficient for females could indicate that women are systematically paid less, are more likely to be informally employed, or are consumed by non-wage responsibilities such as childcare and housework. The coefficients on education variables are large and predictable; more education leads to higher incomes. Finally, those who earned more before treatment continued to earn more than average over the study period.

## 6.2 HETEROGENEOUS EFFECTS

I found that, on average, moving to a PMCMV unit increases participation in the formal labor market. This section tests a series of hypotheses about how treatment effects vary according to specific participant attributes. For each hypothesis, I discretize the attribute in question, unless it is already categorical, and interact it with treatment variables to estimate the CATE as specified in Eq. 4. All of these models still control for all other pre-treatment variables. Since many subjects in the panel participated in the 2015 lotteries, for which I do not have labor market outcomes four years post-treatment, I only consider the first three years of treatment in this section.

**Hypothesis 2a:** Treatment effect does not vary by age.

Figure 23 shows the average treatment effect on income conditioned on the age of the beneficiary the year before moving. The bins conform to categories used in the Brazilian census.

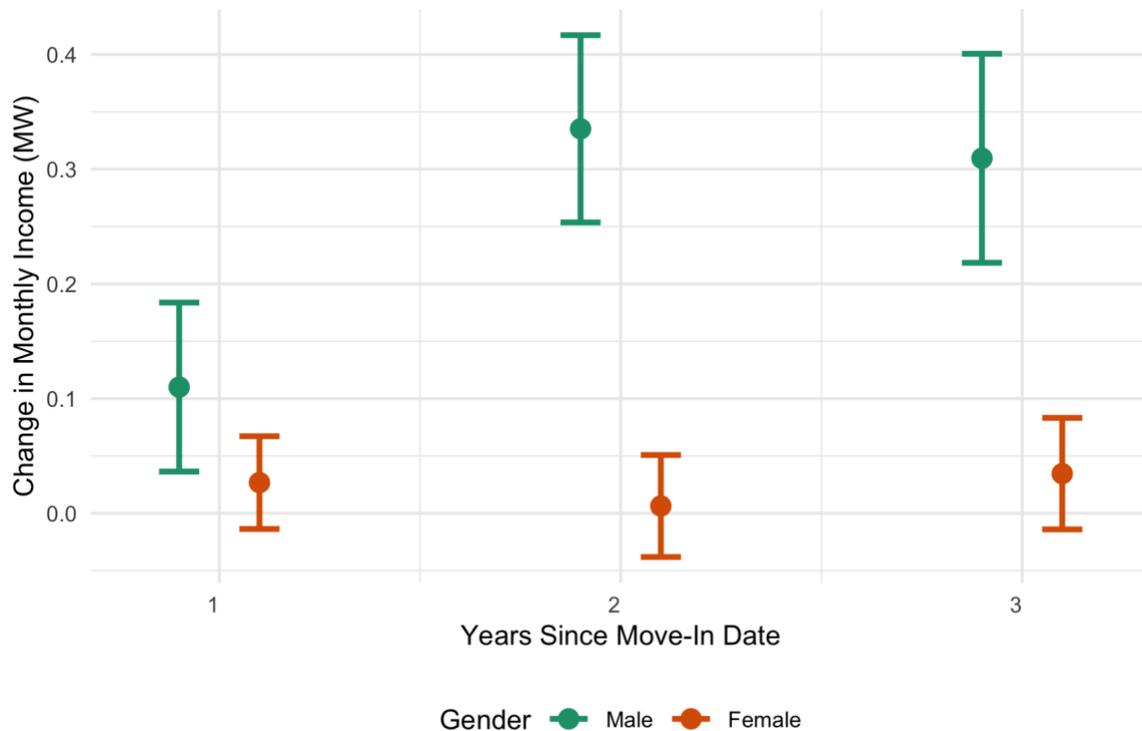


**Figure 23: Treatment Effect Conditional on Age**

Contrary to my hypothesis, treatment effects do depend on the age of the participant. Formal incomes among beneficiaries over 40 years old steadily decline over the first three years after moving. Beneficiaries between 25 and 40 years old enjoy moderate gains before their formal incomes plateau after two years. Participants under 25, however, experience the greatest benefit with treatment boosting incomes by nearly 0.4 MW after four years.

*Hypothesis 2b: Males benefit more from moving.*

Figure 24 shows the average treatment effect on income conditioned on gender.



**Figure 24: Treatment Effect Conditional on Gender**

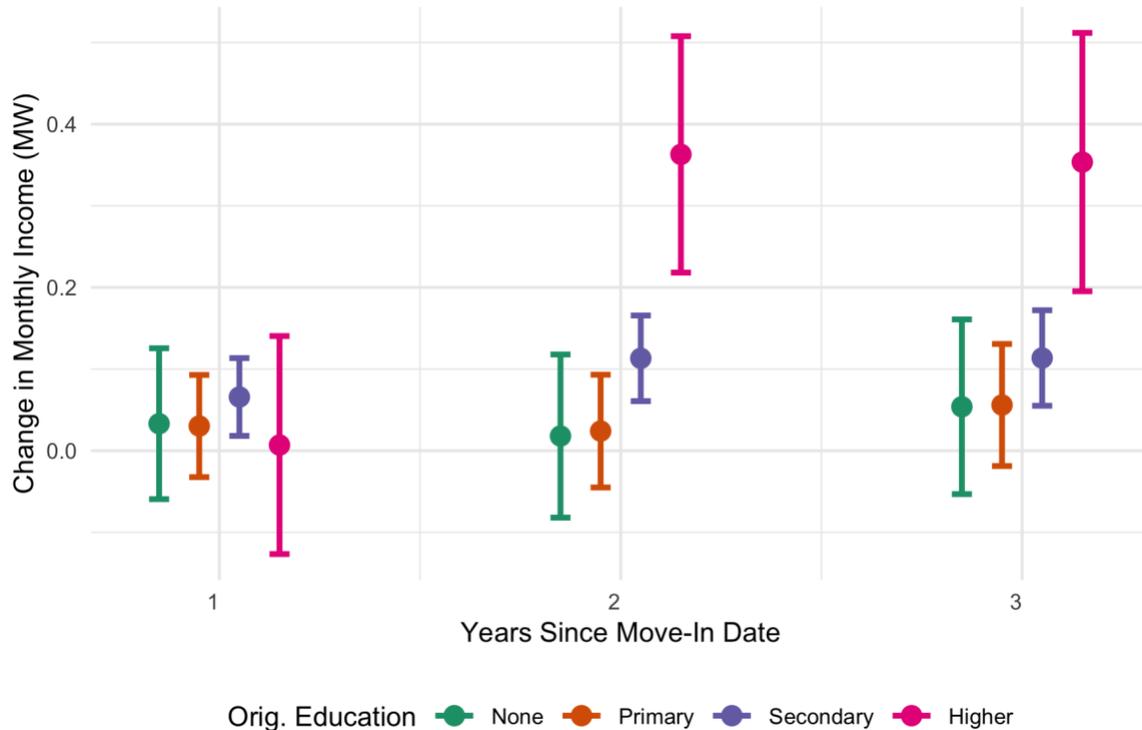
Male beneficiaries earn up to 0.3 MW more than their counterparts three years after moving, while the confidence interval for women straddles zero throughout the study period. The evidence thus supports my hypothesis that treatment benefits men more than women.

*Hypothesis 2c: Non-whites benefit more from moving.*

Contrary to my hypothesis, I did not find that the treatment effect varies significantly according to race. There is some evidence that those who do not identify as black, brown or white suffer a reduction in incomes, but the uncertainty is high for this small population. The results are plotted in Figure 36 in Appendix D.

**Hypothesis 2d:** More educated participants benefit more from moving.

Figure 25 shows how participants experienced treatment according to their education level before moving:



**Figure 25: Treatment Effect Conditional on Original Education Level**

In support of my hypothesis, college graduates do see their formal incomes increase significantly more than less educated beneficiaries, earning 0.35 MW more than counterparts after four years. Those who finished secondary school did not benefit significantly over less educated beneficiaries.

**Hypothesis 2e:** Former favela residents benefit more from moving.

Contrary to my hypothesis, favela residents do not benefit significantly more from moving to PMCMV units. The results are plotted in Figure 37 in Appendix D. Treatment effects are also independent of the murder rate in the beneficiary's original neighborhood, as shown in Figure 38 in Appendix D.

**Hypothesis 2f:** Participants who already lived far from downtown benefit more from moving.

Participants who already lived more than 60km from downtown exhibit a greater increase in income two years after the move-in date, but the differential is small relative to the confidence

intervals and does not persist at Year 3. I thus reject my hypothesis. Results are plotted in Figure 39 in Appendix D.

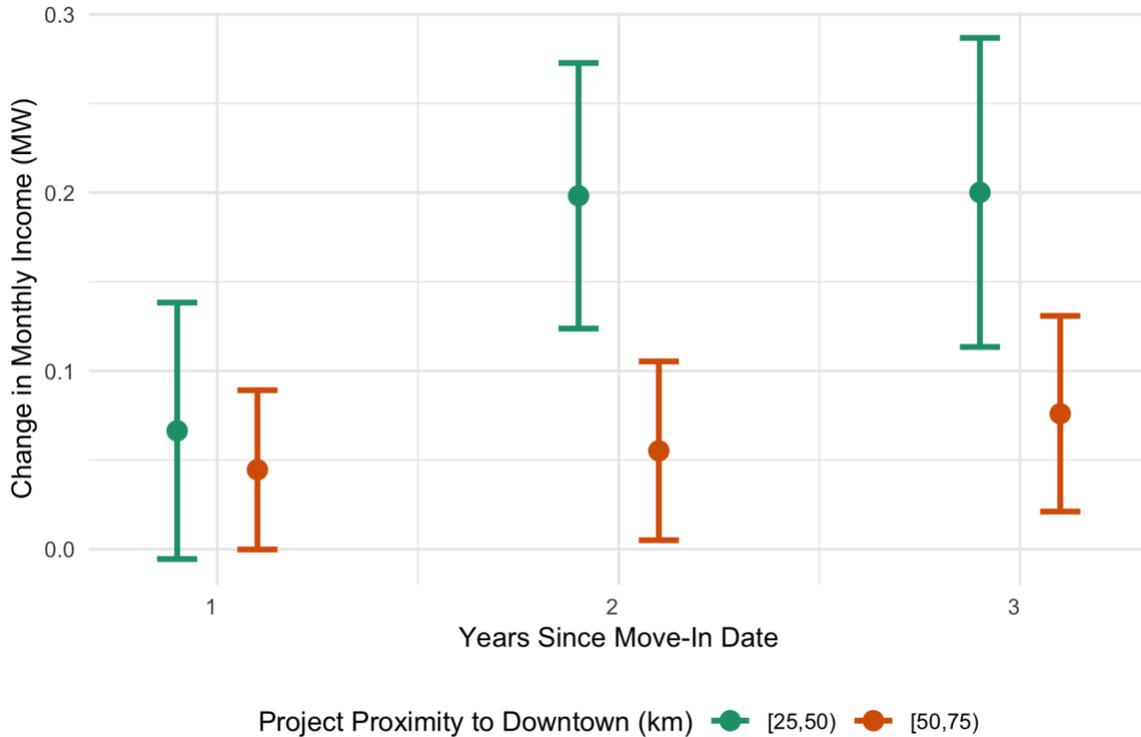
### 6.3 HETEROGENEOUS TREATMENT

While PMCMV projects all guarantee a minimum standard of physical quality, they vary substantially in the quality of their location. The treatment that beneficiaries receive by moving is thus heterogeneous. To test the general hypothesis that the treatment effect depends on the location of the projects offered by the lottery, I estimate the CATE conditional on the mean PMCMV project location attributes offered in each lottery.

Appendix E describes an alternative approach, whereby I test if controlling for location attributes eliminates the significance of the treatment effect. The resulting “independent treatment effect” was still significant, though, suggesting that variables other than Proximity to Downtown and Murder Rate account for the program’s labor market impacts.

**Hypothesis 3a:** Participants who move to more central PMCMV projects benefit more.

Figure 26 shows how treatment effects depend on the Proximity to Downtown of the projects offered in the lottery.



**Figure 26: Treatment Effect Conditional on Project Proximity to Downtown**

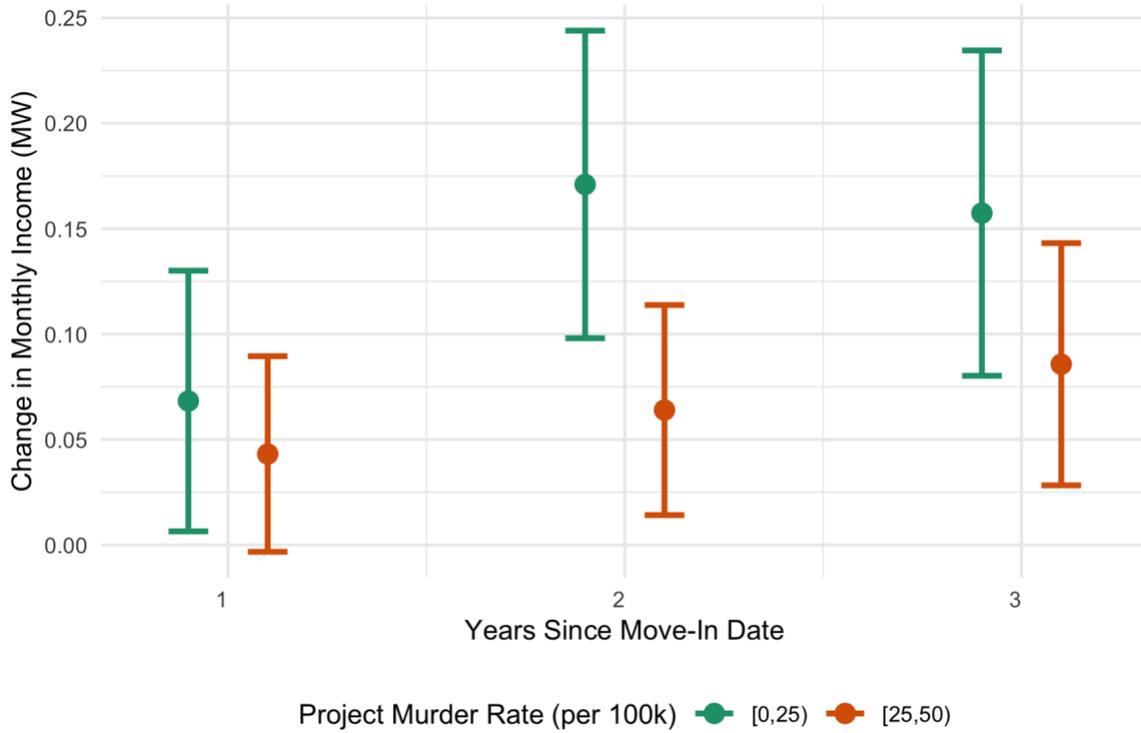
Lotteries offering projects with a mean Proximity to Downtown over 50 km generated less than half of the income benefit as more centrally located projects. The result suggests that building projects closer to downtown could generate even better outcomes than the average treatment effect estimated in Section 6.1.

**Hypothesis 3b:** Participants who move to PMCMV projects with better access to formal jobs benefit more.

Job Accessibility is somewhat bifurcated amongst PMCMV projects, so I defined three bins. Projects from which beneficiaries can access at least 40% of all jobs in the municipality within 90 minutes by transit generated the highest income benefits. Since the result is analogous to my finding for Proximity to Downtown, I provide the results in Figure 40 in Appendix D.

**Hypothesis 3c:** Participants moving to safer areas benefit more.

While treatment effects do not depend on the safety of beneficiaries’ original neighborhoods, Figure 27 illustrates that lotteries assigning units in safer areas do indeed foster greater formal earnings in the short-term.



**Figure 27: Treatment Effect Conditional on Project Murder Rate**

PMCMV projects in areas with over 25 reported murders per 100,000 residents per year increased earnings by roughly half as much as projects in safer areas. The disparity does begin to dissipate three years after move-in, however.

**Hypothesis 3d:** Moving distance will not affect benefit.

Figure 41 in Appendix D shows that outcomes do not significantly depend on the distance that beneficiaries moved from their original homes to their new units. The result supports my hypothesis and corroborates Carneiro (2019)’s finding.

On March 19, 2015, decree 39875 established the “territorial criterion”, which allows PMCMV officials to prioritize participants who already live close to the projects being filled. While the criterion may lead to higher compliance rates, my evidence does not suggest that reducing Moving Distance will improve labor market outcomes.

## 6.4 DECISION TO MOVE

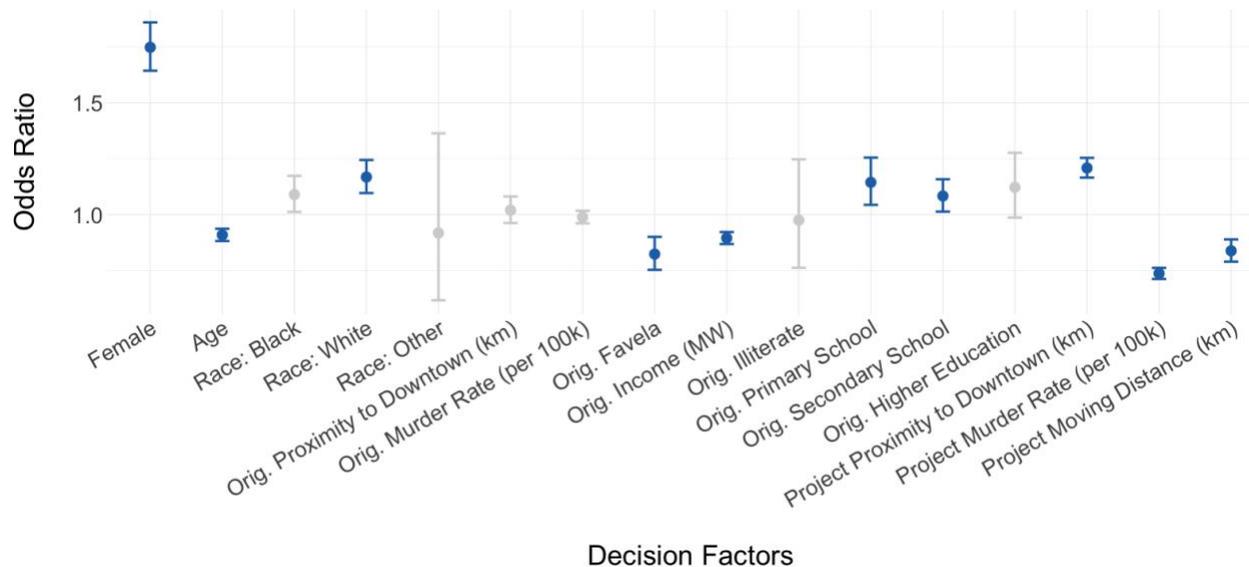
*Hypothesis 4: Lottery winners are more likely to move if they: identify as brown, are more educated, or are residents of a peripheral area.*

*Hypothesis 5: Projects that are: closer to downtown, closer to original homes, or in safer areas are more attractive to lottery winners.*

When I harnessed the random housing lottery as an instrumental variable to estimate the treatment effect of moving to a PMCMV unit via two-stage regression, the first stage regression was doing something interesting. With the help of exogenous variables like gender, race and age, and pre-treatment attributes like education level and income, it predicted which lottery winners would actually comply with treatment and move to a PMCMV unit. This section discusses a similar model that reveals what factors are associated with increased likelihood of moving. I then compare the revealed preferences with the heterogeneous treatment effects I found, highlighting significant disparities.

To test Hypotheses 4 and 5, I conducted a logistic regression among lottery winners with the decision to move as the outcome. I scaled all continuous variables by subtracting their means and dividing by their standard deviations. I also exponentiated the model coefficients to calculate odds ratios. An odds ratio greater than one indicates higher likelihood of moving.

Figure 28 plots the coefficients, highlighting those with p-values below 0.05 in blue.



**Figure 28: Factors Affecting Decision to Move among Lottery Winners**

Although the model cannot explain much of the variation in compliance (the McFadden pseudo R-squared is 0.04), many of the coefficients are statistically significant. Females and low-income participants are much more likely to move to a PMCMV unit. Participants are understandably

less likely to move to areas that have high murder rates or are far from their original home. Surprising, though, is that participants seem to strongly prefer projects that are far from the city center.

***Hypothesis 6:** Lottery winners who are more likely to benefit are more likely to move.*

***Hypothesis 7:** Projects in better locations are more attractive to lottery winners.*

Table 12 juxtaposes the revealed decision preferences with the conditional treatment effects for each variable. Disparities are indicated with bold text.

**Table 12: Decision Logic versus Treatment Effects**

Variable	Decision to Move	Treatment Effect
Age	Younger are more likely to move	Beneficial to younger (under 40)
Gender	<b>Females are much more likely to move</b>	<b>Beneficial to males, no impact on females</b>
Race	<b>Whites are more likely to move</b>	<b>Not significant</b>
Orig. Proximity to Downtown	Not significant	Not significant
Orig. Murder Rate	Not significant	Not significant
From Favela	<b>Favela residents are less likely to move</b>	<b>Not significant</b>
Orig. Education	<b>Primary and secondary educated are more likely to move</b>	<b>College-educated benefit most</b>
Pot. Proximity to Downtown	<b>Lottery winners are much more likely to move to more marginal projects</b>	<b>Projects more than 50 km from the center are not as beneficial</b>
Pot. Murder Rate	Lottery winners are much less likely to move to projects in violent areas	Projects in areas with lower murder rates initially more beneficial
Pot. Moving Distance	<b>Lottery winners are much less likely to move far from current homes</b>	<b>Not significant</b>

Factors associated with deciding to move to a PMCMV unit do not align with those correlated with positive treatment effects on formal income. Even though only male beneficiaries see an income benefit, females are much more likely to move. Whites are more likely to move, but participants of other racial identities benefit just as much. The college-educated are less likely to move, even though they experience the greatest benefit. While participants who moved to PMCMV units over 50 km from downtown did not see their earnings increase as much, these projects were more likely to attract lottery winners.

In a few cases, decision logic aligns with treatment effects. Younger participants are more likely to move and enjoy a more positive income benefit for doing so. Participants are also less likely to

move to PMCMV projects in areas with higher murder rates, which do indeed offer less of an income benefit in the short-term.

Deciding to move is complex and personal. These results do not expose ignorance among participants, but rather provide information that future lottery winners might incorporate into their decision process. The findings also raise new questions: What factors did lottery winners consider when deciding whether or not to move? Did beneficiaries face surprise costs that required them to work more? How has the move affected the quality of their social networks, mental health and families? Such questions call for qualitative approaches, such as those I propose in Appendix C.

## 7. CONCLUSION

Is winning the housing lottery a curse or a cure? In terms of individual formal labor market outcomes for a subset of participants found in a welfare database, this thesis suggests it could be a cure. However, a closer look reveals wide-ranging experiences between types of participants and project locations. Disparities between the factors that drive treatment effects on income and revealed preferences suggest that winners of the housing lottery either do not prioritize potential income gains in deciding whether or not to move, or are uninformed about the potential impacts. To conclude my thesis, this chapter summarizes the main findings, offers recommendations for both program participants and officials, declares the study's most important weaknesses, and suggests directions for future research.

### 7.1 SUMMARY OF FINDINGS

Although economic theory is mixed, recent evidence in Rio and other contexts suggests that receiving housing assistance is likely to reduce earnings and employment in the formal labor market. However, I found that moving to a Tier 1 PMCMV unit in Rio de Janeiro increased earnings by 0.08 MW (13%) and the likelihood of employment by 2%. Since beneficiaries generally sacrifice both safety and access to jobs in moving to a PMCMV unit, other mechanisms such as residential stability or the need to cover higher living costs may account for the increase in labor market activity.

Treatment effects vary significantly, however, according to attributes of participants and PMCMV project locations. PMCMV was most likely to increase incomes for beneficiaries who are male, under 40, or college-educated. Lotteries for projects within 50 km of downtown, with transit access to greater than 40% of the municipality's jobs or with an annual murder rate under 25 per 100,000 were also more likely to boost formal income for beneficiaries.

The factors that predict positive treatment effects on income do not align with the factors that predict moving among lottery winners. Men, non-whites, favela residents and the college educated are less likely to move, even though they are at least as likely to benefit. Projects more than 50 km from downtown are not as beneficial, but lottery winners preferred them. Participants were less likely to move far from home, but moving distance does not significantly affect income benefits. Decision logic only aligns with treatment effects for two of the variables considered: age and the murder rate near the PMCMV unit. These findings point to several recommendations for future lottery winners and program officials, and open questions for further research.

### 7.2 RECOMMENDATIONS

Neither the Brazilian government nor PMCMV participants are necessarily motivated by labor market outcomes. However, this study finds that both actors could potentially alter their decision logic in ways that improve labor market outcomes without compromising the program's primary goals of improving housing quality and stimulating the economy.

The disparity between what encourages lottery winners to move and what drives their participation in the labor market reveals several opportunities. First, the government could inform lottery winners that, for instance, beneficiaries who moved far from their original homes or came from favelas thrived after moving. The government should not, however, discourage certain demographics from participating because they historically have not benefitted. Rather, they might consider reengaging struggling beneficiaries, an approach that has been proven effective in the U.S. (Olsen et al. 2005).

Having found that beneficiaries who move farther from their homes do not benefit less in the long run, my results do not support the use of the territorial criterion to prioritize applicants who already live near PMCMV projects. I also recommend incentivizing the development of PMCMV projects within 50 km from downtown or with transit access to greater than 40% of jobs within 90 minutes by transit because such projects foster higher increases in formal earnings. To better integrate existing PMCMV beneficiaries into the labor market, I suggest reversing the recent decline in transit service. When projects cannot be located within walking distance of high-capacity corridors, providing free feeder buses to terminals could significantly reduce transfer fees and overall commuting costs.

PMCMV officials could also take steps to facilitate research on the program. The external validity of my study is limited because I relied on data from the CADUNICO database that did not include most participants. The city could share postal codes for all participants from the *Banco de Demanda* database with researchers or, as officials do in São José do Rio Preto (Rocha 2018), register all PMCMV applicants in CADUNICO. Furthermore, PMCMV officials could be more willing to collaborate with researchers seeking to conduct research that could potentially improve the program.

### 7.3 LIMITATIONS

As I fused data from multiple sources and specified models to test my hypotheses, I employed several techniques to improve the reliability of my findings. I found that monitoring sample statistics and imbalances between treatment groups throughout the construction of the data panel was particularly helpful in catching errors. As I tested hypotheses, I specified multiple models with various types of treatment variables in order to discover more robust results. Despite my best efforts, though, I submit my thesis aware of four significant shortcomings.

In order to examine location effects, it was necessary eliminate participants who did not have their original home address registered in the CADUNICO database. The remaining sample was unbalanced in terms of labor market variables and I was unable to identify the cause. I suspect that more careful procedures to match individuals not only by CPF identifiers, but also by name, might resolve the issue. I did employ a matching process in order to rebalance the treatment groups, but unobserved variables that affect labor market outcomes may have remained unbalanced. Those unobserved variables may explain the positive average treatment effect I

estimated, which contradicts most theory and evidence. The heterogeneous effects explored here may be less vulnerable to this issue, however.

Combining multiple housing lotteries that occurred at different times into a single dataset enabled me to estimate more general results than recent studies in Rio. It also required that I introduce many dummy variables into my models, which can cause issues of heteroskedasticity. In such cases, calculating cluster-robust standard errors can reveal greater uncertainty than default methods suggest (Cameron and Miller 2015). Since my sample is large and those calculations are costly, I was not able to properly account for heteroskedasticity in this study. As a result, the actual confidence intervals are likely wider than those I present.

In exploring conditional treatment effects, I discretized continuous moderator variables in order to reveal non-linear relationships and facilitate the interpretation of coefficients. While I generally defined bins based on references or equal intervals, researchers could justify different specifications that might lead to different results.

Finally, as I mention in Section 4.3, I could not observe many important phenomena that could have affected beneficiaries' earnings. While I have been careful to qualify that this study only measures activity in the formal labor market, readers must remember that beneficiaries who lost their formal jobs might have found adequate opportunities in the informal sector. Meanwhile, beneficiaries who did increase formal earnings may have only done so out of necessity to cover higher living costs. Although I often refer to increased formal earnings as a "benefit" for efficiency, readers should not consider the outcomes assessed here as indicators of overall self-sufficiency or wellbeing.

## 7.4 FUTURE RESEARCH

Both the findings and the limitations of my thesis point to opportunities for future research. New data sources, more sophisticated methods, and new research questions can all help better evaluate PMCMV in Rio and understand the mechanisms that shape how beneficiaries experience such programs.

Data to be released over the next few years will allow researchers to draw on the methods in this thesis to study a larger sample and consider more variables. RAIS data for 2018 and 2019 will reveal medium-term labor market outcomes for the numerous beneficiaries of lotteries held in 2015. The 2020 census will update the Social Development Index, average household income and other variables that could be used to better represent neighborhood quality. Researchers can also incorporate transit fares into accessibility metrics, thanks to the recent inclusion of fare information in standardized transit data.

Researchers could also employ more sophisticated methods to answer my research questions. In estimating heterogeneous effects, methods that avoid discretizing moderator variables rely on fewer assumptions and could more accurately reveal critical points at which treatment effects

change (Abrevaya, Hsu, and Lieli 2015). These methods might also permit more formula procedures for testing hypotheses. Finally, interacting multiple moderator variables with treatment simultaneously could produce a formula to calculate treatment effects as a function of multiple participant or project attributes (Gelman and Hill 2007).

Although I found that projects in better locations generate more positive labor market outcomes, my thesis does not explain how the program generates benefits overall given that beneficiaries typically sacrifice neighborhood safety and job access to move. To identify which other mechanisms are at play, researchers might consider a mixed-methods approach. Interview strategies, like those I propose in Appendix C, can reveal specific causal impact pathways to be modeled using methods like those presented in this thesis.

Understanding the mechanisms that prevent female beneficiaries from increasing their incomes is particularly urgent. To determine if domestic responsibilities have prevented women from entering the labor market, researchers might assess the impact of a recent initiative to provide domestic appliances in PMCMV projects (Jornal Brasil em Folhas 2018).

Finally, a mixed methods approach could uncover what outcomes participants care about most and if the PMCMV improves them. While I was able to identify some preferences that influence how lottery winners decide whether or not to move, a participant survey like the one I propose in Appendix C could uncover their true priorities. Whether participants seek a safer neighborhood, better schools or the stability of ownership, researchers could then turn to statistical methods to measure if the PMCMV is really a cure for what they really care about.

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# APPENDIX A: DATA SOURCES AND PROCESSING DETAILS

## DATA SOURCES

- *Editais* (enrollment list)
  - Publicly available
  - All PMCMV applicants
  - Lottery winners
- CEF/BB
  - Publicly available
  - All PMCMV beneficiaries
  - *Empreendimento* (project in which housing is located)
- Banco de Cadastro de Demanda (demand registry)
  - Not made available
  - All PMCMV applicants
  - Original address
  - Declared income
- CADUNICO
  - Available for 2012 – 2018 with non-disclosure agreement
  - All recipients of government social benefits
  - Family origin, registration history, age profile
  - Living conditions
  - Individual origin, registration history, address
  - Disabilities, type of assistance
  - Race, indigeneity
  - Expenses (water, gas, transportation, food, rent, medicine)
  - Voting district
  - Education status
  - Employment status and income
  - Contact information
  - Buys, sells or receives training about food
  - Government benefits by type, including subsidies, shelter, rehabilitation
  - Homelessness: reason for losing housing, help received, income
  - Beneficiary of housing program
- RAIS *Establecimientos* (Workplace) 1980 – present
  - Available with non-disclosure agreement
  - All formal employers
  - Postal code
  - Number of employees
  - Sector

- Opening and closing date
- RAIS *Vinculados* (Employees) 1980 – present
  - Available with non-disclosure agreement
  - All residents who have at some point held a formal job
  - Socioeconomic profile
    - Education level
    - Gender
    - Date of birth
    - Nationality
    - Race
    - Disability type
    - Year arrived in Brazil
  - Employment status
    - Employed on December 31
    - Day, month fired
    - Reason for being fired
    - Date hired
    - Means of hiring (transferred, promoted, etc)
    - Number of months employed
  - Job details
    - Type of contract
    - Pay schedule (weekly, monthly, etc)
    - Sector
    - Professional status (diplomat, licenses, etc)
    - Workplace ID
    - Number of employees in workplace
    - Hours of work per week
  - Income
    - Salary in contract
    - In December monthly
    - Average monthly
    - Last monthly
    - By month
  - Leave
    - Start date
    - End date
    - Cause of leave (workplace injury, maternity, etc)
    - Repeated for second and third instance of leave
- GTFS
  - Available with non-disclosure agreement

- Fetranspor
  - Bus and metro
  - 2014, 2015, 2016, 2017
- SuperVia
  - Commuter rail
  - 2015, 2017
  - Same feeds used for previous year

## DATA PROCESSING DETAILS

### JOB ACCESSIBILITY

The following describes in more detail how I calculated the Job Accessibility index described in Section 4.2.5.

To calculate travel times by transit, I used data from Fetransport and Supervia, the two formal operators in Rio, describing the structure and schedule of their transit systems. Both datasets were made available under an agreement with FGV. I adapted an open-source Python script (Pereira et al. 2019) that runs batch queries to an OpenTripPlanner server to create a matrix of travel times between each pair of hexagonal cells in the grid. I then calculate the binary variable Accessible for each pair of hexagonal cells in the matrix based on the computed travel time.

The RAIS database described in section 4.2.2 provides the postal code for each formal job. Pacheco (2018) noted that many jobs in the RAIS database were labeled with the postal code of the company or public entity's headquarters, rather than the actual location of the workplace. Pacheco (2018) removed these jobs from the dataset, since they misrepresent the actual spatial distribution of jobs, and shared the result with me. Then I spatially joined the remaining workplaces with the hexagonal grid and aggregated the result to get Jobs, the total number of jobs per hexagonal cell. Then I calculated Total Jobs by summing all rows in the Jobs table. Finally, I used Jobs, Accessible and Total Jobs to calculate the Job Accessibility index according to the formula.

# APPENDIX B: R CODE

## SCRIPT DESCRIPTIONS

### IMPORT DATA

- `participants.R` – combines PMCMV data to identify applicants, lottery winners and beneficiaries for all lotteries in a single table.
- `import_cadunico.R` – imports, standardizes and combines yearly CADUNICO files, filtering for variables used in balancing and accessibility computation.
- `import_rais.R` – imports, standardizes and combines yearly RAIS – *Vinculados* files, filtering for variables used in balancing, matching and accessibility computation, and for program participants.

### ACCESSIBILITY

- `hex_grid.R` – creates a hexagonal grid over the Rio de Janeiro municipality for raster analysis.
- `hex_opps.R` – calculates the number of jobs in each cell of hex grid by spatially joining the RAIS – *Establecimientos* database.
- `osrm_ttm.R` – calculates travel time matrices for the hex grid for each year using the GTFS feeds, OpenStreetMap and OpenTripPlanner.
- `accessibility.R` – calculates percentage of jobs accessible from each hex grid cell for each year and for a range of travel times. Maps results.

### PANEL CONSTRUCTION

- `balancing_F.R` – conducts omnibus test of orthogonal and normalized differences in means between lottery winners and losers in order to gauge their balance throughout the construction of the panel.
- `correlation.R` – creates a correlation matrix for all variables in the panel
- `panel2.R` – constructs panels and fits linear regression models for analyses described in Deliverables. Coded but cluster required to execute.

### RESULTS

- `decision.R` – runs a logistic regression to estimate the probability of deciding to move among lottery winners.
- `regressions.R` – runs one and two-staged regressions to estimate the effect of moving to a PMCMV unit on the probability of employment, income and weekly contracted hours in the formal labor market
- `hetero_effects.R` – discretizes variables to estimate their CATE on the probability of employment, income and weekly contracted hours in the formal labor market

## CODE CHUNKS

### INTENTION-TO-TREAT

```
### regression functions ###

# ordinary least squares for continuous y
ols1s <- function(panel, yr, y, in_vars, ex_vars) {
  panel <- panel %>%
    filter(year >= yr)

  x <- c(in_vars, ex_vars)
  lm(reformulate(x, y), data = panel)
}

# logistic for binary y
log1s <- function(panel, yr, y, in_vars, ex_vars) {
  panel <- panel %>%
    filter(year >= yr)

  x <- c(in_vars, ex_vars)
  glm(reformulate(x, y), data = panel, family = binomial(link = 'logit'))
  # speedglm(reformulate(x, y), data = panel, family = binomial(link = 'logit'))
  # glmnetUtils::glmnet(formula = reformulate(x, y), data = panel,
  #   family = "binomial", type.logistic = "modified.Newton",
  #   sparse.model.matrix = TRUE)
}
```

### LATE: TWO-STAGE LEAST SQUARES

```
# two-stage least squares
ols2s <- function(panel, yr, y, en_vars, in_vars, ex_vars) {

  panel <- panel %>%
    filter(year >= yr)

  x1 <- c(in_vars, ex_vars)
  x2 <- c(en_vars, ex_vars)

  formula_2s <- paste(y, "~",
    paste(x2, collapse = " + "), "|",
    paste(x1, collapse = " + "))

  ivreg(formula_2s, data = panel)
}
```

## APPENDIX C: FIELD RESEARCH PROPOSAL

Although my statistical analysis did generate some new findings, it also opened questions that existing administrative and survey data cannot answer. In this chapter, I present a strategy for qualitative research I had planned to conduct in Rio de Janeiro before evacuating due to COVID-19. I describe two instruments, a digital survey and a deep interview guide, a recruitment strategy, and statistical techniques for analyzing the data. My hope is that researchers borrow these questions and techniques in future studies of PMCMV beneficiaries.

### SCOPE

#### PRE-TREATMENT HETEROGENEITY

In Chapter 6.2, I found that the impact of moving to a PMCMV unit varied according to pre-treatment attributes like age, gender, and education level. Via surveys or interviews, I could better understand *how* those attributes affect their experiences with the program. Are female beneficiaries no more likely to work because of social norms or childcare responsibilities, or because they can afford not to work with the housing subsidy? Did the more educated beneficiaries obtain job referrals through their academic institutions?

I could potentially retrieve individual attributes by two methods: querying their CPFs in the CADUNICO and RAIS databases or asking them in a survey or interview. The former would be technically straightforward, and allow me to construct a stratified sample of respondents with guaranteed variation. However, using personal information from those databases would represent a departure from the original agreement to use them in aggregate analyses. The latter approach may be more respectful of privacy, but less mindful of the participants' time and comfort. I therefore opted to stratify a sample based only on publicly available information: when the participant won the lottery and moved, and to which project.

#### PROJECT HETEROGENEITY

I found that beneficiaries who moved to the most peripheral projects with lowest access to jobs maintained their formal earnings in the short-term, but then dramatically withdrew from the labor market after three years. Curious to better understand how job accessibility affect beneficiaries over time, I chose to stratify a sample based on those two dimensions. I identified three PMCMV Tier 1 projects with each combination of accessibility and tenure, listed in Table 13 along with the move-in year and Job Accessibility in parentheses.

**Table 13: PMCMV Projects Selected for Qualitative Research**

	Short Tenure	Long Tenure
Higher Accessibility	Guadalupe (2015, 52%) Colonia Juliano Moreira (2016, 25%) Vila Carioca (2018, 17%)	Taroni (2011, 56%) Destri (2011, 48%) Vidal (2012, 35%)
Lower Accessibility	Saboia (2017, 3%) Porto Fino (2018, 7%) Park Onix (2017, 6%)	Sevilha (2012, 4%) Zaragoza (2012, 4%) Cascais (2012, 4%)

With access to only 17% of jobs, Vila Carioca barely qualifies for the “Higher Accessibility” bin. Furthermore, that particular project has attracted negative attention for issues with militia activity (Rubim 2019), which could complicate on-site interviews. I thus include it as a back-up in case the other two projects in the category do not provide enough willing participants.

Table 14 summarizes the hypotheses I planned to test for each stratum:

**Table 14: Expected Experience with Labor Market by Stratum**

	Short Tenure	Long Tenure
Higher Accessibility	Adjusting to new neighborhood, but content with employment opportunities.	Enjoying stable employment, some free time and new social ties
Lower Accessibility	Struggling to maintain or gain employment with long commutes and weak social network for support	Unable to maintain long commutes or find new formal work, turned to informal sector and/or welfare

### UNRECORDED MECHANISMS

In Chapter 3, I introduced a range of theories about how housing programs can affect labor market outcomes that cannot be measured in Rio de Janeiro with available data. Do beneficiaries with lower accessibility adapt by purchasing a car or motorcycle? What factors were most important in deciding whether or not to move? Do any beneficiaries express relief for having moved away from burdensome family or friends? Are beneficiaries able to rebuild social networks informally or through institutions? Do beneficiaries work more out of necessity to cover higher, possibly unexpected living costs? How has moving affected beneficiaries’ children? The following section outlines how I set out to answer such questions.

## METHODOLOGY

### INSTRUMENT DESIGN

As King and Horrocks explain in *Interviews in Qualitative Research*, it is important to understand the limits of qualitative approaches before designing an instrument (King, Horrocks, and Brooks 2019). Only causal inference methods applied carefully to a sufficiently large sample can determine *what* the impacts are (increased formal income) and, to some extent, *why* they occur (moving to a PMCMV unit). Surveys can provide supplementary data, such as transportation mode splits and stated preferences. Interviews, however, can suggest *how* the general phenomena observed statistically might occur, and in turn inspire further statistical analysis. In fact, interviews with MTO participants (Briggs, Popkin, and Goering 2010) inspired several analyses I conducted here. I designed a survey for a sample of 68 beneficiaries to answer *what* questions that would fill gaps in administrative data and an interview guide for *how* questions that would reveal potential mechanisms driving observed outcomes. Both instruments are included in Appendix C.

### RECRUITMENT

To connect with potential respondents, I first contacted PMCMV officials at the City of Rio whom I had met early on in my research. Unfortunately, they were unable to accommodate my timeline, so I developed the following recruitment:

1. Randomly select CPFs of beneficiaries from each category in Table 13.
2. Assign CPF with a ranking according to its position within each category.
3. Query all CPFs in the Serasa4 database, which returns three phone numbers each.
4. Check if each phone number is active.<sup>5</sup>
5. Contact Whatsapp users by text and others by phone.
6. Briefly introduce study and confirm respondent's identity.
7. Ask if interested in participating in an anonymous interview.
  - a. If yes, discuss details and send digital survey with consent form.
  - b. If not, ask if interested in completing a digital survey only.

The Serasa database provided valid numbers for 25% the beneficiaries in my sample. Although a third of those contacted agreed to participate in an interview, none responded after receiving the consent form. Researchers who plan to interview beneficiaries should aim to meet with subjects in person in order to better capture their attention.

<sup>4</sup> <https://empresas.serasaexperian.com.br/consulta-serasa>

<sup>5</sup> <https://cadastropre.com.br/#/consulta>

## ANALYSIS

Most the survey questions can be interpreted with basic statistics. In two cases, though, I have subjects rank factors in order of importance. Interpreting how those responses vary across the group and over-time for the same individual require more sophisticated methods. The Friedman test, which determines if certain factors rank consistently higher among the sample, could test the hypothesis that safety was generally the most important factor in deciding whether or not to move. The Mann-Whitney U test indicates if the ranking of one variable is different between groups; it could test the hypothesis that beneficiaries who moved to lower-accessibility projects value job access more after suffering the loss of it. Finally, the Chi-squared test, Wilcoxon signed-rank test or Bradley-Terry Model can identify statistically significant evolutions in rankings from the same individual over time. That would be useful to test the hypothesis that beneficiaries value home quality less over time, for example.

## SURVEY INSTRUMENT

Online Survey

Platform: Google Forms

Device: Smartphone

Sample size: 68 beneficiaries

### BEFORE THE MOVE

What was the zip code / neighborhood where you lived before moving?

---

What was your primary mode of transportation before moving?

- Public transportation
- On foot
- Own car
- Own motorcycle
- Carpool
- Bike
- Other \_\_\_\_\_

Did you have a job before moving?

- Formal employment
- Informal employment
- Spout
- Did not have

What was the zip code / neighborhood where you worked before moving?

---

### DECISION TO MOVE

How many times did you win a PMCMV lottery before deciding to move?

---

Can you classify the following factors according to their importance in your decision to move?

- Owning your own home
- Have a higher quality housing than the one you had
- Have access to jobs
- Living close to family and friends
- Stay away from people who make life difficult or ask too many favors
- Living in a safe neighborhood
- Enroll children in good schools
- Other \_\_\_\_\_

## AFTER THE MOVE

What is your main mode of transport now?

- Public transportation
- On foot
- Own car
- Own motorcycle
- Carpool
- Bike
- Other \_\_\_\_\_

Did you think about buying a car or motorcycle for better mobility?

- Car
- Motorcycle
- No, I did not think of buying either a car or motorcycle

Do you have a job now?

- Formal employment
- Informal employment
- Spout
- I do not have

What is the zip code / neighborhood where you work now?

\_\_\_\_\_

Can you classify the following factors according to their importance to overall well-being?

- Owning your own home
- Have a higher quality housing than the one you had
- Have access to jobs
- Living close to family and friends
- Stay away from people who make life difficult or ask too many favors
- Living in a safe neighborhood
- Enroll children in good schools
- Other \_\_\_\_\_

## ACCESSIBILITY

Has your likelihood of being late for work changed since you moved?

- I'm more likely to be late now
- A chance that I'm late doesn't change
- I'm less likely to be late now

Since you moved, has the difficulty of finding a new job changed?

- It's harder to find a job now
- The chance of finding a job has not changed
- It's easier to find a job now

## SOCIAL NETWORK

Has the quality of your community of friends changed?

- My group of friends is better after I moved
- The quality of my group of friends has not changed
- My group of friends is worse after I moved

Has the quality of your professional network changed?

- My professional network got better after I moved
- My professional network has not changed
- My professional network got worse after I moved

Has the degree to which your friends and family overburden you changed?

- It got better
- Not changed
- It got worse

How often do you go back to your old neighborhood?

- Weekly
- Monthly
- Rarely

Have you joined any kind of institution since you moved?

- Church
- Sports club
- Club of particular interest
- Neighborhood / residents association
- Other \_\_\_\_\_

## COST OF LIVING

Do you face costs now that you didn't expect when you decided to move?

- Condominium fee
- Utilities (water, electricity, gas)
- Transport
- Taking care of children
- Other \_\_\_\_\_

Has your total cost of living changed?

- It got more expensive
- Not changed
- It got cheaper

## QUALITY OF LIFE

Did your move affect your children's opportunities?

- Improved opportunities
- Not changed
- Worsened opportunities

Has your physical health changed?

- It got better
- Not changed
- It got worse

Has your mental health or anxiety level changed?

- It got better
- Not changed
- It got worse

## REFLECTION

How do you feel about your decision to move to your PMCMV home?

Are there specific things you would have liked to have known before deciding whether or not to move?

Given the opportunity, which scenario would you prefer?

- Receive financial support to improve your house in the neighborhood where you lived originally?
- Move to a PMCMV house as you did?

Would you be willing to pay a bit more in order to live in a neighborhood closer to the center of the city?

Would you be willing to pay a bit more in order to have better public transit service?

# INTERVIEW GUIDE

Telephone Interview

Format: individual semi-structured interview

Duration: ~ 30 min each

Subjects: 12 beneficiaries

## DECISION TO MOVE

Why did you decide to enroll in the PMCMV program?

Can you describe your process of deciding whether to move your PMCMV home?

How did you consider the costs of living in a PMCMV house?

## ACCESSIBILITY

Has your new location affected your ability to work?

Has your new location affected your life outside of work?

Do you spend your time differently now?

What have you been doing to adapt the new location?

What have you considered doing to adapt the new location?

## SOCIAL NETWORK

Without identifying anyone, can you describe relationships that overwhelmed you in your old neighborhood?

Is it a relief to have some separation from these costly relationships?

Can you describe your friends and family who provided support in your old neighborhood?

Do you still benefit from this community or do you now live far away?

Did you manage to make new friends?

Did you join community institutions to meet people?

Have you adapted to changes in your social network in other ways?

Do you think your social network is important when it comes to getting a job?

Do you find it easier to get a job with the social network of the new neighborhood?

## COST OF LIVING

How has your cost of living changed since you moved?

What did you do to cover unexpected costs?

## OTHERS

Did your new location affect your physical and mental health?

Has the change affected your children's quality of life?

Did the change affect your children's opportunities?

## RETROSPECTIVE

How do you feel about your decision to move to your PMCMV home?

Are there specific things you would like to know before deciding whether or not to move?

Additional comments without recorder

# APPENDIX D: ADDITIONAL TABLES AND FIGURES

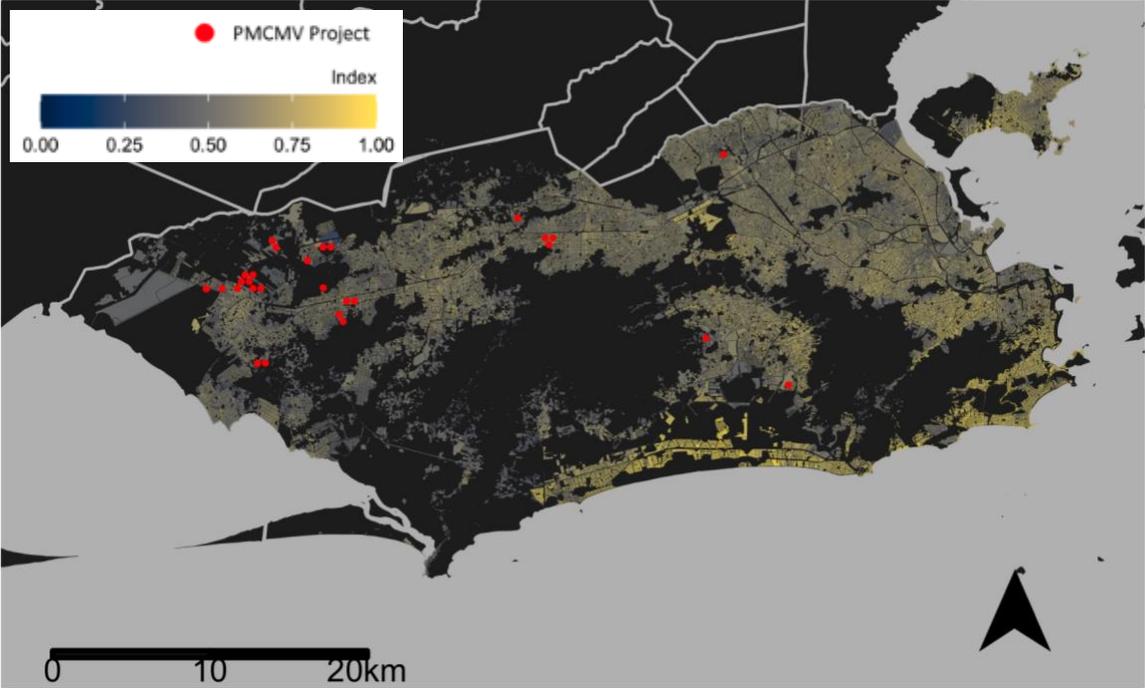


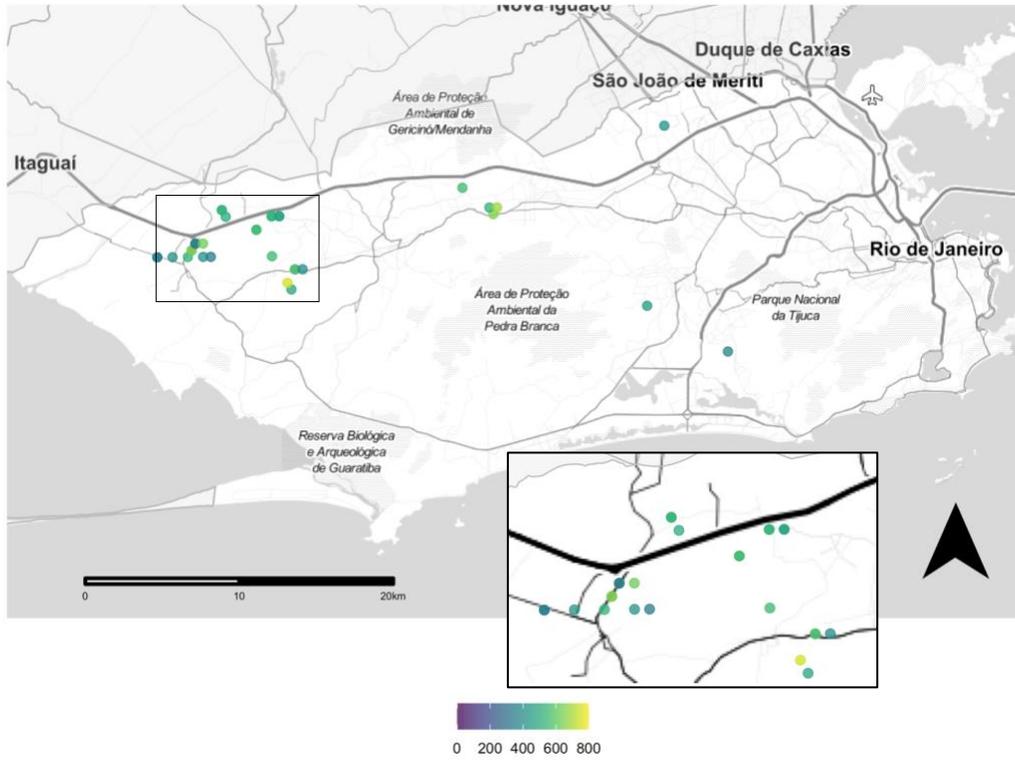
Figure 29: Social Development Index (2010 Census) in Rio de Janeiro

**Table 15: PMCMV Projects - Mean Pre-treatment Attributes**

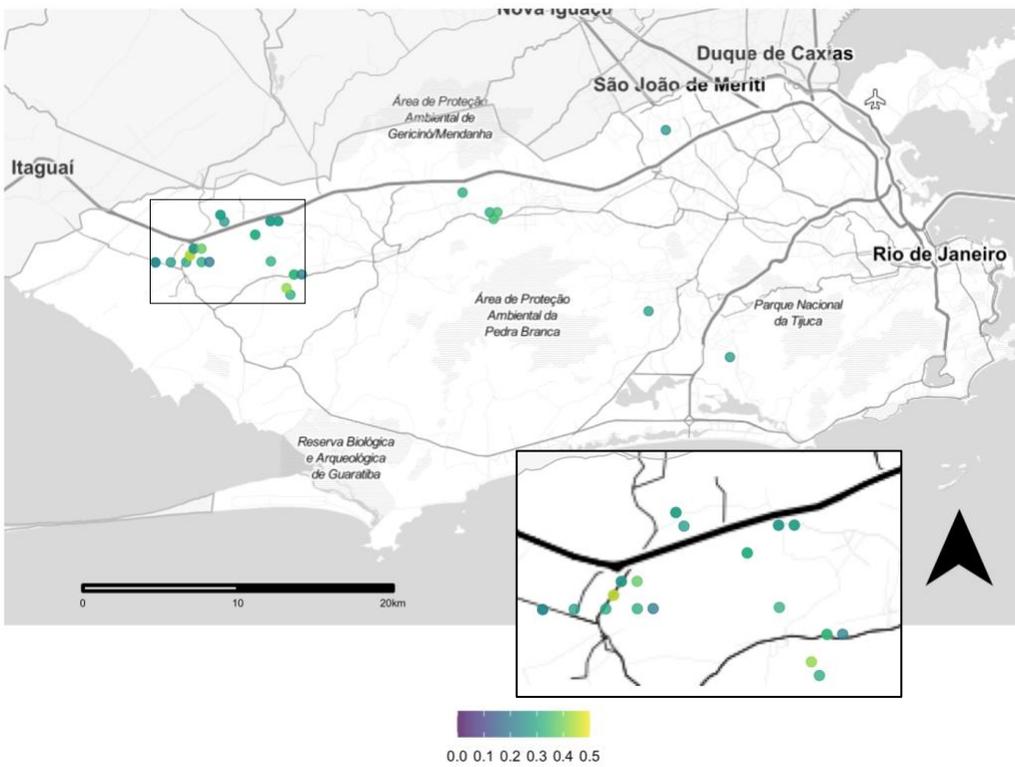
<b>Name</b>	<b>From Favela</b>	<b>Female</b>	<b>Age</b>	<b>Race: Black</b>	<b>Race: Brown</b>	<b>Race: White</b>	<b>Illiterate</b>	<b>Primary School</b>	<b>Secondary School</b>	<b>Higher Education</b>
Cascais	0.0930	0.808	40.6	0.1940	0.408	0.389	0.01410	0.831	0.561	0.0620
Colônia Juliano Moreira	0.0870	0.739	42.3	0.2100	0.464	0.312	0.02900	0.855	0.594	0.0652
Dellos	0.1030	0.755	45.1	0.2360	0.489	0.266	0.00858	0.863	0.601	0.0644
Destri	0.1040	0.803	40.3	0.1880	0.400	0.412	0.01160	0.861	0.542	0.0493
Estoril	0.0790	0.740	40.6	0.2020	0.418	0.380	0.01460	0.827	0.544	0.0731
Évora	0.1030	0.751	41.4	0.2380	0.424	0.332	0.02430	0.843	0.511	0.0568
Guadalupe	0.1040	0.667	40.2	0.0729	0.458	0.469	0.00000	0.844	0.573	0.0417
Mikonos	0.1280	0.755	45.5	0.2000	0.514	0.283	0.01380	0.852	0.548	0.0379
Park Ágata	0.1850	0.716	50.6	0.1360	0.481	0.370	0.04940	0.864	0.605	0.0494
Park Ametista	0.1150	0.775	44.9	0.1990	0.419	0.382	0.02090	0.885	0.628	0.0471
Park Imperial	0.0798	0.748	38.9	0.2100	0.429	0.357	0.00840	0.887	0.622	0.0882
Park Jade	0.1030	0.794	41.6	0.1760	0.529	0.279	0.00000	0.926	0.632	0.0882
Park Ônix	0.0769	0.769	51.2	0.1540	0.308	0.538	0.00000	1.000	0.692	0.1540
Park Royal	0.0966	0.761	39.8	0.1600	0.408	0.429	0.01260	0.861	0.630	0.0630
Park Topázio	0.0800	0.880	60.9	0.1600	0.440	0.400	0.04000	0.600	0.320	0.0400
Porto Belo	0.1330	0.744	41.0	0.2040	0.479	0.308	0.02840	0.924	0.640	0.0427
Porto Fino	0.1210	0.759	34.6	0.3100	0.310	0.379	0.01720	0.948	0.741	0.1210
Porto Seguro	0.0843	0.777	44.0	0.2350	0.488	0.271	0.00000	0.843	0.608	0.0783
Recanto do Paçuaré	0.0949	0.742	39.6	0.1840	0.422	0.392	0.01660	0.896	0.580	0.0256
Rio Bonito	0.0569	0.797	40.1	0.1540	0.350	0.496	0.00813	0.886	0.610	0.0813
Santorine	0.0861	0.708	45.3	0.2280	0.491	0.270	0.01120	0.891	0.637	0.0524
Sevilha	0.0721	0.784	40.4	0.1970	0.409	0.385	0.01440	0.870	0.543	0.0769
Taroni	0.0707	0.734	40.9	0.2390	0.397	0.364	0.01090	0.870	0.592	0.0761
Toledo	0.0986	0.738	40.2	0.2280	0.406	0.361	0.00845	0.845	0.549	0.0423
Vidal	0.0674	0.758	39.8	0.1910	0.421	0.388	0.00562	0.876	0.590	0.0955
Vila Carioca	0.0850	0.749	40.5	0.2460	0.473	0.270	0.00871	0.880	0.610	0.0610
Vivenda das Coleirinhas	0.1060	0.674	42.2	0.1740	0.513	0.314	0.01270	0.928	0.644	0.0297
Vivenda das Cotovias	0.0960	0.727	43.8	0.2070	0.434	0.348	0.00000	0.864	0.616	0.0657
Vivenda das Gaivotas	0.1060	0.722	41.7	0.1790	0.334	0.483	0.00993	0.891	0.626	0.0331
Vivenda das Garças	0.1110	0.783	38.1	0.1500	0.407	0.438	0.00885	0.889	0.655	0.0487
Vivenda dos Colibris	0.0917	0.708	36.8	0.2080	0.492	0.300	0.00833	0.958	0.733	0.0333
Vivenda dos Pintassilgos	0.1360	0.667	39.0	0.2650	0.352	0.383	0.01230	0.877	0.679	0.0309
Zaragoza	0.0978	0.754	39.4	0.2290	0.408	0.363	0.00279	0.863	0.556	0.0335

**Table 16: PMCMV Projects - Mean Attributes at End of Study Period (Dec. 2017)**

<b>Name</b>	<b>Age</b>	<b>Illiterate</b>	<b>Primary School</b>	<b>Secondary School</b>	<b>Higher Education</b>
Cascais	41.6	0.01410	0.831	0.559	0.0621
Colônia Juliano Moreira	42.3	0.02900	0.855	0.594	0.0652
Dellos	45.1	0.00862	0.862	0.599	0.0603
Destri	41.3	0.01160	0.861	0.542	0.0493
Estoril	41.6	0.01460	0.827	0.544	0.0731
Évora	42.5	0.02450	0.842	0.508	0.0543
Guadalupe	40.2	0.00000	0.844	0.573	0.0417
Mikonos	45.5	0.01380	0.852	0.548	0.0379
Park Ágata	50.6	0.04940	0.864	0.605	0.0494
Park Ametista	44.9	0.02090	0.885	0.628	0.0471
Park Imperial	39.9	0.00840	0.887	0.622	0.0882
Park Jade	41.6	0.00000	0.926	0.632	0.0882
Park Ônix	51.2	0.00000	1.000	0.692	0.1540
Park Royal	40.8	0.01260	0.861	0.630	0.0630
Park Topázio	60.9	0.04000	0.600	0.320	0.0400
Porto Belo	41.0	0.02840	0.924	0.640	0.0427
Porto Fino	34.6	0.01720	0.948	0.741	0.1210
Porto Seguro	44.0	0.00000	0.842	0.606	0.0788
Recanto do Paçuaré	39.6	0.01660	0.896	0.580	0.0256
Rio Bonito	41.2	0.00820	0.885	0.607	0.0820
Santorine	45.3	0.01120	0.891	0.637	0.0524
Sevilha	41.4	0.01440	0.870	0.543	0.0769
Taroni	41.9	0.01090	0.870	0.592	0.0761
Toledo	41.2	0.00845	0.845	0.549	0.0423
Vidal	40.8	0.00562	0.876	0.590	0.0955
Vila Carioca	40.5	0.00871	0.880	0.610	0.0610
Vivenda das Coleirinhas	42.2	0.01270	0.928	0.644	0.0297
Vivenda das Cotovias	43.8	0.00000	0.864	0.616	0.0657
Vivenda das Gaivotas	41.7	0.00993	0.891	0.626	0.0331
Vivenda das Garças	38.1	0.00885	0.889	0.655	0.0487
Vivenda dos Colibris	36.8	0.00833	0.958	0.733	0.0333
Vivenda dos Pintassilgos	39.0	0.01230	0.877	0.679	0.0309
Zaragoza	40.4	0.00279	0.863	0.556	0.0335



**Figure 30: Mean Monthly Income by PMCMV Project (Dec. 2017)**



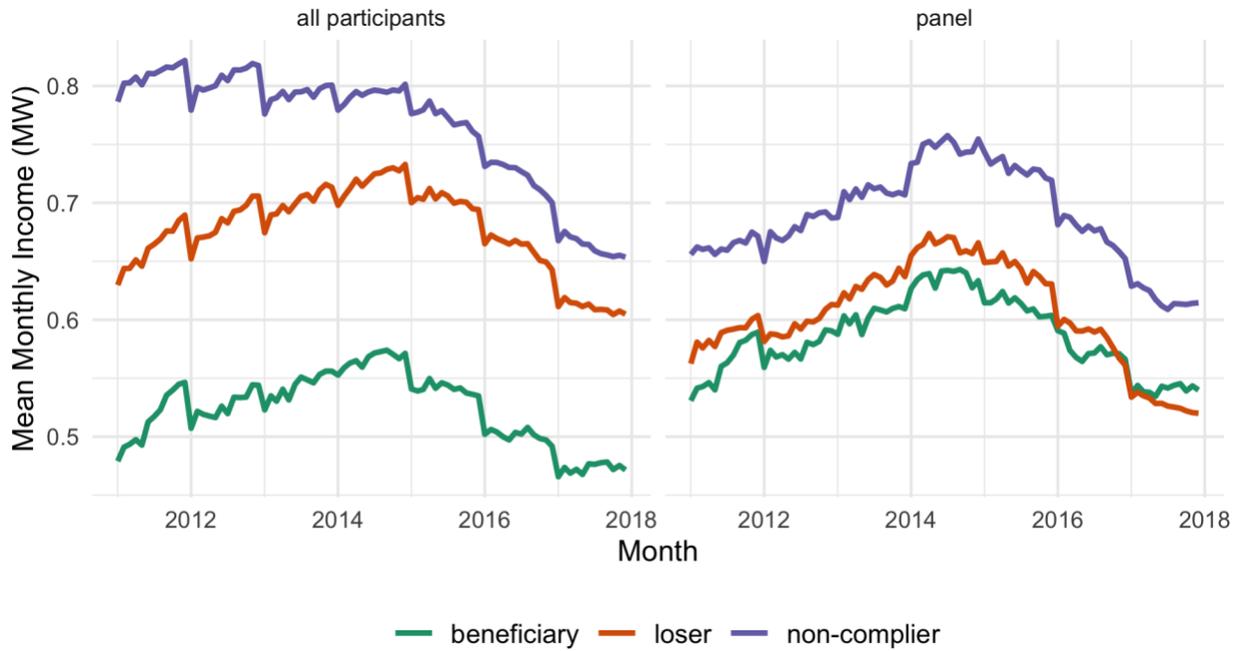
**Figure 31: Mean Employment Rate by PMCMV Project (Dec. 2017)**

**Table 17: Tier 1 General Lotteries – Mean Project Attributes Part 1**

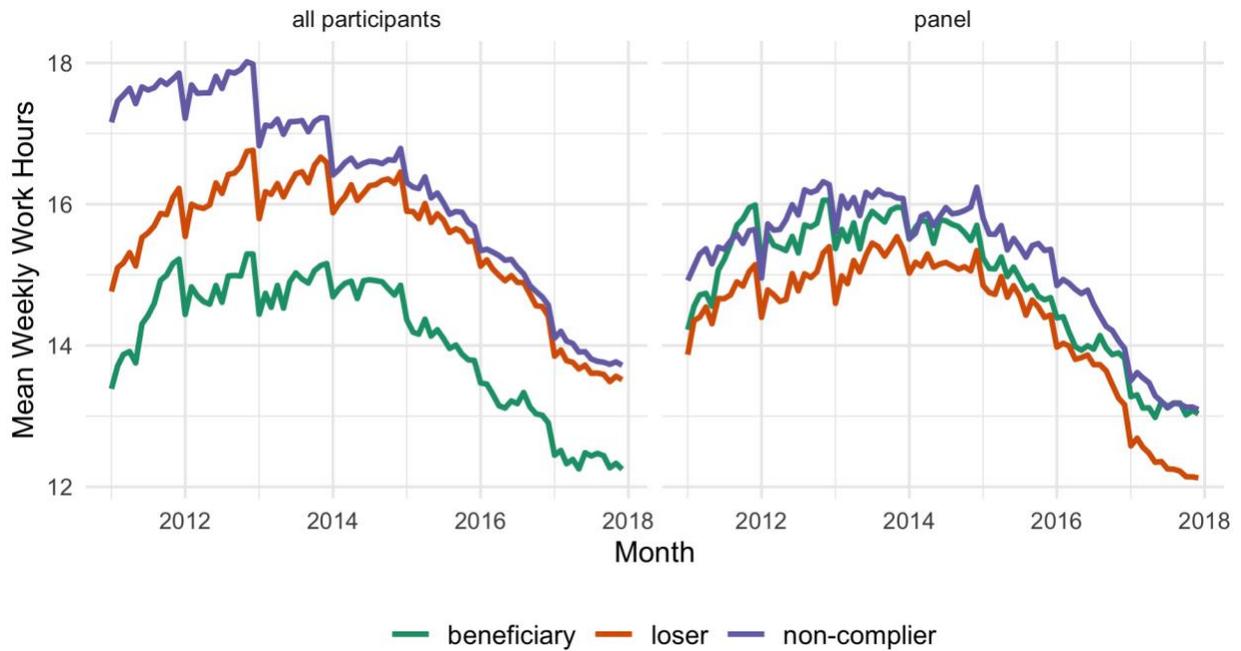
Lottery	Project Name	Proximity to Downtown (km)		Job Accessibility (% of jobs)		Murder Rate (per 100k)	
		Project	Mean	Project	Mean	Project	Mean
#03 of 2011	Destri	37.6	52.2	47.6	15.4	23.2	27.0
	Estoril	60.0		4.6			
	Park Imperial	55.6		5.9			
	Park Royal	55.6		5.9			
	Rio Bonito	50.8		16.2			
	Toledo	53.8		12.5			
#06 of 2011	Cascais	59.3	51.8	4.4	19.2	30.3	28.5
	Sevilha	57.0		3.8			
	Taroni	36.9		56.2			
	Toledo	53.8		12.5			
#09 of 2011	Cascais	59.3	55.1	4.4	9.0	30.3	29.5
	Estoril	60.0		4.6			
	Évora	60.0		4.6			
	Park Imperial	55.6		5.9			
	Park Royal	55.6		5.9			
	Sevilha	57.0		3.8			
	Toledo	53.8		12.5			
	Vidal	37.4		35.4			
	Zaragoza	57.0		3.8			
#12 of 2012	Guadalupe	30.0	30.0	52.3	52.3	38.4	38.4
#03 of 2013	Vivenda das Garças	52.1	52.1	24.1	24.1	17.6	17.6
#06 of 2013	Recanto do Paçuaré	53.0	49.2	7.9	18.3	17.6	19.5
	Vivenda das Gaivotas	52.1		24.1			
	Vivenda dos Pintassilgos	42.6		23.0			
#01 of 2015	Guadalupe	30.0	46.0	52.3	26.3	38.4	22.9
	Recanto do Paçuaré	53.0		7.9			
	Vivenda das Gaivotas	52.1		24.1			
	Vivenda das Garças	52.1		24.1			
	Vivenda dos Pintassilgos	42.6		23.0			

**Table 18: Tier 1 General Lotteries – Mean Project Attributes Part 2**

Lottery	Project Name	Proximity to Downtown (km)		Job Accessibility (% of jobs)		Murder Rate (per 100k)	
		Project	Mean	Project	Mean	Project	Mean
#04 of 2015	Dellos	62.3	59.4	8.7	8.0	30.3	28.2
	Mikonos	63.5		7.9		30.3	
	Santorine	63.5		7.9		30.3	
	Vivenda das Coleirinhas	57.3		5.9		30.3	
	Vivenda das Cotovias	57.3		5.9		30.3	
	Vivenda dos Colibris	52.3		11.5		17.6	
#07 of 2015	Recanto do Paçuaré	53.0	53.0	7.9	7.9	17.6	17.6
#18 of 2015	Dellos	62.3	63.1	8.7	8.2	30.3	30.3
	Mikonos	63.5		7.9		30.3	
	Santorine	63.5		7.9		30.3	
#19 of 2015	Vivenda das Coleirinhas	57.3	55.6	5.9	7.7	30.3	26.1
	Vivenda das Cotovias	57.3		5.9		30.3	
	Vivenda dos Colibris	52.3		11.5		17.6	
#27 of 2015	Porto Seguro	62.5	62.5	10.2	10.2	30.3	30.3
#28 of 2015	Braga	66.0	65.9	3.1	3.2	30.3	30.3
	Serpa	66.0		3.1		30.3	
	Viseu	65.5		3.6		30.3	
#34 of 2015	Colônia Juliano Moreira	28.4	28.4	26.4	26.4	17.3	17.3
#05 of 2016	Colônia Juliano Moreira	28.4	28.4	26.4	26.4	17.3	17.3
#06 of 2016	Park Ágata	61.1	61.4	8.7	8.4	30.3	30.3
	Park Jade	61.1		8.7		30.3	
	Park Ônix	62.0		6.2		30.3	
	Park Topázio	60.4		8.0		30.3	
	Porto Seguro	62.5		10.2		30.3	
#10 of 2016	Porto Belo	60.4	61.5	8.0	7.6	30.3	30.3
	Park Ametista	63.4		8.2		30.3	
	Porto Fino	60.7		6.5		30.3	
#17 of 2016	Sabóia	66.0	51.9	3.1	9.1	30.3	26.0
	Park Safira	61.1		7.6		30.3	
	Vila Carioca	28.7		16.7		17.3	
#20 of 2016	Park Ametista	63.4	62.0	8.2	7.4	30.3	30.3
	Porto Fino	60.7		6.5		30.3	



**Figure 32: Sample Comparison - Income by Treatment Group over Time**



**Figure 33: Sample Comparison - Weekly Contracted Hours by Treatment Group over Time**

**Table 19: Impact of PMCMV on Likelihood of Employment**

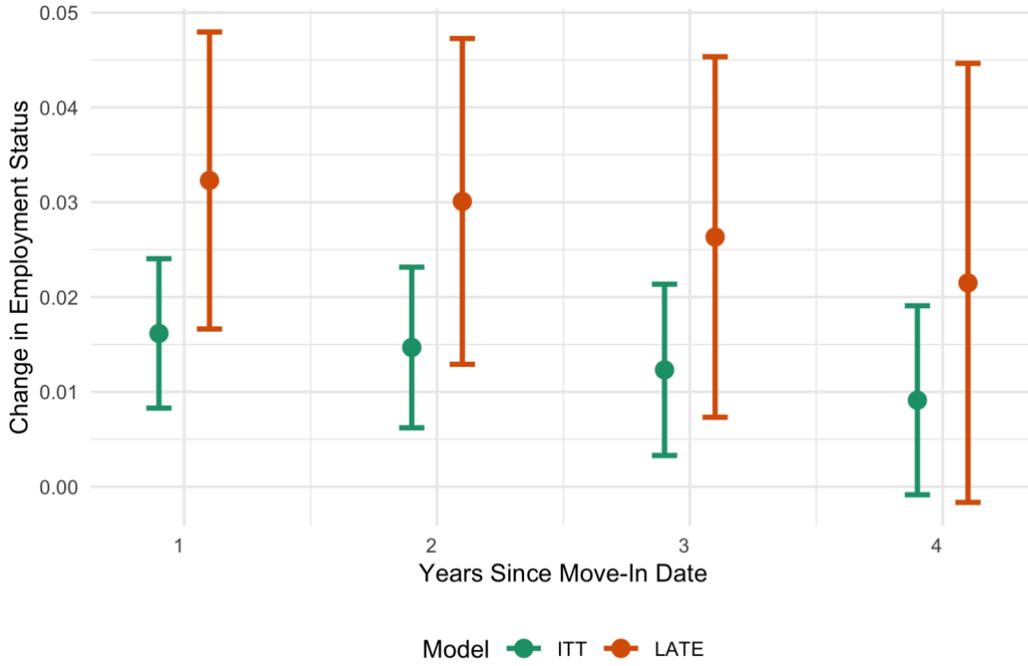
Term	ITT				LATE			
	Est.	C.I. low	C.I. high	p-value	Est.	C.I. low	C.I. high	p-value
Year 1	0.0162	0.00829	0.024	0.001	0.0323	0.0166	0.048	0.001
Year 2	0.0147	0.00621	0.0232	0.004	0.0301	0.0129	0.0473	0.004
Year 3	0.0123	0.00328	0.0213	0.025	0.0263	0.00732	0.0453	0.023
Year 4	0.00911	-0.000855	0.0191	0.133	0.0215	-0.00166	0.0446	0.127
Orig. Favela	0.0012	-0.00472	0.00711	0.739	0.00181	-0.00411	0.00774	0.615
Orig. Proximity to Downtown (km)	-0.0000803	-0.00019	0.0000299	0.231	-0.000109	-0.00022	0.00000153	0.105
Female	-0.0547	-0.0589	-0.0505	0.000	-0.0562	-0.0604	-0.052	0.000
Age	0.00309	0.00218	0.004	0.000	0.00317	0.00226	0.00408	0.000
Sq. of Age	-0.0000606	-0.0000703	-0.0000508	0.000	-0.0000612	-0.0000709	-0.0000514	0.000
Race: Black	0.00467	-0.000307	0.00965	0.123	0.00443	-0.000553	0.00941	0.144
Race: White	-0.00993	-0.0143	-0.00552	0.000	-0.0105	-0.0149	-0.00606	0.000
Race: Other	0.0308	0.00406	0.0575	0.058	0.0314	0.00472	0.0582	0.053
Orig. Illiterate	-0.00454	-0.0207	0.0116	0.644	-0.00438	-0.0206	0.0118	0.656
Orig. Primary School	0.0168	0.0104	0.0231	0.000	0.0166	0.0103	0.023	0.000
Orig. Secondary School	0.0416	0.037	0.0462	0.000	0.0418	0.0372	0.0464	0.000
Orig. Higher Education	0.0366	0.0278	0.0453	0.000	0.0362	0.0274	0.0449	0.000

<sup>a</sup> Sample: 28259 participants, 2011 - 2017

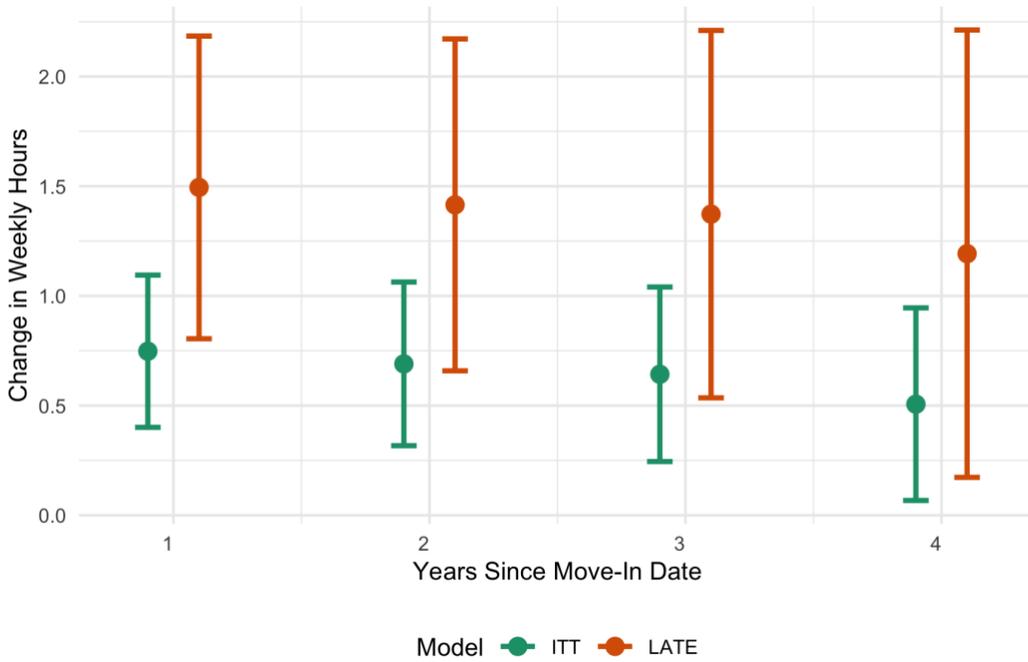
**Table 20: Impact of PMCMV on Weekly Contracted Hours**

Term	ITT				LATE			
	Est.	C.I. low	C.I. high	p-value	Est.	C.I. low	C.I. high	p-value
Year 1	0.748	0.401	1.09	0.000	1.49	0.805	2.18	0.000
Year 2	0.69	0.317	1.06	0.002	1.42	0.659	2.17	0.002
Year 3	0.643	0.245	1.04	0.008	1.37	0.535	2.21	0.007
Year 4	0.506	0.0674	0.945	0.058	1.19	0.173	2.21	0.054
Orig. Favela	0.0461	-0.214	0.307	0.771	0.0766	-0.184	0.338	0.629
Orig. Proximity to Downtown (km)	-0.00349	-0.00835	0.00136	0.236	-0.00492	-0.00981	-0.0000391	0.097
Female	-2.56	-2.75	-2.38	0.000	-2.64	-2.83	-2.45	0.000
Age	0.128	0.0877	0.168	0.000	0.132	0.0915	0.172	0.000
Sq. of Age	-0.00258	-0.00301	-0.00215	0.000	-0.00261	-0.00304	-0.00218	0.000
Race: Black	0.235	0.0154	0.454	0.078	0.223	0.00319	0.442	0.095
Race: White	-0.395	-0.589	-0.201	0.001	-0.423	-0.618	-0.229	0.000
Race: Other	1.31	0.135	2.49	0.067	1.34	0.167	2.52	0.060
Orig. Illiterate	-0.386	-1.1	0.326	0.373	-0.378	-1.09	0.334	0.383
Orig. Primary School	0.769	0.49	1.05	0.000	0.764	0.484	1.04	0.000
Orig. Secondary School	1.79	1.58	1.99	0.000	1.79	1.59	2	0.000
Orig. Higher Education	1.46	1.08	1.85	0.000	1.44	1.06	1.83	0.000

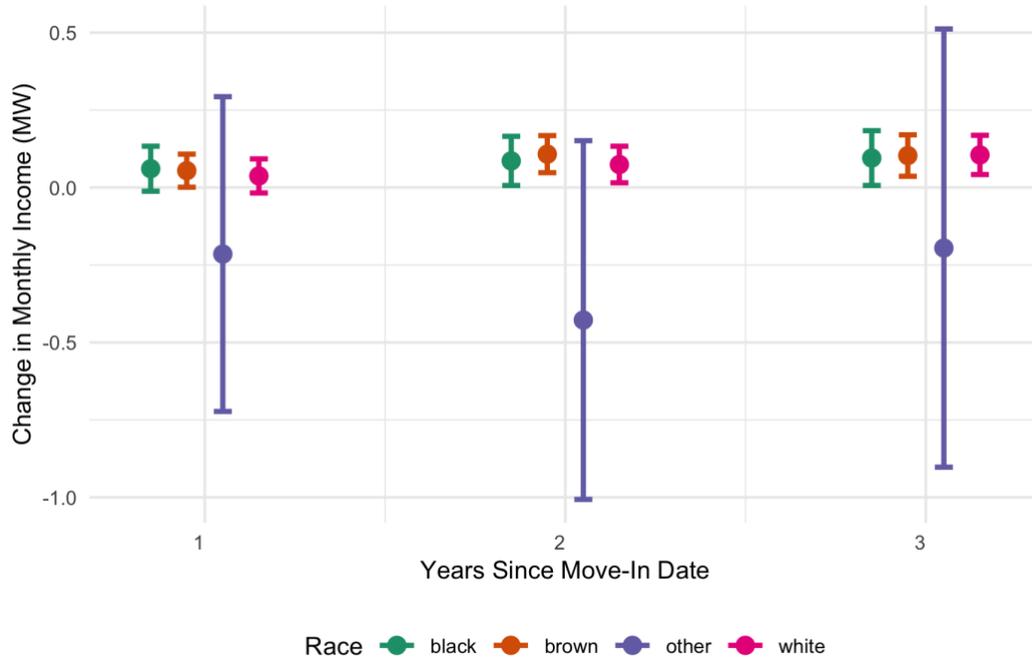
<sup>a</sup> Sample: 28259 participants, 2011 - 2017



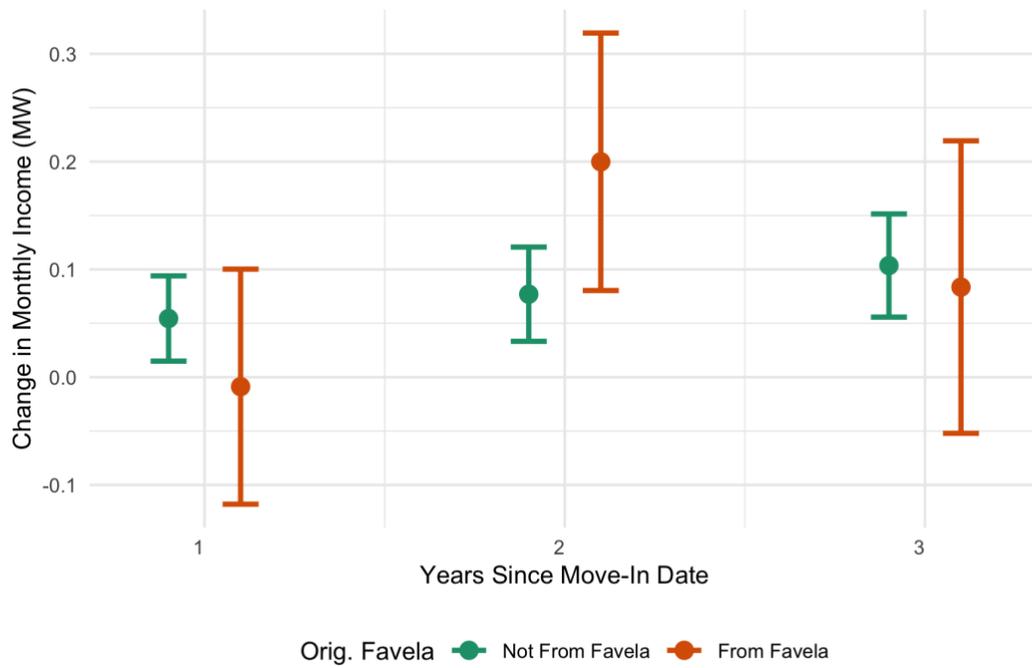
**Figure 34: Treatment Effect on Employment (ITT vs. LATE)**



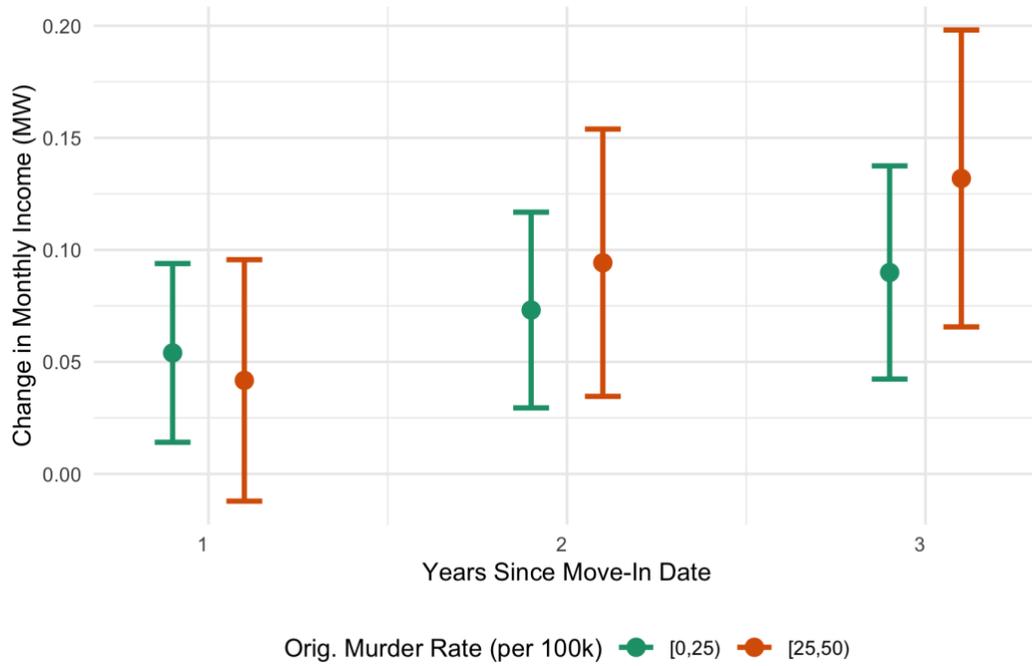
**Figure 35: Treatment Effect on Weekly Contracted Hours (ITT vs. LATE)**



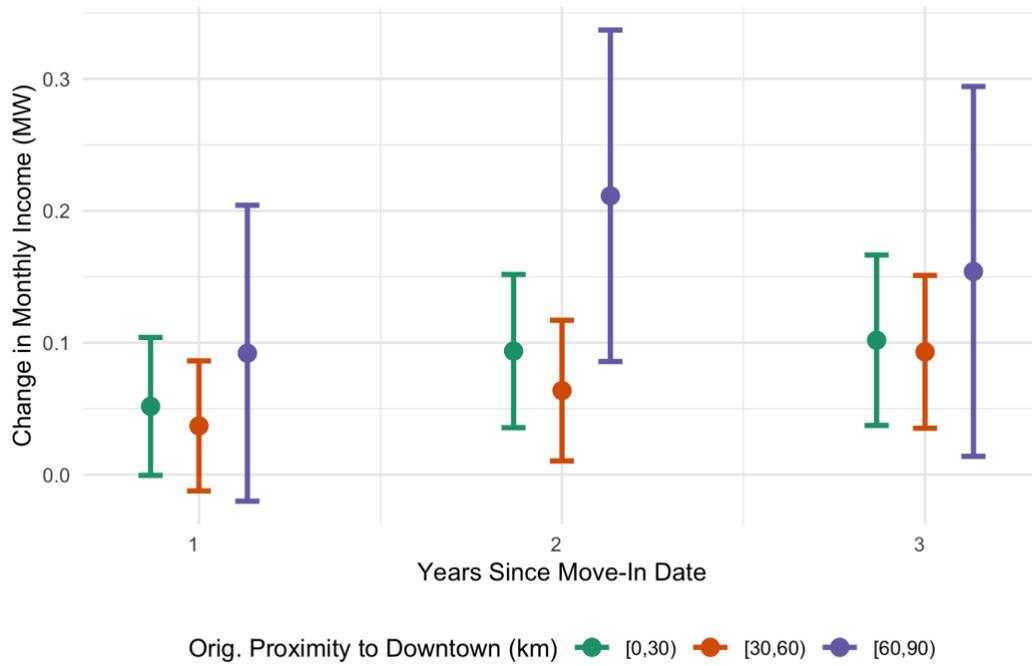
**Figure 36: Treatment Effect Conditional on Race**



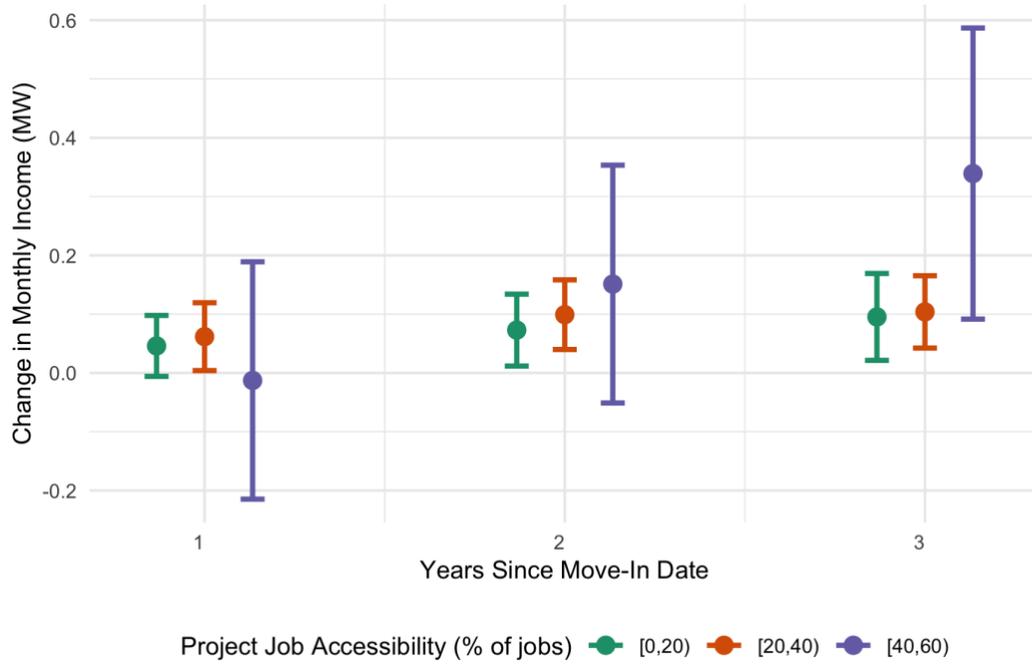
**Figure 37: Treatment Effect Conditional on Moving From Favela**



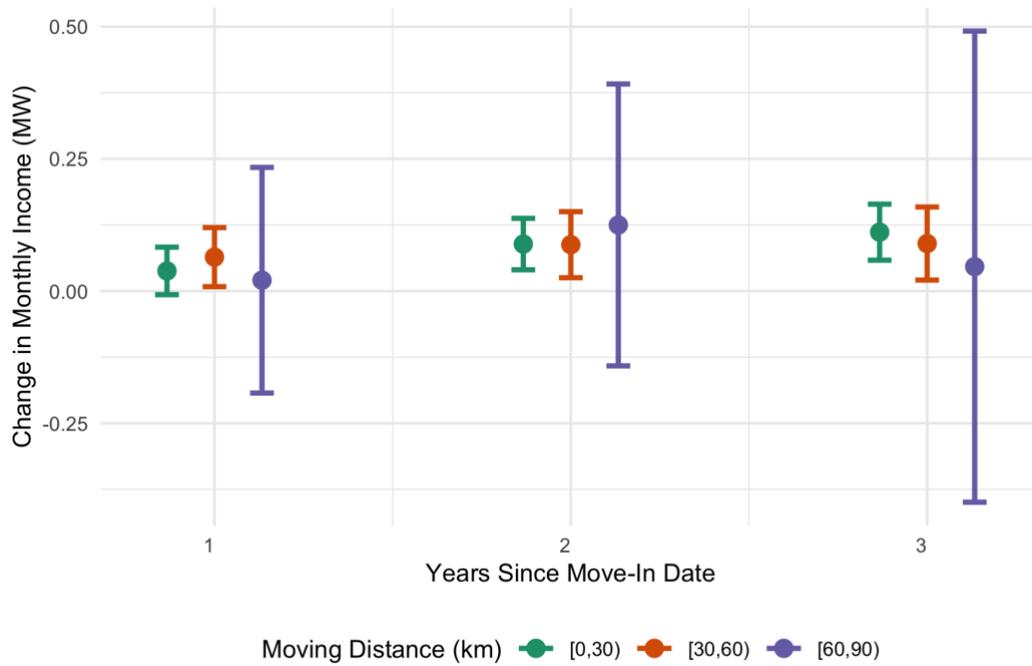
**Figure 38: Treatment Effect Conditional on Original Murder Rate**



**Figure 39: Treatment Effect Conditional on Original Proximity to Downtown**



**Figure 40: Treatment Effect Conditional on Project Job Accessibility**



**Figure 41: Treatment Effect Conditional on Moving Distance**

## APPENDIX E: INDEPENDENT TREATMENT EFFECT

Pacheco (2018) found that moving to a PMCMV unit reduces job accessibility and, in two lotteries, the likelihood of employment. In this analysis, I estimate treatment effects controlling for locational attributes in order to determine if they account for labor market outcomes. Since moving to a PMCMV unit potentially disrupts social networks, improves residential stability, and increases living costs, all of which can affect labor market activity, I formulate the following null hypothesis:

*Hypothesis: Location attributes do not completely account for observed treatment effects.*

In order to test it, I added Proximity to Downtown and Murder Rate as covariates to the LATE model in Section 4.1.2. Since moving affects location variables, they are endogenous and must be handled appropriately. I added IVs to Eq. 2 for each location variable based on the location attributes that the PMCMV randomly offers to lottery winners. I then estimated the following models in the first stage:

$$T = \beta_0 + \beta_1 * Z + \beta_2 * M_{pot} + \beta_3 \cdot X + \varepsilon \quad \text{Eq. 6}$$

$$M_{act} = \gamma_0 + \gamma_1 * Z + \gamma_2 * M_{pot} + \gamma_3 \cdot X + \varepsilon \quad \text{Eq. 7}$$

Using predictions from the first stage, I then estimate the second stage:

$$Y = \theta_0 + \theta_1 * \hat{T} + \theta_2 * \hat{M}_{act} + \theta_3 \cdot X + \varepsilon \quad \text{Eq. 8}$$

Where:

$$M_{pot} = \begin{cases} \text{Mean PMCMV location attribute for lottery winners} \\ \text{Original home location attribute for non – winners} \end{cases}$$

$$M_{act} = \begin{cases} \text{Actual PMCMV location attribute for compliers} \\ \text{Original home location attribute for all others} \end{cases}$$

and all other variables defined as in earlier equations.

For all lottery winners,  $M_{pot}$  is updated from the location attribute of the individual's original home to the mean location attributes of all projects involved in the lottery. Defined this way,  $M_{pot}$  harnesses the random assignment of the lottery to serve as a suitable IV.  $M_{act}$ , on the other hand, is updated for beneficiaries with the location attributes of the PMCMV project to which they actually moved.

The coefficient  $\theta_2$  in Eq. 8 indicates the correlation between the location attribute M and outcome Y across all subjects in the sample. Coefficient  $\theta_1$  represents the independent treatment

effect after controlling for M. If  $\theta_1$  is significant, mechanism M fails to fully account for the treatment effect.

I used Months Since Move and its square as treatment variables, instrumented each separately in the first stage. Table 21 presents the estimated model.

**Table 21: Treatment Effect on Income Controlling for Location (LATE)**

<b>Term</b>	<b>Est.</b>	<b>C.I. low</b>	<b>C.I. high</b>	<b>p-value</b>
Months Since Move	0.00455	0.00412	0.00499	0.000
Sq. of Months	-0.0000349	-0.0000434	-0.0000264	0.000
Proximity to Downtown (km)	-0.000201	-0.000262	-0.00014	0.000
Murder Rate (per 100k)	0.000467	0.000374	0.000561	0.000
Orig. Favela	0.00742	0.00461	0.0102	0.000
Female	-0.147	-0.149	-0.145	0.000
Age	0.00538	0.00496	0.0058	0.000
Sq. of Age	-0.0000916	-0.0000961	-0.0000871	0.000
Race: Black	0.00119	-0.00115	0.00353	0.401
Race: White	-0.0064	-0.00847	-0.00432	0.000
Race: Other	0.00492	-0.00756	0.0174	0.517
Orig. Illiterate	-0.0133	-0.0208	-0.00576	0.004
Orig. Primary School	0.0211	0.0181	0.0241	0.000
Orig. Secondary School	0.0913	0.0891	0.0934	0.000
Orig. Higher Education	0.205	0.201	0.209	0.000

<sup>a</sup> Sample: 28259 participants over 84 months, starting in 2011

The treatment coefficients remain highly significant, supporting the null hypothesis that location attributes do not account for treatment effects.