

Sheltering Refugees in Cities: Crime, Public Services, and Voting

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Abstract

An extensive literature documents that immigration flows frequently trigger native backlash, often reflected in heightened support for far-right parties. Yet, the mechanisms driving this response remain unclear, whether rooted in economic competition or cultural threat. Because these channels operate locally and through daily contact, identifying them requires granular data that are typically scarce. This paper examines how the reception of refugees affects local public education, crime, and ultimately voting behavior, exploiting detailed within-city data and plausibly exogenous variation from the quasi-random location of refugee shelters. Using a differences-in-differences strategy, I find that refugee shelters had no impact on crime or congestion in local public schools. However, they boosted natives' support for far-right candidates and reduced votes for the incumbent. Effects are largely driven by shelters hosting culturally diverse refugees comprising different indigenous ethnicities. Together, the results reveal that cultural perceptions can dominate economic channels in shaping local political responses to migration, and that aggregated data can miss essential nuances in locals' attitudes towards migrants.

Keywords: Refugees; Political Behavior; Public Services; Social Cohesion

JEL Codes: F22, O15, D72

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1 Introduction

The number of refugees and people in need of international protection has more than tripled over the past decade, surpassing 41 million people in 2023 ([UNHCR Statistics](#)). Low- and middle-income countries, despite facing limited state capacity and fiscal resources, host the majority (75%) of them.

At the same time that future displacement will likely intensify, an extensive literature documents that migration flows often trigger natives' discontent, increasing support for anti-migration, far-right, and populist candidates and parties - Mayda, Peri, and Steingress ([2022](#)) (U.S. counties), Campo, Giunti, and Mendola ([2021](#)) (Italian municipalities), Dustmann, Vasiljeva, and Piil Damm ([2019](#)) (Danish municipalities), and Edo et al. ([2019](#)) (French departments). Such political backlash can then increase social tensions and steer political decisions, ultimately threatening the effectiveness and sustainability of the reception efforts.

Despite the breadth of this literature and this recurrent pattern, there is little agreement on *why* these reactions occur, what exactly locals are responding to, and what drives this backlash. Previous studies have emphasized economic channels, such as labor market and welfare competition - Becker, Fetzner, et al. ([2016](#)) (UK), Mayda, Peri, and Steingress ([2022](#)) (US), and Halla, Wagner, and Zweimüller ([2017](#)) (Austria). Other, have focused on non-economic forces, such as media, propaganda, and cultural differences - Campo, Giunti, and Mendola ([2021](#)) and Barone et al. ([2016](#)) (Italy), and Rozo and Vargas ([2021](#)) (Colombia). However, there is no consensus on how to measure those channels and which ones are most relevant. Additionally, much of the existing literature relies on aggregated data, typically at the municipality or state level, and often uses indirect proxies for these mechanisms.

Yet, many of the consequences of migration unfold at the local level: from competition for shared public goods and services, to changes in neighborhoods' amenities. Moreover, daily direct contact with migrants can shape locals' attitudes towards migrants through both integration and conflict channels, as suggested by the contact hypothesis and conflict theory (Allport, Clark, and Pettigrew ([1954](#)), Blalock et al. ([1967](#)), and Schlueter and Scheepers ([2010](#))). Therefore, granular data that captures these neighborhood or community dynamics on both voting and relevant mechanisms

would be more appropriate for understanding the nature of the discontent.

This paper fills this gap by studying how the sudden and concentrated displacement of Venezuelan migrants into Brazil affected outcomes in receiving area. This large and sudden inflow of migrants was triggered by Venezuela’s economic and political upheaval. Since 2014, nearly 8 million Venezuelans left their country, with the majority settling in neighboring counties. In 2018 alone, more than 150,000 Venezuelans crossed into Brazil through the border state of Roraima. In response, the Brazilian government established urban shelters in the state capital, Boa Vista, and granted Venezuelans documentation, access to public services and welfare, and work permits.

This setting allows me to study the hyperlocal effects of these refugee shelters. I assemble rich and granular data across several dimensions. Specifically, I examine detailed crime reports to capture externalities on local amenities and safety. I use comprehensive information on public school enrollment and quality to measure congestion of shared public goods. I examine voting behavior as an indirect downstream measure of political attitudes and discontent. Finally, I gather novel data on refugees’ integration and ethnic composition, distinguishing between indigenous and non-indigenous refugee groups, which allows me to assess the role of cultural backlash in shaping these responses.

I causally estimate the impact of refugee reception by leveraging two features of the Venezuelan displacement and reception policy in Brazil. First, migrant inflows and the government’s response were highly concentrated in Roraima, with limited salience in the rest of the country. Second, refugee assistance was implemented rapidly and with substantial spatial variation, as shelters were established in different areas of Roraima’s capital. I use this variation to estimate a difference-in-differences design that compares areas located closer to refugee shelters with those further away.

My results show that refugee shelters reshaped within-city voting patterns. In particular, proximity to shelters reduced support for the incumbent governor while increasing votes for far-right governor and presidential candidates by 2 to 4 percentage points. In contrast, I find no evidence that shelters influenced crime, based on geo-referenced reports of robbery, homicide, and assaults. Similarly, although shelters raised the share of Venezuelan students in nearby schools, they had no discernible

impact on classroom size, student–teacher ratios, or school infrastructure.

Importantly, the political effects were driven entirely by facilities hosting Indigenous Venezuelans. According to UNHCR reports, Indigenous refugees were especially vulnerable, with higher adult illiteracy, lower vaccination rates, and lower levels of integration as measured by social security registration and work permit possession. Moreover, though Indigenous shelters housed relatively more children, surrounding schools did not experience a corresponding rise in Venezuelan enrollment. This indicates that the salience of refugee presence and locals’ exposure to poverty and vulnerability, such as children out of school and child labor, may underlie the political response. Therefore, ethnic-specific contact triggered political backlash even in the absence of worsening crime or congestion of public services.

I complement the within-city analysis with a municipality-level synthetic control approach, using non-affected municipalities in Brazil as the donor pool. The results show that the city’s overall far-right voting closely mirrored those of other non-affected comparable municipalities, indicating that the localized effects of shelters were not large enough to shift aggregate electoral outcomes and raise the overall vote share for far-right populist candidates. This finding assures that the variation I explored captures meaningful exposure to refugees and highlights how aggregate data can hide important nuances in natives’ attitudes towards migrants.

This paper’s voting results go in a similar direction as a large body of research in the field of political economy of migration, documenting that inflows of migrants often increase support for populist, far-right, and anti-immigration candidates and parties.¹ Overwhelmingly, these studies rely on county or municipality-level data and, thus, overlook key within-city variation, given that migrants are unevenly distributed.²

A smaller and more recent set of studies uses more spatially granular data to study electoral behavior in response of refugees. For instance, Fremerey, Hörnig, and

¹See Alesina and Tabellini (2024) for a review of the literature.

²Existing studies examine electoral responses to migration across a range of administrative units, including French cantons and municipalities (Edo et al. (2019) and Vertier, Viskanic, and Gamaleiro (2023)), Italian municipalities (Barone et al. (2016) and Campo, Giunti, and Mendola (2021)), Spanish provinces (Mendez and Cutillas (2014)), regions in twelve European countries (Moriconi, Peri, and Turati (2022)), USA counties (Mayda, Peri, and Steingress (2022)), Austrian communities and municipalities (Halla, Wagner, and Zweimüller (2017) and Steinmayr (2021)), Swiss communities (Brunner and Kuhn (2018)), Greek islands (Dinas et al. (2019)), and Danish municipalities (Harmon (2018)).

Schaffner (2024) use 1km grids across Germany, Endrich (2024) examine refugee housing centers in Hamburg, Pettrachin et al. (2023) focuses on refugee reception centers in Berlin, and Schmidt, Jacobsen, and Iglauer (2024) explore refugee accommodations across Germany. My setting offers two main advantages. First, while these papers use finer spatial identification focusing on electoral outcomes, the evidence they provide on channels driving native backlash remains mixed and limited given the lack of granular data at the same geographic levels. This paper contributes by combining highly localized exposure measures with rich data on public services and crime at 1 Km radius areas even within neighborhoods. Both are important potential mediators, especially in developing country settings. In addition to data availability, my setting, with its unique feature of ethnic separation of refugee shelters, allows me to pinpoint the cultural channel and how the characteristics of the sheltered population shape political reactions.

Second, I look at this question in the context of a developing country. Despite the fact that developing countries host the majority of the world’s displaced population, the literature on the political economy of migration in these contexts remains limited.³ This paper examines the Brazilian reception policy, which was considered “*a global example*” in South America, whose history of violence and democratic erosion, combined with climate change, poses significant risks for future displacement in the region.

This paper also contributes to the literature on political accountability, which studies how voters associate policies with policymakers.⁴ Specifically, it does so by studying the effects on support for the incumbent involved in the refugee reception policy. Considering that in most contexts migrants have limited to no voting rights, locals’ political reactions and voting behavior can be consequential to shaping the implementation and maintenance of policies targeting immigrants. In fact, my results suggest that voters indeed react to refugee inflows once ethnic diversity and visible vulnerability enter their local neighborhoods.

³Exceptions are Rozo and Vargas (2021) and Lebow et al. (2024), who look at Venezuelan migration in Colombia, and Ajzenman, Dominguez, and Undurraga (2022), who explores immigration in Chile.

⁴Ferraz and Finan (2008), for example, shows that Brazilian voters punished politicians when corruption was revealed in municipalities. Ajzenman and Durante (2023) shows that the infrastructure quality of polling stations in Argentina (usually public schools) signaled for the incumbent’s education policies and shifted voters’ decisions. See also Bobonis, Cámara Fuertes, and Schwabe (2016) and Weitz-Shapiro and Winters (2017).

More broadly, this study expands the literature on the effects of refugee camps and shelters in host communities by looking at public education and crime. Prior work has focused primarily on protests, rents, earnings, employment, and consumption among local populations (Coniglio, Peragine, and Vurchio (2023), Batut and Schneider-Strawczynski (2022), Hennig (2021), Sanghi, Onder, and Vemuru (2016), Tumen (2016), Alix-Garcia, Walker, et al. (2018), and Alix-Garcia and Saah (2010)). I complement this evidence by examining additional dimensions that represent central components of how local communities experience refugee arrivals.

The rest of the paper is organized as follows. First, I describe the Venezuelan refugee inflow into Brazil, the reception policy, and elections system. The third section describes the data. Section 4 presents the empirical strategy and the tests for data quality and identification assumptions. In Section 5, I discuss the main results. I evaluate the differential effects between indigenous and non-indigenous shelters in Section 6. Finally, Section 7 concludes.

2 Background

2.1 Venezuelan Refugee Inflow to Brazil

Venezuela’s deep political and economic crisis led to a 65% decrease in its GDP between 2014 and 2019 and yearly inflation rates above 1000%.⁵ Human Rights Watch reported constant violations of human rights, including the persecution of journalists and civil society organizations and the capture of the judiciary by the government. UNHCR estimates that 7.7 million citizens emigrated, more than 84% to other countries in Latin America and the Caribbean.⁶

Between January 2017 and April 2024, more than 1 million Venezuelans entered Brazil, and around half left to go to other South American countries.⁷ According to Baeninger, Demétrio, and Domeniconi (2022), Venezuelan immigration to Brazil can be organized in three waves. The first and second waves occurred between 2012 and 2017 and consisted of highly qualified and middle-class immigrants who mostly arrived

⁵IMF statistics.

⁶See [R4V Platform](#) for statistics by hosting country.

⁷Source: [Ministry of Justice and Public Security report on Venezuelan Migration for April 2024](#).

at the main international airports.

Figure 1: Brazil-Venezuela Border and Roraima's Municipalities



The third wave started in 2018, with the worsening of the economic crisis in Venezuela, and is made up of poorer immigrants arriving at the border of Venezuela and Brazil in the state of Roraima. After crossing the border at the city of Pacaraima, immigrants usually go to Boa Vista, Roraima's capital and biggest city, with a population close to 400,000 people in 2017 - see Figure 1.

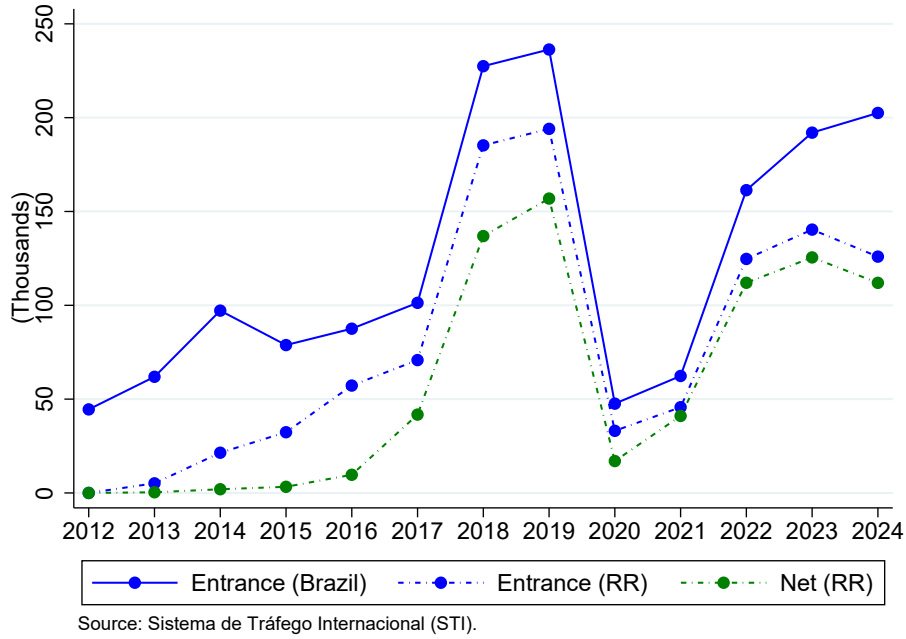
Between 2018 and 2019, almost 400,000 Venezuelan border crossings were registered in Roraima, representing more than 80% of the national inflow - see Figure 2. After a sharp decline in 2020 and 2021, when the border was closed due to the COVID-19 pandemic, entries rebounded in 2023 and 2024, suggesting that migration inflow pressures are still present in the region. ⁸

According to a survey conducted by the Boa Vista government in June 2018, 25,000 refugees were living in the city (7.5% of its population), and around 10% were homeless.⁹ I use UNHCR shelters' reports and the Brazilian state-level household survey (PNAD) to compare Roraima's population and sheltered refugees. Sheltered refugees are younger, with disproportionately more 11-year-old kids or younger and considerably fewer 60-year-old or older individuals. Moreover, illiteracy is two times less common among adult Venezuelans; on the other hand, the proportion of adult refugees

⁸See Figures 27 and 28 in the Appendix A for more details about the gender and age composition of the inflow.

⁹See [newspaper article](#)

Figure 2: Venezuelan Migration Flows to Brazil and Roraima (RR)



without a high-school degree is larger. Finally, the two populations present a similar gender composition.^{10 11}

2.2 Reception Policy

In Brazil, immigrants and refugees, disregarding their legal status, can access public schools and the free and universal national health care system. Once documented, they can access the formal labor market and welfare programs, such as cash transfers. In addition, refugees have free movement within the country.¹²

To obtain refugee status (one of the regularization options), the foreigner must first fill out an online form and schedule an appointment to present the required documents and get a temporary ID. The refugee status grant decision can take several months, however, individuals waiting are already considered documented and can use their temporary ID to obtain a social security number and a work permit either by going to

¹⁰For more details, see Figure 29, 30, and 31 in the Appendix.

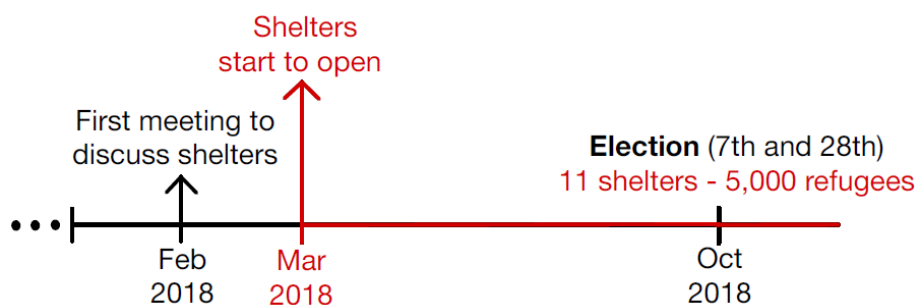
¹¹PNAD data are only available at the state level and don't allow us to separate foreign and Brazilian individuals. Therefore, if anything, the differences between the two populations are underestimated.

¹²This differs from some European countries, where government displacement policies place all arriving refugees in specific municipalities. For example, asylum seekers are obligated to stay in reception centers during their initial asylum proceedings in Germany and throughout their refugee status determination process in Denmark - see Ginn et al. (2022).

government offices or online through cellphone apps. Another option for regularization is through residency permits, which follow a similar process, but it is not free and requires different documents. Comparing the number of documented Venezuelans to the estimated size of the Venezuelan community using entrance and exit flows, the documentation rate is close to 100%.

The Brazilian Federal Government launched the "*Operação Acolhida*" (*Reception Operation*) in February 2018 to deal with the increasing number of refugees crossing Roraima's border. The operation consists of a humanitarian task force coordinated by the federal, state, and local governments with UN agencies, international and civil society organizations, and private entities. Different reception, accommodation, regularization, sanitary inspection, and immunization structures were set up at the border and in Boa Vista. The Operation consisted of three main foundations: border planning, dispersal policy, and reception/shelters.¹³

Figure 3: 2018 Timeline



Shelters started to be open in March, they provided food and protection for documented refugees. Teams of NGOs, UN, and government workers offered health services, portuguese classes, and informal education activities for children. Some shelters consisted of the "Refugee Housing Units" model of the UNHCR, while others had tents and overlays provided by the Brazilian army - see Figure 4. The shelters were jointly managed by the Brazilian army (2 exclusively), NGOs, UNHCR, and state and municipality governments. The bathrooms were shared, and some shelters didn't have a dining area. The entrance was allowed until 10 pm, and identification cards were used

¹³Since April 2018, more than 140,000 Venezuelans have participated in the voluntary dispersal policy and moved to more than 750 Brazilian municipalities. For updated statistics about the dispersal policy access: [Dispersal Strategy Statistics Platform](#).

to control entrance.¹⁴ In October 2018 (the election month), 5,000 refugees lived in one of the 11 shelters in Boa Vista. From the opening, shelters were at full capacity (some above it), the smallest one hosted 279 Venezuelans, and the biggest more than 650 refugees.¹⁵

Figure 4: Shelters’ Photos

(a) Inside Photos



(a.1) Tancredo Neves Shelter



(a.2) Rondon 1 Shelter

(b) “Operação Acolhida” logo and shelters’ name on outside signs



(b.1) Jardim Floresta Shelter



(b.2) Santa Teresa Shelter

2.3 Elections

Voting is mandatory for 18- to 65-year-old Brazilians living in the country and optional for 16- and 17-year-olds. It is restricted to citizens, and the naturalization of individuals without specific family ties with Brazilians can take up to 180 days and

¹⁴For more details about the shelters’ logistics and the discussion behind the militarization of the reception policy, see Machado and Vasconcelos (2022).

¹⁵See Table 10 in the Appendix B for shelter-specific statistics.

requires a minimum number of years living in the country (4 years in most cases), besides proof of Portuguese proficiency. Therefore, Venezuelan refugees are very unlikely to be voting.¹⁶

Elections take place every two years, in even years, alternating between municipal and general elections. They occur on the first Sunday of October, and the second round (if necessary) happens on the last Sunday of the same month. On October 7th, 2018, more than 150,000 registered voters in the Boa Vista voted for: President, State Governor, National Congress (8 vacancies), Senators (2 vacancies), and State Congress (24 vacancies). Since no candidate for President and Governor reached 50% or more of the valid votes, a second round was held on October 28th.

Presidential Election Candidates

"Operação Acolhida" was launched during Michel Temer's administration. He became president in 2016 after the impeachment of President Dilma Rousseff, whom he had served as vice president.¹⁷ He decided not to run for reelection; therefore, there was no incumbent candidate in the 2018 presidential election.¹⁸ The main national left party, the Workers Party (PT), launched Fernando Haddad, who lost the election to Jair Bolsonaro (55% of the votes). Jair was a federal deputy for the Rio de Janeiro State between 1991 and 2018, and during these 27 years (6 consecutive reelections), he was known for his conservative, populist, and controversial statements.

"Refugees arriving in Brazil are the scum of the world."

Bolsonaro (2015)

The Venezuelan migration crisis was not a major part of the national presidential debate. However, Haddad (PT) and Bolsonaro (PSL) had considerably different views about immigrants. The 2018 Bolsonaro government program doesn't mention immigrants or refugees directly. Contrastingly, Haddad's program explicitly aimed to

¹⁶Information about the number of naturalized citizens among the voters is unavailable. However, naturalized citizens represent less than 0.1% of the country's total population according to the 2022 Census.

¹⁷For a complete timeline of recent Brazilian Presidents, see Figure 33 in Appendix C.

¹⁸His party launched the finance minister as a candidate, who got less than 1.3% of the valid votes nationally.

promote refugees' and immigrants' rights and refers to them as a target population for public policies.

Haddad's (PT) Presidential Government Program (2018):

"The Government will promote the rights of migrants through a National Migration Policy and will broadly recognize the rights of refugees."

"Health improving actions will be implemented for women, ..., immigrants, refugees,, and people from the forests."

PT had a candidate in all presidential elections in the data (2006 to 2022). However, for some election years before 2018, Bolsonaro's Party (PSL) didn't launch a candidate, so I will use the performance of the candidate it supported. See Table 12 in Appendix D for a complete description of the parties used in each presidential election.

Governor Election Candidates

Figure 5: National Newspaper Headlines Covering Roraima's 2018 Election



Translation: *"Migration crisis becomes the main issue of the election in Roraima"*
and *"In Roraima's election, what really matters is Venezuela"*

From 2014 to 2018, Suely Campos (from PP, an important national right-wing party) was Roraima's Governor. She won the 2014 second-round election with 54.9% of the votes and unsuccessfully ran for reelection in 2018, obtaining less than 12% of the votes. According to reports and meeting minutes, Suely's administration participated directly in the *Reception Operation* efforts. The state government received extra funds for social and health services and, together with the federal government, created different commissions addressing topics related to the refugee flow, such as the "State Commission to Eradicate Slave Labor". The state government also directly managed

two shelters and participated in interventions targeting the sheltered population (such as STD testing, distribution of condoms, vaccine campaigns, and nutrition surveillance).

Antônio Denarium was elected governor in 2018 with 53.34% of the votes. He shared the same party (PSL) as Bolsonaro, who visited Roraima and joined him in campaign events. The second most-voted (46.66%) candidate was Anchieta Júnior (PSDB), a former governor from 2007 to 2014.

Antônio Denarium - 2018 Roraima's Elected Governor:

"Together with refugees, drug dealers, and criminals are entering; one country, Venezuela, does not fit inside Roraima."

"... all these NGOs that are here should go to Venezuela and serve these people there, preventing them from entering Brazil."

"...(we want to) restrict the entry of Venezuelans by requiring a passport, a criminal record certificate, and a vaccination certificate, which is also very important."

Suely, Denarium, and Anchieta defended some type of border restriction.¹⁹ Therefore, all three leading gubernatorial candidates proposed migration restrictions, even the incumbent, who participated in the shelter policy efforts.

The main outcomes for the governor election will be voting for the three leading candidates' parties (PP, PSL, and PSDB) and, similarly to the presidential election, will complete the years with no candidate from such parties with the voting for the party they support.²⁰

3 Data

3.1 Shelters and Refugees

UNHCR produced a summary of the *Reception Policy* with a timeline of shelter openings and a description of services and programs targeting Venezuelans. Additionally,

¹⁹[Roraima's Governor Candidates Interview](#).

²⁰For more details on political context, see Appendix C and Table 11.

shelter-specific monthly reports published in 2018 contain shelters’ locations, total capacity, and their sheltered refugees’ socioeconomic and demographic information. Government meeting minutes available at the [Receptio Policy website](#) were used for shelters and months not covered by the UNHCR reports.

3.2 Election

Data for the 2006, 2010, 2014, 2018, and 2022 election results is provided by the Superior Electoral Court (TSE). It contains the number of votes for each candidate in each section (room) in each polling station (building). Additionally, from the 2010 election onwards, the characteristics (age, sex, marital status, and education) of the registered voters are also provided at the section level.²¹

I use data on the geographic coordinates of polling stations from [F. Daniel Hidalgo’s code output](#). It leverages different administrative datasets to fuzzy string match the address and the polling station name (usually the name of the building). The coordinates come from TSE data and other administrative datasets (such as schools’ geographic location from the Education Ministry). See Appendix E for the details on how this data was used and the procedures taken to confirm each polling station’s latitude and longitude.

3.3 Crime

Boa Vista crime data was provided by Roraima’s State Police Department (CIOPS-CAD-SESP). It includes all reported incidents of the following types of crimes: homicides, robbery, sexual assault/rape, and felony murder (robbery resulting in death). The incidents are reported at the address level and include the date (day, month, year) they occurred. The data covers the period from January 2016 to December 2022 and also includes incidents classified as “attempted”.

First, I used the list of all streets, avenues, and alleys in Boa Vista from the [Brazilian Postal Service](#) to string match each crime address, correcting it for typos, spelling, and accentuation errors. To geo-locate the cleaned addresses, I use the [OpenCage](#)

²¹The marital status information contains a considerable amount of missing; therefore, only voters’ education, gender, and age were used.

[Geocoding API](#) that uses different open datasets (like [OpenStreetMap](#)) to find the best possible latitude and longitude match. Around 80% of the crime data was successfully geolocated. I excluded addresses in the rural area of the municipality and dropped observations without latitude and longitude. The final data includes 24,063 reports, 59% are robbery, 35% are assault or battery - see Table 1.

Table 1: Crime Reports Data Statistics

Crime Type	Number of Reports (% Total)	% Classified as “Attempted”
Robbery	14,117 (58.7%)	2%
Assault/Battery	8,339 (34.6%)	2%
Homicides/Murder	1,096 (4.5%)	47%
Rape/Sexual Assault	436 (1.8%)	18%
Felony Murder (robbery resulting in death)	75 (0.3%)	33%
Total	24,063	5%

Source: NEAC/DENARC/PCRR reports from January 2016 to December 2022.

3.4 Education

The administrative Ministry of Education’s yearly school census (with the date of reference being the end of May) covers all public schools in Boa Vista from 2010 to 2024. It provides information on location, enrollment, staff, and infrastructure. Students’ information includes age, gender, and nationality. I exclude rural and private schools from the sample, given that this paper focuses on the urban area of the municipality, and private schools accounted for less than 1% of Venezuelan enrollment. In 2017, the year before shelters were set up, the city had 118 public urban schools with an average of 495 students each, and 26 students per classroom - see Table 2.

Table 2: Public Schools Statistics - Boa Vista (2017)

	N	mean	sd	min	max
Share of Venezuelans (2019)	109	12.05	10.14	0	60.14
Number of Students	118	494.8	290.4	38	1,580
Number of Classrooms	118	18.53	9.935	2	57
Auditorium (Dummy)	118	0.144	0.353	0	1
Library or Reading Room (Dummy)	118	0.822	0.384	0	1
Science Lab (Dummy)	118	0.212	0.410	0	1
Students per Classroom	118	25.71	3.514	12	34.35
Students per Teacher	118	18.97	4.898	7.053	32.83
Distance Closest Shelter	118	1.684	1.054	0.149	4.518
Average Distance to Shelters	118	4.482	1.289	2.820	7.960

Source: 2017 and 2019 INEP School Census.

4 Empirical Strategy

4.1 Voting

Defining the Unit of Observation

Given the different aggregation options allowed by the detailed voting data, I first describe the chosen unit of observation for the main specifications.

Brazilian election logistics doesn't use voting districts to allocate voters; instead, it works at two different allocation levels. First, voters are assigned to a polling station (i.e., a building, usually a public school). Then, they are separated into different sections (i.e., rooms) within that building. The Brazilian Electoral Code describes the criteria behind those assignments:

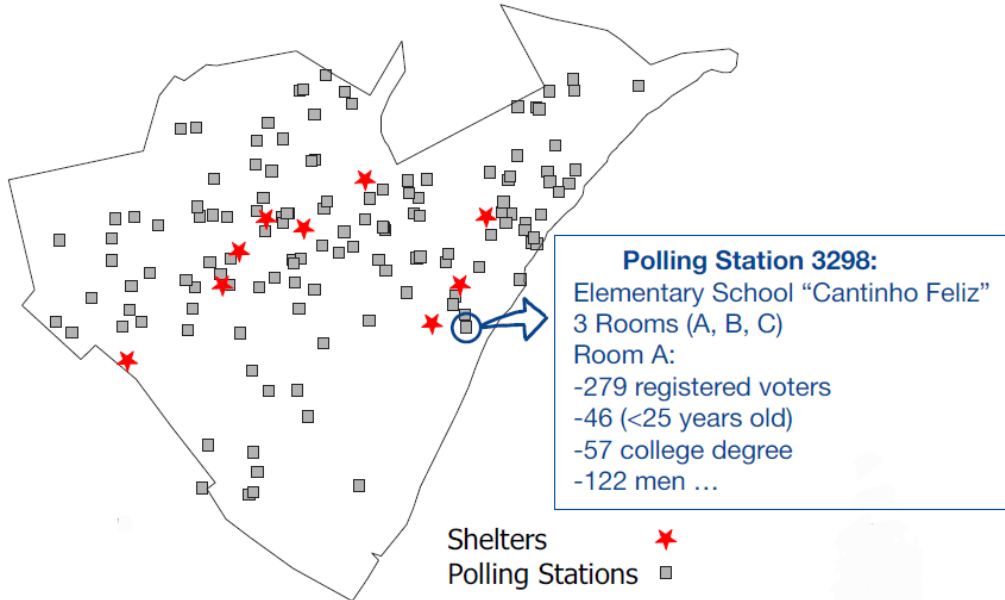
§ 1º (...) (Polling Station) will be located within the judicial or administrative district of your residence and the closest to it, considering the distance and means of transport.

Moreover, according to § 3º, the voter will be permanently linked to the room number indicated in their voter's ID. If voters move to another municipality, they must go to the office and update the polling station. If voters move within the same mu-

nicipality to a different neighborhood, they can (not mandatory) update their polling station to one closer to their new residence address.

Therefore, the assignment of voters to polling stations and sections presents two interesting features for the purpose of this study. First, the location of polling stations can work as a proxy for the area of residency. Second, there is a certain inertia once you are assigned to a room (it is unlikely to be voting at different places or even rooms in each election). Given these electoral logistics features, I explore a room-level panel as the main dataset - see Figure 6 for an example of how the data looks.

Figure 6: Election Data on a Map



Regression Equations

To obtain the causal impact of the shelters on the electoral outcomes, I estimate a Diff-in-Diff using the following TWFE specification:

$$Y_{ijt} = \beta \text{Treated}_j \times \text{Post}_t + \gamma_i + \mu_t + \text{Controls} + \epsilon_{ijt} \quad (1)$$

Y_{ijt} is the voting outcome of the section "i" in polling station "j" in the electoral year "t". Treated_j is a dummy variable indicating whether polling station "j" is less than 1 kilometer away from the closest Venezuelan refugee shelter. μ_t is the year fixed effects and γ_i is the section fixed effect. The 2006, 2010, and 2014 elections are the pre-treatment periods, and 2018 and 2022 are the post-treatment periods. Given

that the treatment assignment level is more aggregated than the observations, standard errors are clustered at the polling station level. A neighborhood-level clustered errors were also explored for robustness to capture underlying spatial correlations. I explore different specifications, adding two sets of controls: 23 different demographic variables (interaction of education, gender, and age) of section "i" registered voters, and an interaction of time dummies and the distance of polling station "j" and the city downtown.

Table 3: Descriptive Statistics (2006-2022)

	N	mean	sd	min	max
Polling Station Constant Variables:					
Distance (Km) to the closest shelter	238	1.480	1.056	0.168	5.014
Average Distance (Km) to all shelters	238	4.689	1.282	3.161	9.188
Distance (Km) to Boa-Vista center/downtown	238	4.731	3.165	0.212	10.18
Treatment Dummy (1 km)	238	0.340	0.475	0	1
Section-Level Variables (2006-22):					
Number of Registered Voters	1,190	326.3	65.46	75	444
Turnout Rate 1st Round	1,190	85.40	4.009	70.19	95.57
Turnout Rate 2nd Round	1,190	81.82	4.614	57.47	95.07
Section-Level Variables (2014):					
Share Illiterate	714	1.258	1.387	0	7.407
Share with some college	714	28.66	18.44	0	82.78
Share Less than High-School	714	39.67	17.37	3	91.49
Share < 25 Years Old	714	16.87	8.911	0	58.11
Share < 40 Years Old	714	42.48	14.40	3.333	77.78
Share > 65 Years Old	714	7.821	5.473	0	40.79
Share Men	714	47.32	7.523	16.67	78.95
Share of less than High-school degree Men	714	20.79	10.39	1	70.53
Share of less than High-school degree Women	714	18.88	9.112	0	55.66

Source: TSE.

The data includes 911 sections (in 238 polling stations), each with 330 voters on average, 33% are located in treated polling stations, and 28% of the sections are balanced (operate every election year in my data). Sections can be destroyed or created during this period for different reasons, such as changes in the voters' population size or logistical reasons, such as building renovations.

Adding covariates, however, biases the TWFE even in a non-staggered design with two time periods - see Sant'Anna and Zhao (2020). Callaway and Sant'Anna (2021)

proposes a Doubly Robust Diff-Diff for multiple periods with a conditional (on pre-treatment covariates) parallel trends assumption. The DRDiD is a combination of outcome regression and IPW (propensity score model). Therefore, I also estimate a DRDiD using the 2014 voters' characteristics covariates. Additionally, I estimate a Matching DiD that first uses 2014 covariates to match control units to treated ones before calculating a conventional DiD.²²

Data Quality and Identification Assumptions Tests

This section will discuss and test the identification assumptions required for the causal interpretation of " β ".

Exogenous Location of Shelters

The Defense Ministry was responsible for visiting available lands, and some shelters were either established in areas around the Federal Police building (built between 2010 and 2013) or in empty areas and buildings (such as public gymnasiums) provided by the local governments. The reception operation meeting minutes don't include any details or describe any specific strategies behind the choice of places. According to the Diff-in-Diff parallel trends assumption, shelters shouldn't be located in areas presenting different political preference dynamics before 2018 (becoming more conservative, for example).

²²For the Matching DiD, I use the command "diff" in Stata that runs a kernel-based propensity score matching.

Table 4: Balance Table on Pre-Migration Variables

	Treatment			Control			
	n	mean	sd	n	mean	sd	Diff
Section Constant Variables:							
Distance (Km) to the closest shelter	81	0.59	0.25	157	1.94	1.02	-1.354***
Average Distance (Km) to all shelters	81	3.87	0.52	157	5.11	1.35	-1.248***
Distance (Km) to Boa-Vista center/downtown	81	5.62	2.85	157	4.27	3.23	1.352***
Section Variables (2014):							
Share Men	81	47.27	3.26	157	47.09	3.89	0.178
Share <25 Years Old	81	19.82	6.02	157	18.20	7.54	1.620*
Share <40 Years Old	81	48.94	11.19	157	46.80	13.82	2.143
Share >65 Years Old	81	5.50	3.05	157	6.05	3.91	-0.544
Share Illiterate	81	1.75	1.08	157	1.21	1.37	0.538***
Share Less than High-School	81	46.01	13.01	157	34.46	17.02	11.552***
Share with some college	81	20.44	12.20	157	33.69	19.49	-13.252***
Share of less than High-school degree Men	81	24.24	7.28	157	17.82	8.74	6.418***
Share of less than High-school degree Women	81	21.77	6.53	157	16.64	8.73	5.134***

Notes: Includes only balanced sections (main sample). *Source:* TSE.

One could argue that even if there were no reasoning coming from policymakers, locals could have engaged in lobbying to prevent shelters from being set up in some areas. If lobby movements existed (no media found about it) and were connected with locals' attitudes towards migrants, this would attenuate the estimated effects on far-right and incumbent performance (shelters would endogenously be located in neighborhoods with a trend to be more welcoming to refugees and shelters). However, "Operação Acolhida" was considered an emergency effort (shelters started to open a month after the first operation meeting). Moreover, since the shelters mainly used tents and pre-made housing units, they are logistically fast to set up. Consequently, lobby organizations would have had a considerably limited time to organize.

Table 4 reports the differences between control and treated units on pre-migration (2014) variables. Treated sections possess less educated voters and are further away from the city downtown. As long as those differences are only connected with differential levels of political preferences and not trends, the DiD assumptions hold. To test this formally, I estimate an event study version of equation (1) to verify for any pre-treatment statistically significant effect of the shelters.

Outcomes are accurately capturing residents' political preferences

The section's voting results should capture the political preferences of locals living around the section's polling station. As discussed in Section 4.1, this is partially granted by the Brazilian Electoral Code. Still, individuals who move within the same municipality don't need to update their polling stations. Therefore, there might be a group of voters who are not voting close enough to their residence. However, in 2013, all voters in Boa Vista had to scan their fingerprints and update their information. This became an opportunity to change your polling station in case you are voting far from home.²³ Therefore, after 2013 the correlation between where you vote and where you live likely became even stronger. Voters' address data is not publicly available to formally test this. However, we observe considerable stability over time on the section's registered voters' characteristics (education, age, and gender) after 2013 - see Appendix I for more details.

No Spillover Effects

A potential leakage of treatment to controls, likely to happen in this within-city setting, would violate the SUTVA assumptions of the DiD and attenuate my estimates. Therefore, I also estimate a version of equation (1) using the distance to the closest shelter as a continuous treatment - see equation (2). This allows for a more flexible shelter effect across the Boa Vista urban area.

$$Y_{ijt} = \beta \frac{1}{Distance_j} \times Post_t + \gamma_i + \mu_t + Controls + \nu_{ijt} \quad (2)$$

No locals' endogenous migration and assignment to polling stations

Finally, we also assume that the voters have no compositional change due to treatment assignment. In other words, Brazilians (especially the most conservative/anti-migration ones) didn't move in response to shelters. This would represent a compositional change in our sample, leading to misleading zero or even wrong sign results.

²³According to TSE: "Some voter registration data are confidential (membership, address, telephone, date of birth, biometric data, among others) and must be updated whenever necessary, such as in cases where the voter must change personal data, *register fingerprints*, request transfer, etc."

The election logistics minimize this concern, given that voters had until May 9, 2018, to change polling stations. Considering 8 out of 11 shelters opened after March 2018, Brazilians had minimal time to do so if they moved (either to a different neighborhood or municipality). Therefore, even if Brazilians changed their residences, responding to the shelters' location, we would still likely capture their political preferences in their original polling station. Nonetheless, the possibility of moving gives the estimates an ITT interpretation.

To formally test if treatment affected voters' characteristics (a sign of voters' compositional change), I estimate equations (1) and (2) using those voters' education, age, and gender characteristics as outcomes. According to the results, the shelter's location had a null effect on different voters' characteristics - see Table 5.

Table 5: DiD Results - Control Variables as Outcome

Outcomes	$\text{Treated}_j \times \text{Post}_t$	R2	$\frac{1}{\text{Distance}_j} \times \text{Post}_t$	R2
% Men	-0.876 (0.674)	0.002	0.118 (0.330)	0.001
% Illiterate	-0.135 (0.118)	0.025	0.023 (0.035)	0.023
% Less than High School	0.495 (0.894)	0.029	-0.503 (0.349)	0.031
% Some College	0.302 (0.715)	0.008	0.404 (0.257)	0.009
% 16-17 Years Old	-0.331 (0.587)	0.042	-0.349* (0.181)	0.050
% <25 Years Old	1.317 (1.355)	0.087	-0.924 (0.761)	0.090
% >65 Years Old	0.083 (0.361)	0.336	-0.022 (0.155)	0.336
% Men Less than High School	-0.099 (0.685)	0.015	-0.610*** (0.215)	0.020
% Working-Age Men	-0.504 (0.786)	0.022	0.375 (0.311)	0.022
% Women Less than High School	0.594 (0.644)	0.009	0.108 (0.213)	0.008
% Working-Age Women	0.732 (0.771)	0.035	0.082 (0.259)	0.034

Notes: standard errors clustered at the polling station level in parentheses.

No Differential Electoral Logistics

Another concern for the causal interpretation of the results would be that election logistics differed in sections closer to shelters. For example, sections closer to shelters could have been manipulated to make voting more difficult by, for example, increasing the number of registered voters or reducing the number of rooms. Following the same strategy used to investigate voter compositional change, I estimated a version of equations (1) and (2) using election logistics variables, both at the section and polling station levels, as the outcome.

According to the results presented in Table 6, there was no differential logistic capacity between treated and control units. Therefore, combining those estimates with the null effects found for turnout, it is unlikely that the election organization explains the results.

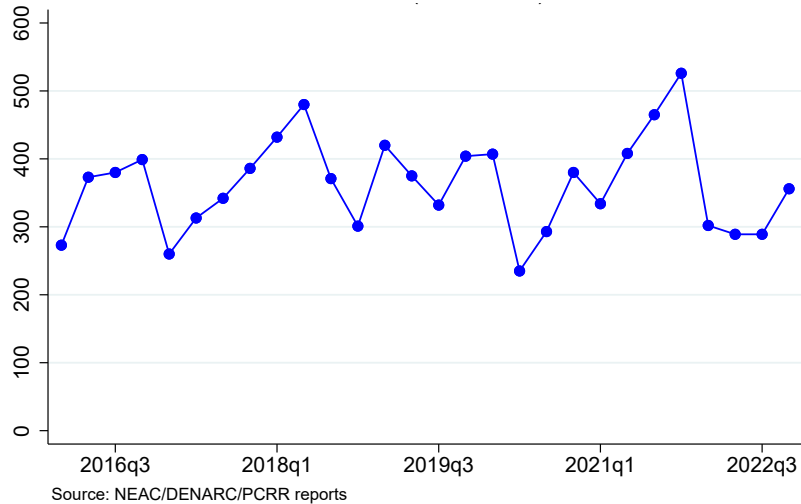
Table 6: DiD Results - Election Logistics Variables as Outcome

Outcomes	$\text{Treated}_j \times \text{Post}_t$	R ²	$\frac{1}{\text{Distance}_j} \times \text{Post}_t$	R ²
Polling Station Level:				
Number of Sections	0.069 (0.160)	0.308	-0.087 (0.199)	0.308
Number of Registered Voters	-14.628 (70.093)	0.167	-32.307 (75.469)	0.168
Average Section Size	-9.938 (9.391)	0.135	-2.453 (3.890)	0.134
Size Biggest Section	-6.321 (9.709)	0.176	-0.444 (4.163)	0.176
Size Smallest Section	-14.820 (15.699)	0.073	-5.168 (7.343)	0.073
Not Operating in year t	-0.009 (0.038)	0.129	0.023 (0.026)	0.132
Section Level:				
Number of Registered Voters	3.772 [11.785]	0.335	2.088 [2.869]	0.335
Not Operating in year t	0.011 [0.057]	0.315	-0.025 [0.034]	0.316

Notes: robust standard errors in parentheses and standard errors clustered at the polling station level in brackets.

4.2 Crime

Figure 7: Quarterly Number of Crimes - Boa Vista



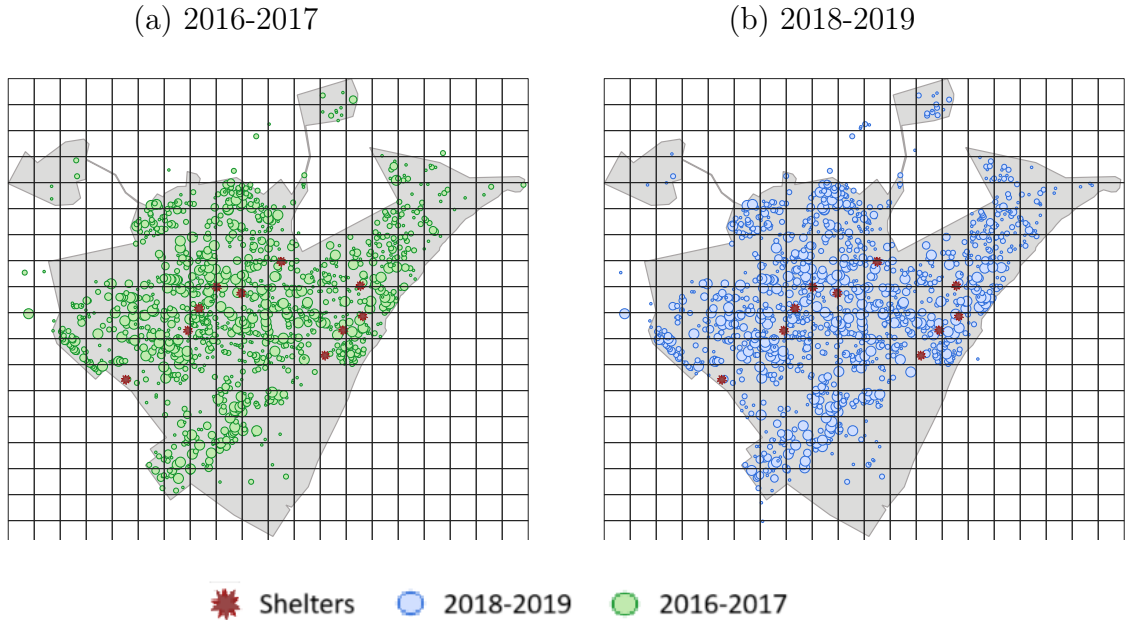
Crime is commonly mentioned in the media, surveys, and politicians' speeches as one of the main concerns related to migration flows. To verify whether shelters affected

crime, I divided the urban area of Boa Vista into 1 Km x 1Km grids and calculated the total number of crimes registered in each grid for each quarter from the first quarter of 2016 to the last quarter of 2022 - see Figure 8 for a map visualization. Then I estimate a Diff-in-Diff using the following TWFE specification:

$$\text{Crime}_{jst} = \beta \text{ Treated}_j \times \text{Post}_t + FE + \text{Controls} + \nu_{jst} \quad (3)$$

Crime_{jst} represents the inverse hyperbolic sine (IHS) of the number of crimes of type s (homicides, robbery, or assault) registered in grid j in quarter t . Treated_j is a dummy variable indicating whether grid "j" is less than 1 kilometer away from the closest Venezuelan refugee shelter. Post_t is a dummy for after the second quarter of 2018. To capture the differential trend in suburban and more central areas of the city, I added the distance to downtown interacted with dummies of quarter (Controls). Fixed effects are a combination of time, grid, type, or grid-type. In addition, I explore a quarter number (1, 2, 3, or 4) interacted with grid j dummies to capture potential seasonality patterns. Finally, I also estimate a Poisson regression, given that the outcome is a count variable.

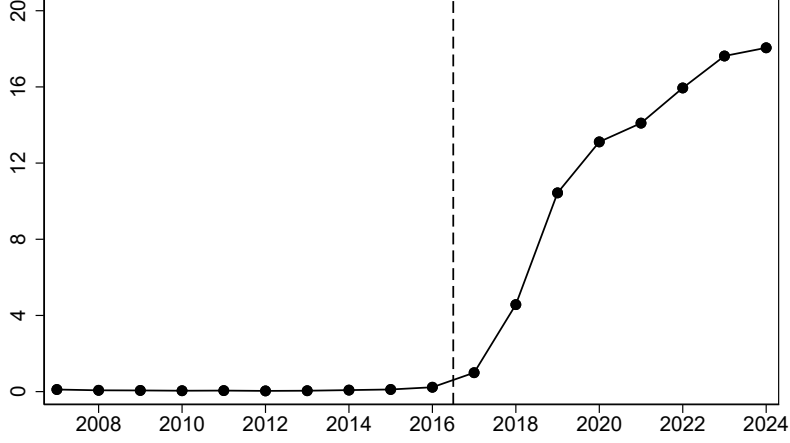
Figure 8: Crime Map Before and After Shelters



Notes: To keep both maps representing crime pattern across the same time window (2 years), 2020 to 2022 data is not used in this plot.

4.3 Public Education

Figure 10: % Venezuelan Students in Boa Vista's Public Schools



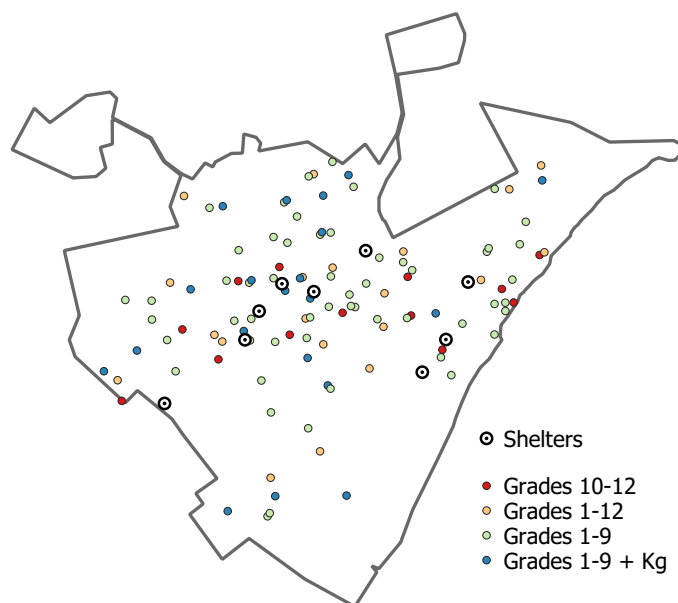
Notes: The sample consists of all urban public schools in Boa Vista, including kindergarten, nursery schools, and grades 1 to 12.

From 2017 to 2024, the number of foreign students enrolled in public schools in Boa Vista increased more than 20 times, reaching almost 20% of the student population. I use the public school yearly data from 2010 to 2024 to verify the effect of indigenous and non-indigenous shelters on student composition, congestion, and infrastructure. In particular, I estimate the following event study specification using a panel of schools:

$$Y_{st} = \alpha + \sum_{\tau=2010}^{2015} \beta_{pre\tau} Treated_s + \sum_{\tau=2017}^{2024} \beta_{post\tau} Treated_s + \gamma_s + \gamma_t + \varepsilon_{st} \quad (4)$$

Y_{st} is the outcome for schools s (such as average classroom size, students-per-teacher ratio, and share of Venezuelan students) in year t . $Treated_s$ is a dummy for whether the school is less than 1 kilometer away from a shelter, respectively. γ_s and γ_t are the school and year fixed effects. See the schools and shelters' location in Figure 11.

Figure 11: Schools and Refugee Shelters - Boa Vista (2019)



5 Results

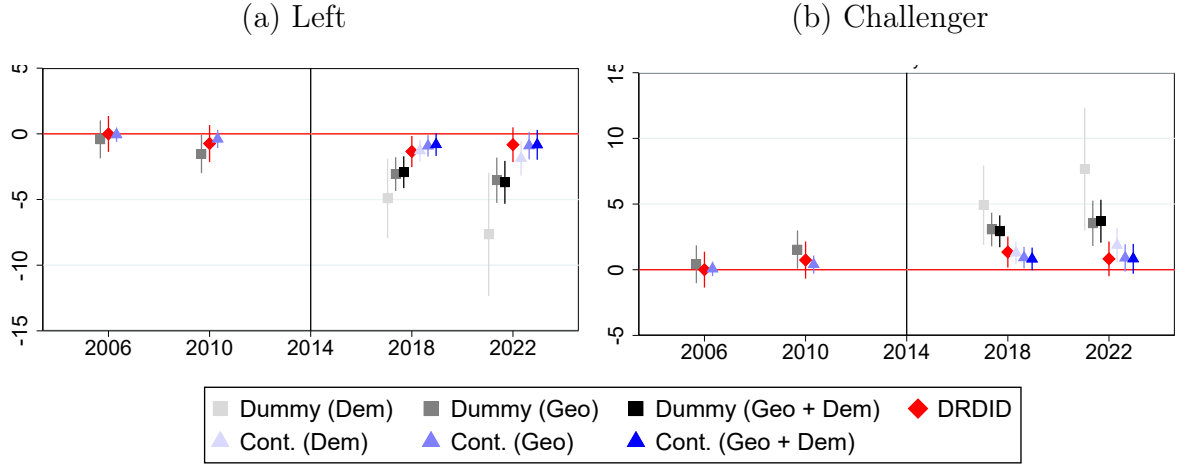
5.1 Voting

Presidential Election

According to Figure 12, Haddad (Workers' Party candidate) was negatively affected (by 2 to 4 percentage points) in the 2018 second round. Since only two candidates were in the second round, the negative effect on Haddad translates into a positive effect for the Far-Right candidate (Jair Bolsonaro).²⁴ Finally, the results persist for the 2022 election.

²⁴The results for the other candidates were not statistically significant

Figure 12: Presidential Election (2nd Round) - Event Study

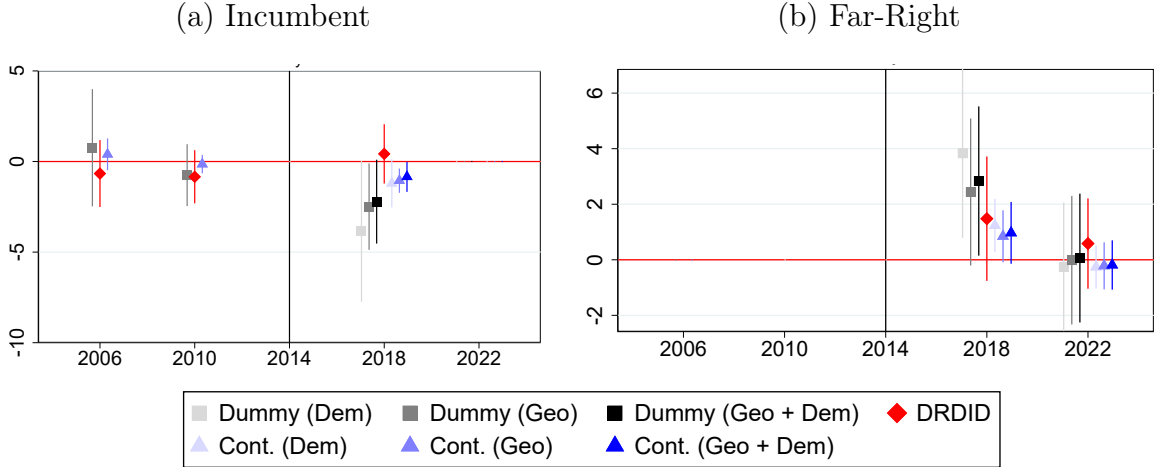


Notes: Dependent Variable = % of valid votes for each category/candidate. Dummy = Treatment in the dummy form. Cont. = Treatment in the continuous form. *Dem* = 23 demographic (age, education, and gender) controls; *Geo* = time dummies interacted with polling station distance to downtown. DRDID = Doubly Robust DiD. MDID = Matching DiD. *Challenger* = voting for the party not *Left* (PT). Given that PT participated in every second round, *Challenger* = 100 - *Left*.

Governor Election

Figure 14 summarizes the main results of the Governor's election. According to the estimates, there is suggestive evidence that the incumbent governor (Suely) lost between 2 and 4 percentage points of the valid votes in sections within treated polling stations. This incumbent "punishment" accountability result is interesting, given that even though Suely participated in the "Operação Acolhida" effort, she engaged in anti-migration proposals during the 2018 campaign (tried to close the state's border and restrict refugees' access to public services).

Figure 14: Governor Election - Event Study



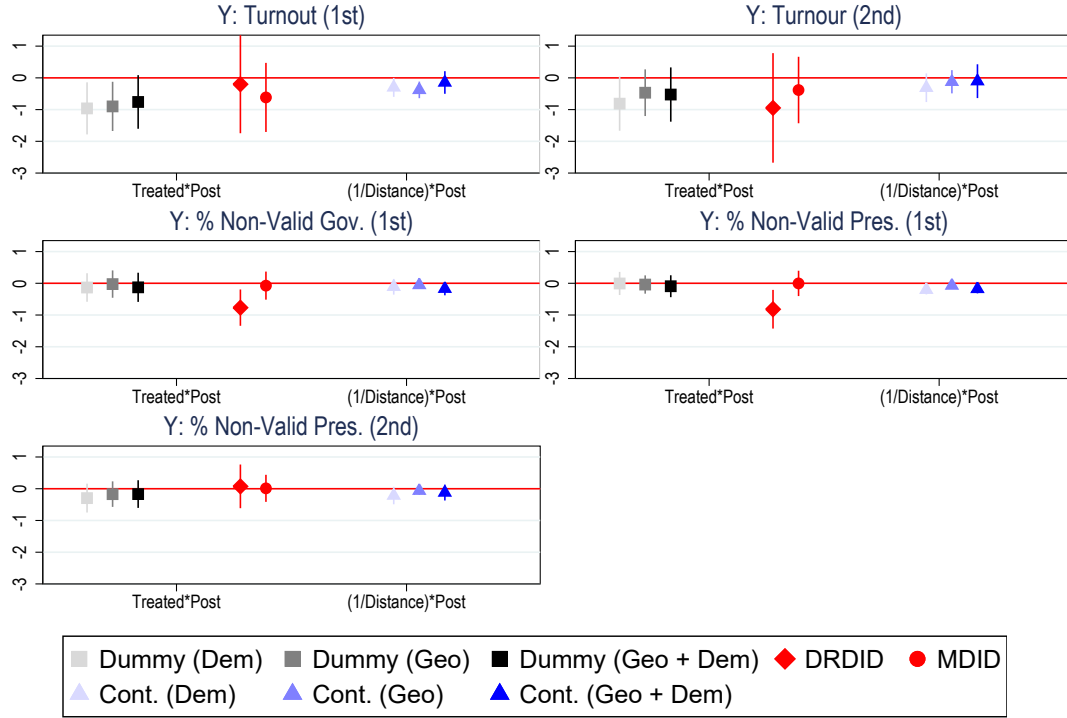
Notes: *Far-Right* Party (PSL) did not participate or support any candidate in the 2006 and 2010 state elections. Dependent Variable = % of valid votes for each category/candidate. Dummy = Treatment in the dummy form. Cont. = Treatment in the continuous form. *Dem* = 23 demographic (age, education, and gender) controls; *Geo* = time dummies interacted with polling station distance to downtown. DRDID = Doubly Robust DiD. MDID = Matching DiD.

The incumbent's voting loss translated into increased support for the far-right. There is no longer statistically different from zero in the 2022 election. This result goes in the same direction as other papers in the literature that found positive causal effects of exposure to immigrants on vote shares for right and far-right parties.

Turnout and Non-Valid Votes

Turnout and non-valid votes could explain the results for the governor and presidential elections. In other words, the shelters could have triggered voters who normally don't show up to vote (turnout increase) or voters who usually don't choose a candidate to select one (decrease share of non-valid votes). According to Figure 16, we don't observe any consistent non-zero effect on the share of non-valid votes. Additionally, the results for turnout rates are noisier, and their statistical significance is inconsistent across the different specifications.

Figure 16: Turnout and Non-Valid Votes



Notes: *Dem* = 23 demographic (age, education, and gender) controls; *Geo* = time dummies interacted with polling station distance to downtown. DRDID = Doubly Robust DiD. MDID = Matching DiD.

Party Affiliation

Voting for a particular candidate is only one way of expressing political preferences in a democratic system; citizens can also become members of a party and run for office, for example. To further analyze the political consequences of urban refugee shelters, I explore party affiliation data, which has not yet been explored by the political economy of migration literature. Brazil's party affiliation is among the highest across democracies at 10% of the adult population (2018). Boa Vista registered 1,243 new affiliates (all parties) in 2018, an average of 8.75 per polling station.

The data on political affiliation organized by the Superior Electoral Court (TSE) provides individual affiliation information, including the gender, age, party, and the dates of affiliation and disaffiliation. Moreover, it also includes the polling station and room identifiers where the affiliate votes. Following the same election results empirical strategy, I explore a yearly (from 2010 to 2022) panel of polling stations and use as dependent variables the share of voters affiliated to the Workers' Party (PT),

Bolsonaro’s party (PSL), and the incumbent governor’s party (PP).

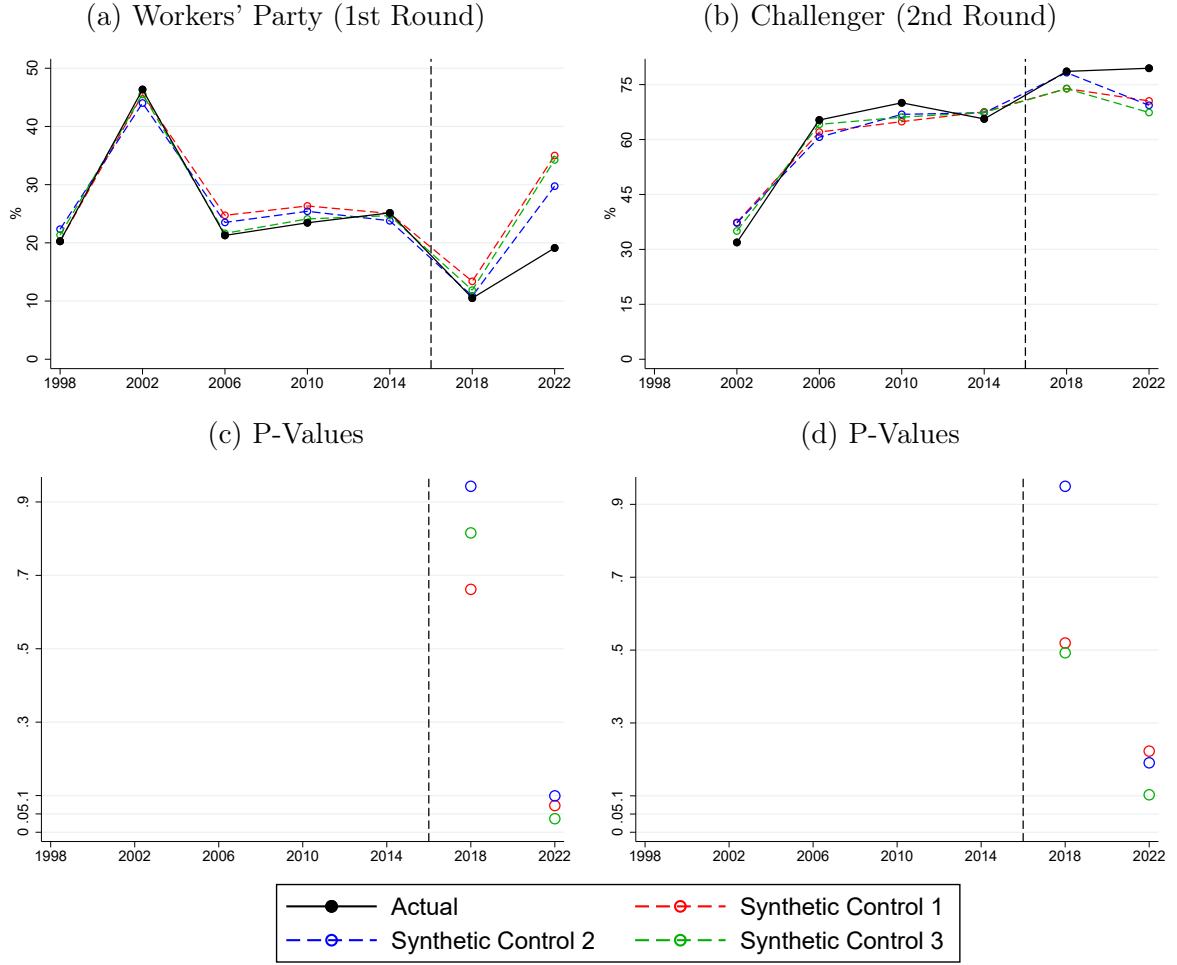
The results (see Figures 42, 43, and 44 in the Appendix G.2) reveal a null effect of shelters on party affiliation. Therefore, the reception policy’s political effects were restricted to voting and didn’t trigger a more “extreme” political participation behavior. The event study versions reassuringly present no differential trends before 2018.

Putting the results into perspective

To assess the magnitude of the shelter’s effect on elections, I estimate its impact on the city’s aggregated election results. In other words, in this section, I verify whether the shelters’ impact was responsible for leading Boa Vista to a shift to the far-right. To respond to this, I estimate a synthetic control exploring a municipality panel and using other Brazilian municipalities outside Roraima as the control donor pool. Given the computational cost of leading to a large number of potential controls (more than 5,500 municipalities), I use three different smaller samples: a random sample of 300 municipalities, 300 municipalities with the closest pre-2018 average population to Boa Vista, and 300 municipalities with the closest pre-2018 average GDP per capita to Boa Vista.

According to the results (see Figure 17 below and Figures 49, 50, and 51 in the Appendix H), Boa Vista’s increase in far-right vote and the decrease in support for the workers’ party was also observed in other municipalities of the country. The far-right captured voters even in municipalities that were not directly affected by the Venezuelan flow and its reception policy. Consequently, the shelters shaped within city voting, but they did not disproportionately push Boa Vista towards those candidates. The estimates are robust to the different control groups.

Figure 17: Overall Effect of Reception Policy



Notes: *Synthetic Control 1*: random 5% sample of Brazilian municipalities outside Roraima. *Synthetic Control 2*: 5% sample of Brazilian municipalities outside Roraima with the closest pre-migration average population to Boa Vista. *Synthetic Control 3*: 5% sample of Brazilian municipalities outside Roraima with the closest pre-migration average GDP per capita to Boa Vista.

5.2 Crime

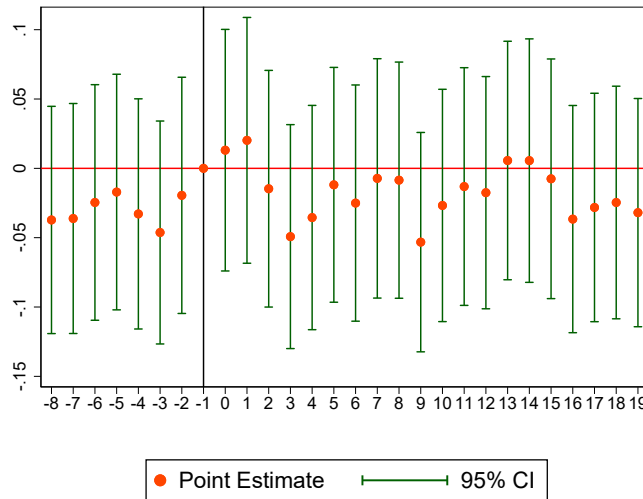
According to the results (see Table 7), shelters had no effect on criminal activity. The estimates are robust to specifications using different sets of fixed effects and are also non-significant when estimating a Poisson regression. Moreover, estimates are small in magnitude, and we can reject changes of more than 5% of the mean. The event study estimates (see Figure 18) also reassures parallel trends.

Table 7: Shelters' Effect on Number of Reported Crimes ($Crime_{jst}$)

	OLS				Poisson
	(1)	(2)	(3)	(4)	(5)
$Treated_j \times Post_t$	0.003 (0.012) [0.003]	0.003 (0.012) [0.003]	0.003 (0.012) [0.003]	0.003 (0.012) [0.003]	-0.038 (0.079) [3.73%]
Mean ($Crime_{jst}$)	0.26	0.26	0.26	0.26	0.32
Observations	92,904	92,904	92,904	92,904	76,342
R-squared	0.059	0.071	0.060	0.072	
<i>Fixed-effects</i>					
Time FE	Y	Y	Y	Y	Y
Grid FE	Y	N	N	N	N
Crime-Type FE	Y	N	Y	N	N
Grid-Crime-Type FE	N	Y	N	Y	Y
Quarter-Grid FE	N	N	Y	Y	Y

Notes: The dependent variable for columns (1) to (4) is the IHS transformation of the number of crimes of type "s" (homicides, robbery, or assault). For column (5), the outcome is the number of crimes of type "s" (homicides, robbery, or assault). Marginal effects on the number of crimes in brackets - for columns (1) to (4) using the transformation on the estimated coefficients suggested by Norton (2022) and for column (5) using $100 \times (e^\beta - 1)\%$. Pseudo R-squared reported for column (5). All models include a constant term. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Figure 18: Shelters' Effect on Total Number of Crimes - Event Study

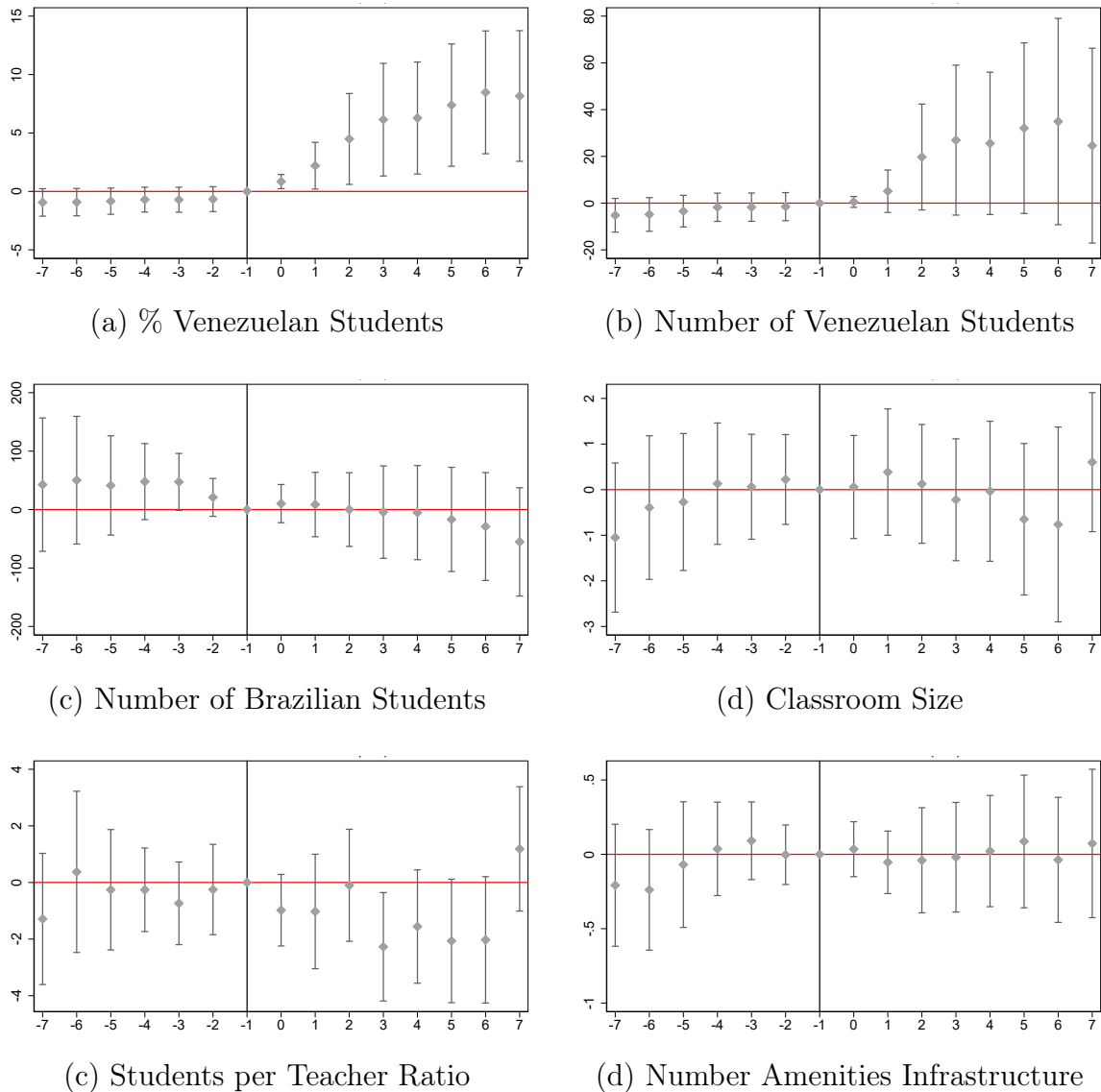


Notes: Event Study based on a "treatment" dummy equal to 1 for a grid with a centroid less than 1 km away from a shelter. The first quarter of 2018 is the baseline period. Estimates from the specification with time and grid-crime-type fixed effects and distance to downtown interacted with time dummies as control.

5.3 Public Education

According to the event study results, proximity to shelters increased the share of Venezuelans in the schools - see Figure 19. However, this composition effect is not followed by a congestion effect; in other words, it doesn't look like the number of students per classroom increased due to shelter proximity. This is also true for other measures of school congestion, such as students per teacher or availability of infrastructure amenities (such as reading rooms, libraries, and labs).

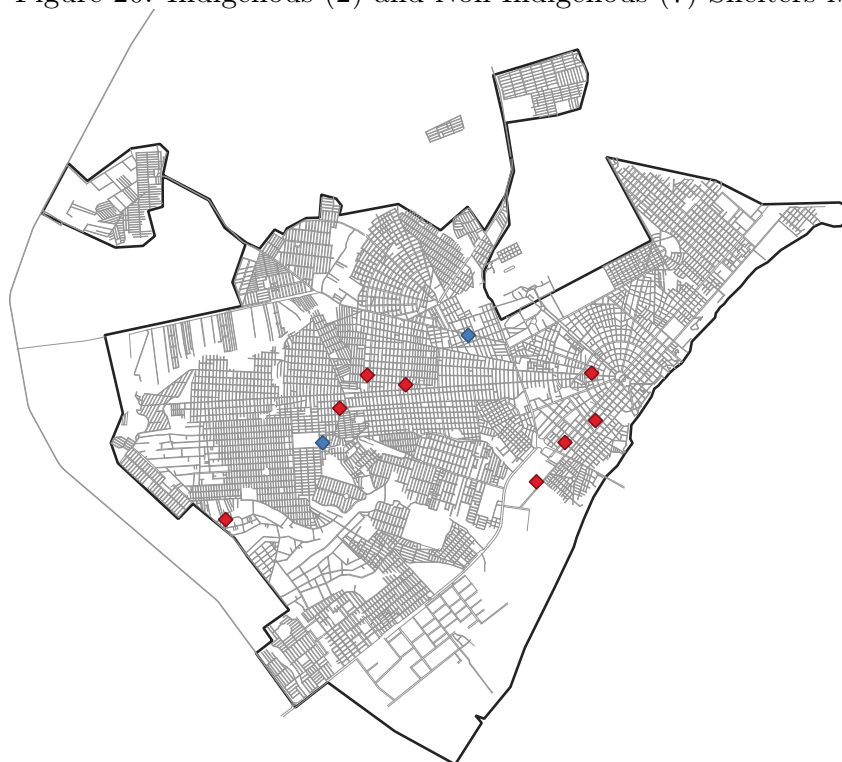
Figure 19: Shelters' Effect on Schools



Notes: Number Amenities Infrastructure = total number of labs, reading rooms, and libraries. Event Study based on a "treatment" dummy equal to 1 for a school less than 1 km away from a shelter. 2016 is the baseline year. The sample consists of all urban public schools in Boa Vista, including kindergarten, nursery schools, and grades 1 to 12.

6 Indigenous Vs Non-Indigenous Shelters

Figure 20: Indigenous (2) and Non-Indigenous (7) Shelters Map



The entrance of Venezuelan Indigenous groups was also registered at Roraima's border. They are from multiple ethnicities with no prior history in Brazil. The Warao, or "people of the water," from the Orinoco River delta in Venezuela, are the main group (more than 60%).²⁵ They relied on fishing, agriculture, and crafts, and mentioned the political and economic crisis and environmental and climate-related reasons (flooding, water contamination, and heavy rains) for leaving their territories in Venezuela.²⁶

Indigenous and non-indigenous Venezuelans were housed in separate shelters due to distinct cultural and population profiles and for logistical reasons - see [UNHCR Fact Sheet report \(2024\)](#). Among the 11 shelters, two are designated exclusively to host Venezuelan Indigenous refugees - see Figure 20. Table 8 describes the main demographic and socio-economic differences between indigenous and non-indigenous shelters using the UNHCR shelter reports for October 2018. Indigenous migrants were

²⁵Other groups include the Taurepang, Pemón, Arekuna, and many more, with over 13 Indigenous ethnicities registered across Brazil - see the "Warao Refugees in Brazil Report" by UNHCR

²⁶For more, see [IOM Report](#).

younger on average, with a larger share of school-age individuals. Moreover, they were less educated, exhibiting an adult illiteracy rate more than five times higher than that of the non-Indigenous sheltered population. The two groups of refugees also present important differences in integration measures. Sheltered Indigenous Venezuelans exhibit lower vaccination rates and possession of documents. The UNHCR also produced a [report](#) describing reported vulnerability points (such as homelessness concentration and cases of child labor) in Boa Vista in June 2018. Indigenous shelters are closer on average to those identified points than non-indigenous ones. 45% of all identified vulnerability points (a total of 26) are within 1 km of a shelter, and 50% of those points are closer than 1 km from an indigenous shelter (even though there are only two indigenous shelters and nine non-indigenous).

Table 8: Differences between hosted refugee population (October 2018):

	Indigenous Shelters	Non-Indigenous Shelters
Hosted Population*	1,236	2,636
Capacity	109%	87%
Share Male	51,5%	52,4%
Share Some College	9,0%	12,7%
Share High School	46,2%	66,3%
Share Less than High-School	28,9%	18,3%
Share Illiterate	15,9%	2,7%
Share Children (0-11 Years Old)	34,2%	29,6%
Share Teenagers (12-17 Years Old)	11,1%	8,9%
Share Male 60+ Years Old	3,0	1,2
Share Male 18-59 Years Old	50,2%	58,2%
Share Female 60+ Years Old	3,2	1,6
Share Female 18-59 Years Old	52,9%	61,4%
Vaccination Rate	24,4%	64%
% Has Social Security Number	35,5%	74,8%
% Has work permit card (18+)	25%	44%
“Vulnerability Points” < 1 Km per Shelter **	3	0.67

Notes: (*) considering all operating shelters. The remaining variables are available for seven out of the eleven shelters (Jardim Floresta, Nova Canaa, Pintolandia, Rondon 1, Rondon 3, São Vicente, and Tancredo Neves). (**) “Vulnerability Points” are: homeless concentrations, reported areas of child labor, or areas with families living in vulnerable situations such as informal housing or overcrowded spaces. *Source:* UNHCR and Federal Emergency Assistance Committee reports for June and October 2018.

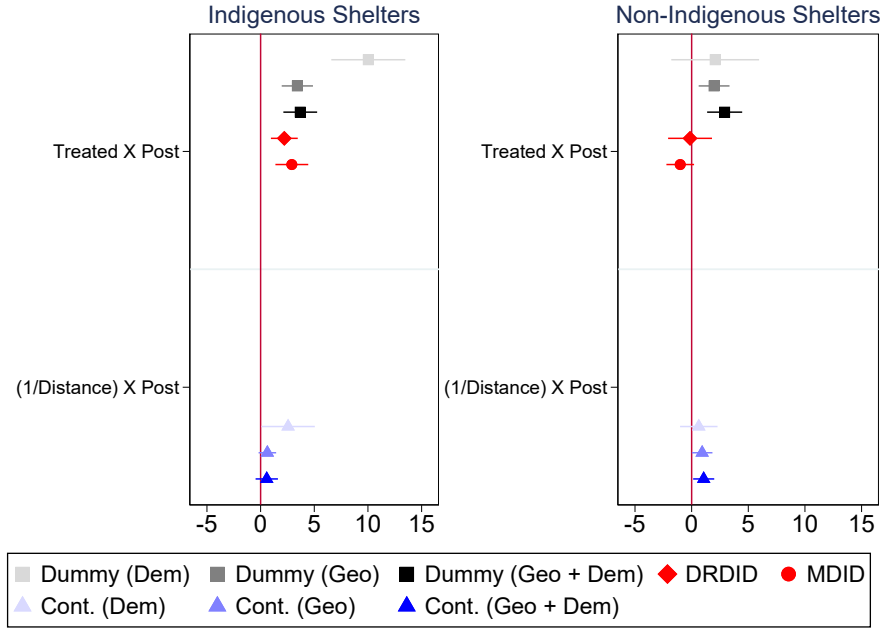
To investigate the heterogeneous shelters’ election effect based on the sheltered population’s ethnicity, I estimate the following specifications, separating the treatment dummy (Treated_j) from equation (1):

$$Y_{ijt} = \beta_1 \text{ Treat-Ind.}_j \times \text{Post}_t + \beta_2 \text{ Treat-Non-Ind.}_j \times \text{Post}_t + \gamma_i + \mu_t + \text{Controls} + \nu_{ijt} \quad (5)$$

$Treated-Ind_j$ and $Treated-Non-Ind_j$ are dummy variables indicating whether polling station "j" is less than 1 kilometer away from the closest indigenous and non-indigenous Venezuelan refugee shelter, respectively.

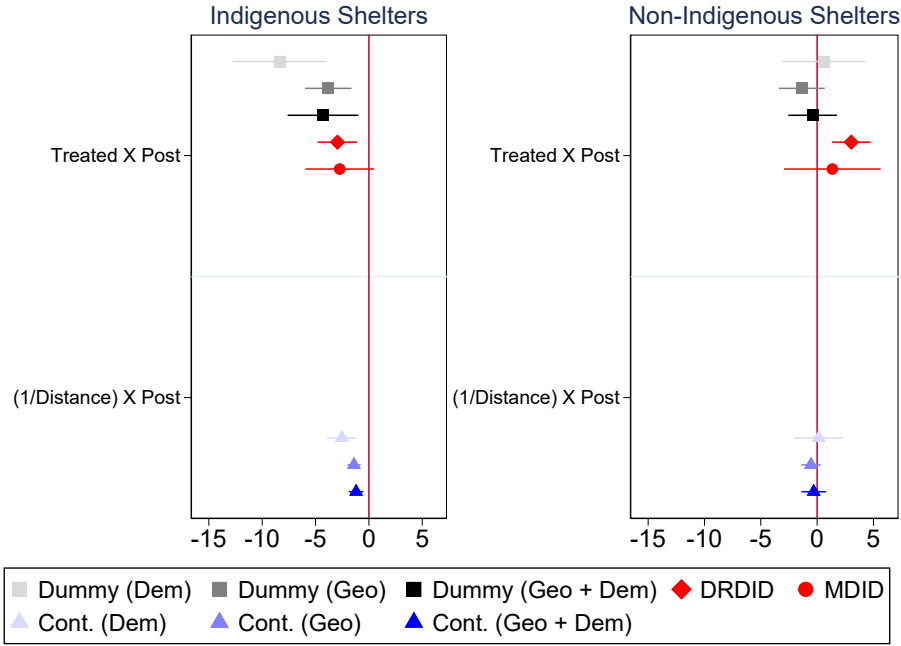
According to the results in Figures 21, 22, and 23, the indigenous shelters are the ones driving the results for both the governor and presidential elections. It highlights that establishing an urban refugee shelter might be less important for political backlash than the cultural, socioeconomic, and integration features of the housed population.

Figure 21: President Election - Challenger



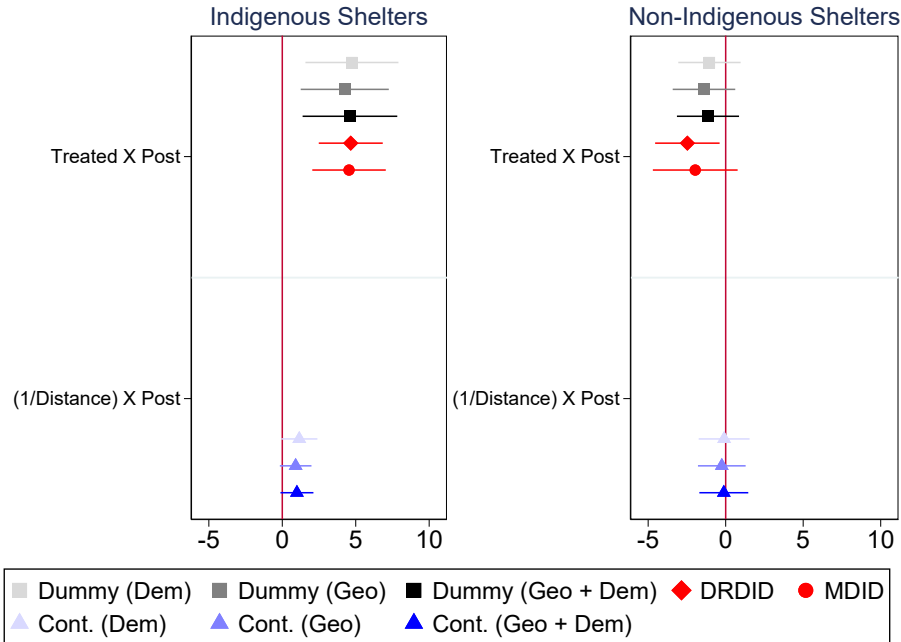
Notes: Dependent Variable = % of valid votes. Dummy = Treatment in the dummy form. Cont. = Treatment in the continuous form. Dem = 23 demographic (age, education, and gender) controls; Geo = time dummies interacted with polling station distance to downtown. DRDID = Doubly Robust DiD. MDID = Matching DiD. Challenger = voting for the party not Left (PT). Given that PT participated in every second round, Challenger = 100 - Left.

Figure 22: Governor Election - Incumbent



Notes: Dependent Variable = % of valid votes. Dummy = Treatment in the dummy form. Cont. = Treatment in the continuous form. Dem = 23 demographic (age, education, and gender) controls; Geo = time dummies interacted with polling station distance to downtown. DRDID = Doubly Robust DiD. MDID = Matching DiD.

Figure 23: Governor Election - Far-Right



Notes: Dependent Variable = % of valid votes. Dummy = Treatment in the dummy form. Cont. = Treatment in the continuous form. Dem = 23 demographic (age, education, and gender) controls; Geo = time dummies interacted with polling station distance to downtown. DRDID = Doubly Robust DiD. MDID = Matching DiD.

Party Affiliation

The results (see Figures 42, 43, and 44 in the Appendix G.2) confirm the null effect of both non-indigenous and indigenous shelters on party affiliation. Therefore, the reception policy's political effects were restricted to voting and didn't trigger a more "extreme" political participation behavior. The event study versions reassuringly present no differential trends before 2018.

Crime

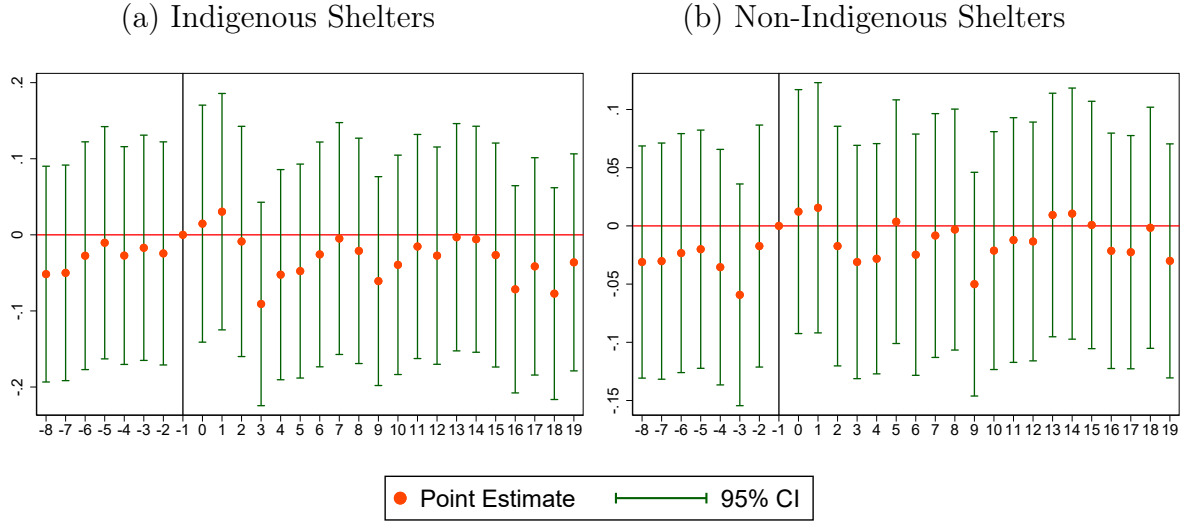
According to the results (see Table 9), neither shelter type affected criminal activity. The estimates are robust to specifications using different sets of fixed effects and are also non-significant when estimating a Poisson regression. The event study version of Equation (1) estimates (see Figure 24) also reassures parallel trends.

Table 9: Shelters' Effect on Number of Reported Crimes ($Crime_{jst}$) - Shelter Type

	OLS				Poisson
	(1)	(2)	(3)	(4)	(5)
Treated (Ind. Shelter) $_j \times Post_t$	-0.012 (0.021) [-0.012]	-0.012 (0.021) [-0.012]	-0.012 (0.021) [-0.013]	-0.012 (0.021) [-0.013]	-0.140 (0.134) [-13.1%]
Treated (Non-Ind. Shelter) $_j \times Post_t$	0.010 (0.014) [0.010]	0.010 (0.014) [0.010]	0.010 (0.014) [0.010]	0.010 (0.014) [0.010]	-0.001 (0.097) [-0.01%]
Mean ($Crime_{jst}$)	0.26	0.26	0.26	0.26	0.32
Observations	92,904	92,904	92,904	92,904	76,342
R-squared	0.059	0.071	0.060	0.072	0.223
<i>Fixed-effects</i>					
Time FE	Y	Y	Y	Y	Y
Grid FE	Y	N	N	N	N
Crime-Type FE	Y	N	Y	N	N
Grid-Crime-Type FE	N	Y	N	Y	Y
Quarter-Grid FE	N	N	Y	Y	Y

Notes: The dependent variable for columns (1) to (4) is the IHS transformation of the number of crimes of type "s" (homicides, robbery, or assault). For column (5), the outcome is the number of crimes of type "s" (homicides, robbery, or assault). Marginal effects on the number of crimes in brackets - for columns (1) to (4) using the transformation on the estimated coefficients suggested by Norton (2022) and for column (5) using $100 \times (e^\beta - 1)\%$. Pseudo R-squared reported for column (5). All models include a constant term. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Figure 24: Shelters' Effect on Total Number of Crimes - Event Study



Notes: Event Study based on a "treatment" dummy equal to 1 for a grid with centroid less than 1 km away from Indigenous or Non-Indigenous shelters. The first quarter of 2018 is the baseline period. Estimates from the specification with time and grid-crime-type fixed effects and distance to downtown interacted with time dummies as control.

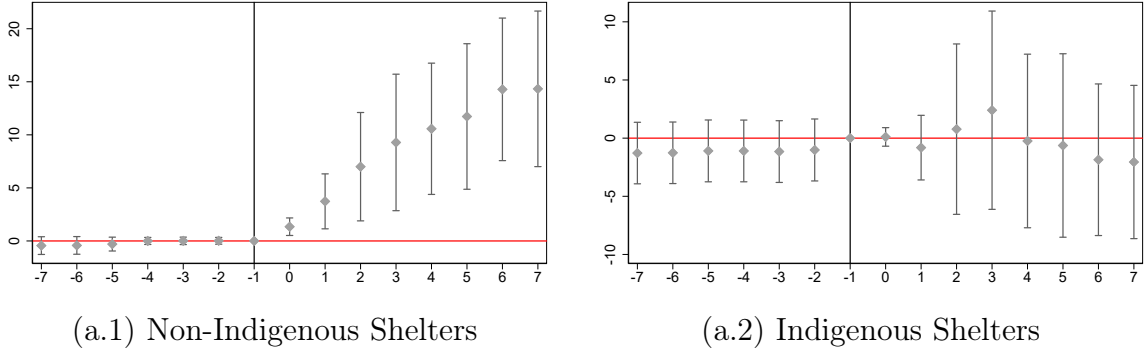
Public Education

The event study estimates from equation (2) for the share of Venezuelan students and classroom sizes are plotted in Figure 26. Despite hosting a larger share of school-age Venezuelans, Indigenous shelters do not affect the surrounding schools' share or number of Venezuelan students. Contrastingly, non-indigenous shelters increased Venezuelan enrollment in schools less than one kilometer away.²⁷ Moreover, neither shelter had an effect on different measures of school congestion or infrastructure: number of students per teacher or number of infrastructure amenities such as libraries and laboratories - see Figures 40, and 41 in the Appendix G.

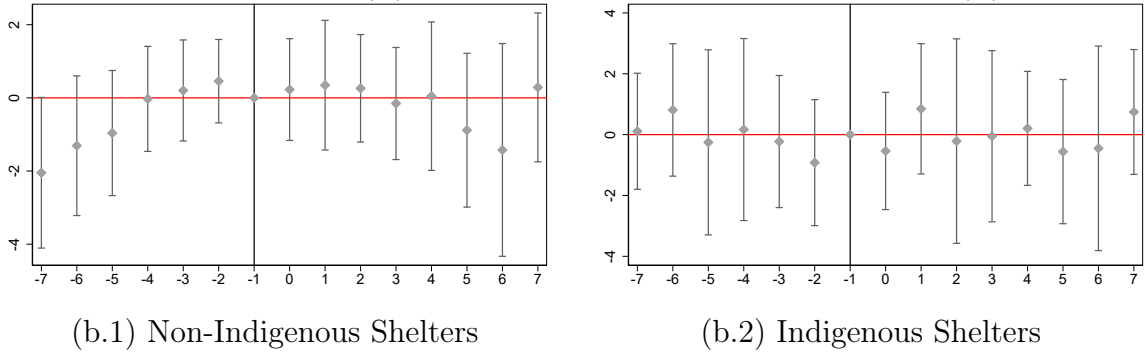
²⁷See Figures 38 and 39 in Appendix G, for results on number of Brazilian and Venezuelan students.

Figure 26: Shelters' Effect on Schools - Shelter Type

(a) % Venezuela Students



(b) Classroom Size



Notes: Event Study based on a "treatment" dummy equal to 1 for a school less than 1 km away from an Indigenous shelter. 2016 is the baseline year. The sample consists of all public schools in Boa Vista, including kindergarten, nursery schools, and grades 1 to 12.

Robustness Checks

First, I explore two alternative data aggregations. First, I aggregate all the outcomes and covariates at the polling station level and adjust the specifications for a panel of polling stations to estimate the results. Second, leveraging the features behind voter allocation, I construct a fake voting district using Voronoi Polygons that partition space into regions based on the nearest polling station.²⁸ The estimates from both polling stations and polygon panels confirm the section-level results for the governor and presidential elections (results not reported in this draft).

I also run the same benchmark specifications using as control only sections in polling stations more than 1.8 km from a shelter (70th percentile of the distance distribution).

²⁸See Appendix J for details.

This group of controls is more likely not to have been treated by the shelters. The results go in the same direction as the main findings - see Figure 58 in Appendix K. However, as expected, the estimates possess larger standard errors given the smaller sample size.

For the type of shelter heterogeneous effect specifications, given that there are only 2 Indigenous shelters compared with nine non-indigenous, I also run the specification using randomly selected two non-indigenous shelters for each observation and obtaining *Treated-Non-Ind_j* and *Dist. Non-Ind_j* based on this random selection - see Figure 60 in Appendix K..

Finally, clustering standard errors at the neighborhood level, weighting the regressions by the section's number of registered voters, or exploring an unbalanced panel of sections, don't change the results - see Figure 59 in Appendix K..

7 Conclusion

Since 2014, over one million Venezuelans have entered Brazil, making the country's northern bordering state of Roraima the center of an unprecedented forced migration inflow. Brazil adopted a local integration model by granting refugees extensive rights and access to public services and opening urban shelters in Roraima's capital. This paper studied how this reception policy, better suited to today's urban and long-term displacement realities, shaped crime, public service congestion (public schools), and, consequently, voting.

I leverage the quasi-random placement of shelters to estimate a Diff-in-Diff comparing areas close to further away from them. First, I don't observe any adverse effect of shelters on public schools' congestion or crime. Looking at election results, I find that natives closer to refugee shelters increased support for the far-right for both the governor and presidential elections, and penalized the incumbent governor who participated in the reception efforts. The results cannot be explained by changes in voters' composition or election logistics. Moreover, estimates are robust to different specifications and definitions of treatment.

Using a synthetic control, I verified that the city's overall far-right voting mirrored that observed in other municipalities not affected by the migration flow. Therefore,

the effects of shelters were not strong enough to produce a citywide rise in populist far-right voting, and the nuances observed would not have been captured using aggregated data. Moreover, it confirms that shelters' location captures the relevant variation in exposure to migrants.

Importantly, the results are largely driven by shelters hosting Indigenous Venezuelans. According to UNHCR reports and public school enrollment data, Indigenous refugees are an especially vulnerable and low-integrated subgroup of the refugee population. The salience of refugees' presence and locals' exposure to poverty and vulnerability, such as children outside school, child labor, and homelessness, can be behind the effects. Therefore, ethnic-specific contact triggered political backlash even when we don't observe worsening crime and public goods congestion.

These findings suggest that political reactions to refugee reception can be highly localized and that establishing a refugee shelter might be less important for political backlash than the cultural features of who is housed. Finally, this paper's results also document a trade-off to tailored or culturally specific reception strategies: while they can address the particular needs of certain groups, depending on their logistics, they can also enhance perceived social distance and trigger stronger locals' reactions.

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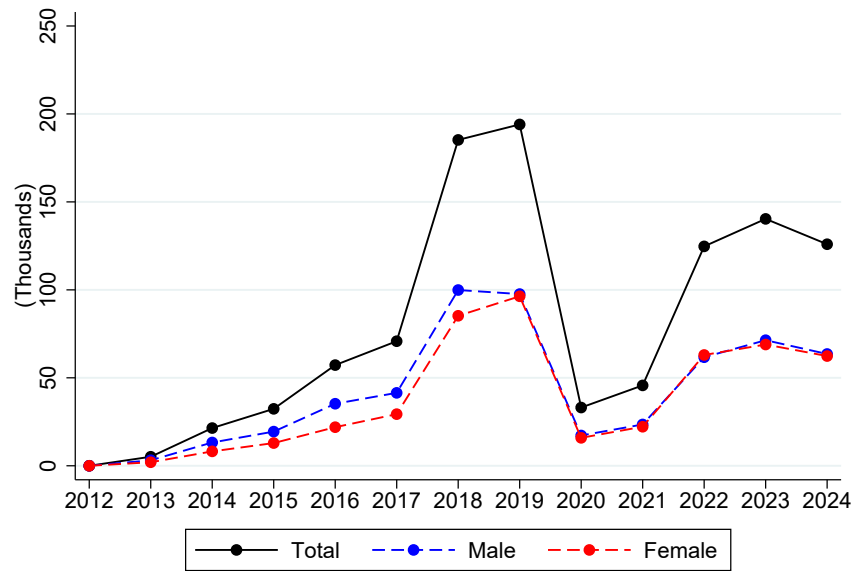
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Appendix

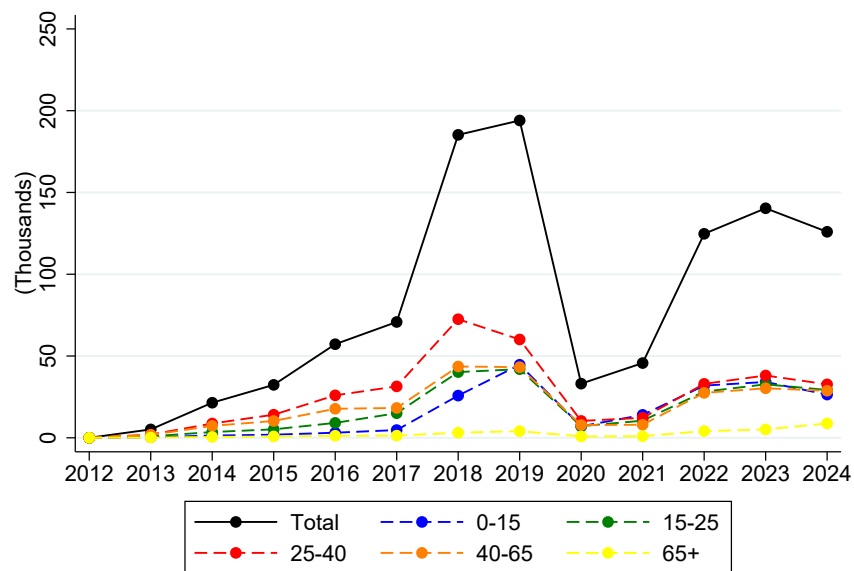
A Venezuelan Refugee Flow

Figure 27: Venezuelan Entrance Flows to Roraima



Source: Sistema de Tráfico Internacional (STI).

Figure 28: Venezuelan Entrance Flows to Roraima



Source: Sistema de Tráfico Internacional (STI).

Figure 29: Sheltered Refugees Vs Roraima's Population - Age

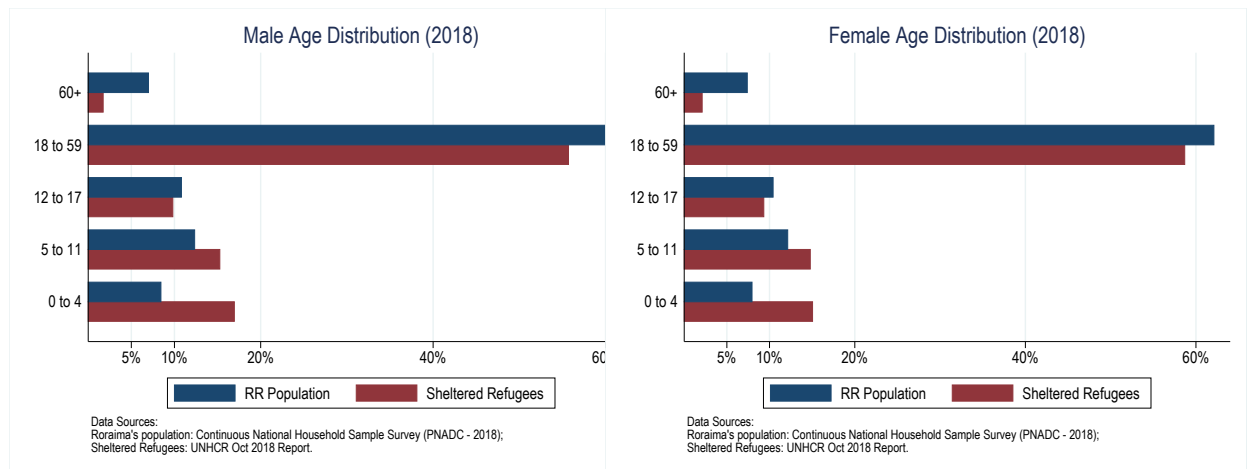


Figure 30: Sheltered Refugees Vs Roraima's Population - Education

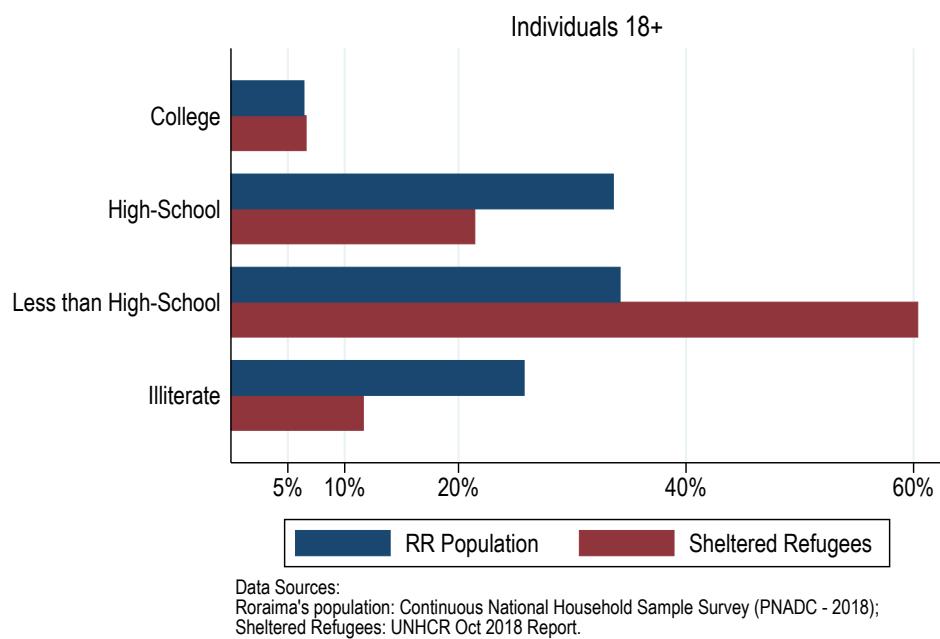
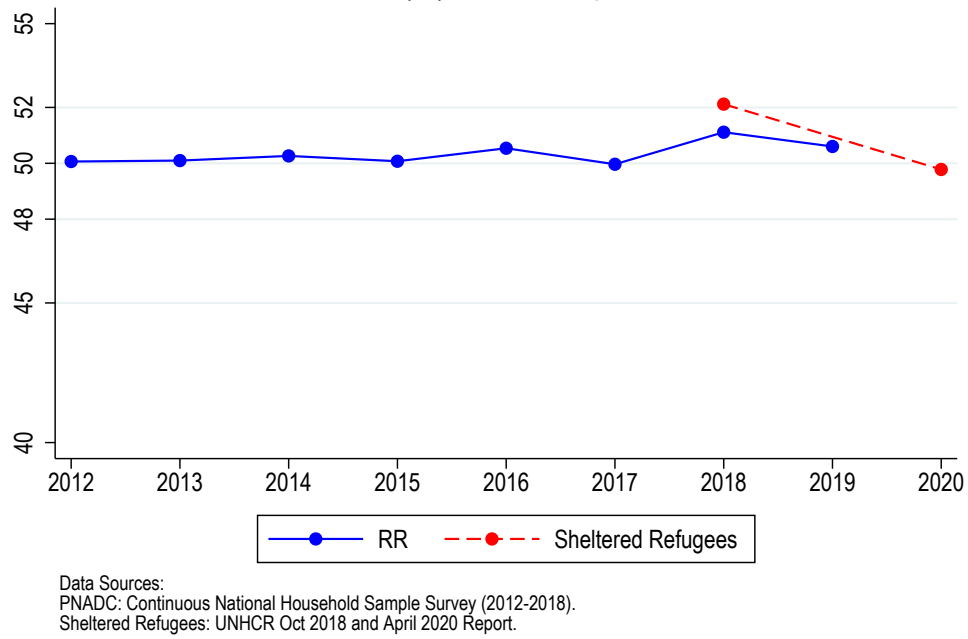


Figure 31: Sheltered Refugees Vs Roraima's Population - Gender (% Male)



B Reception Policy Details

Figure 32: “Operação Acolhida” Annual Budget (Millions R\$)

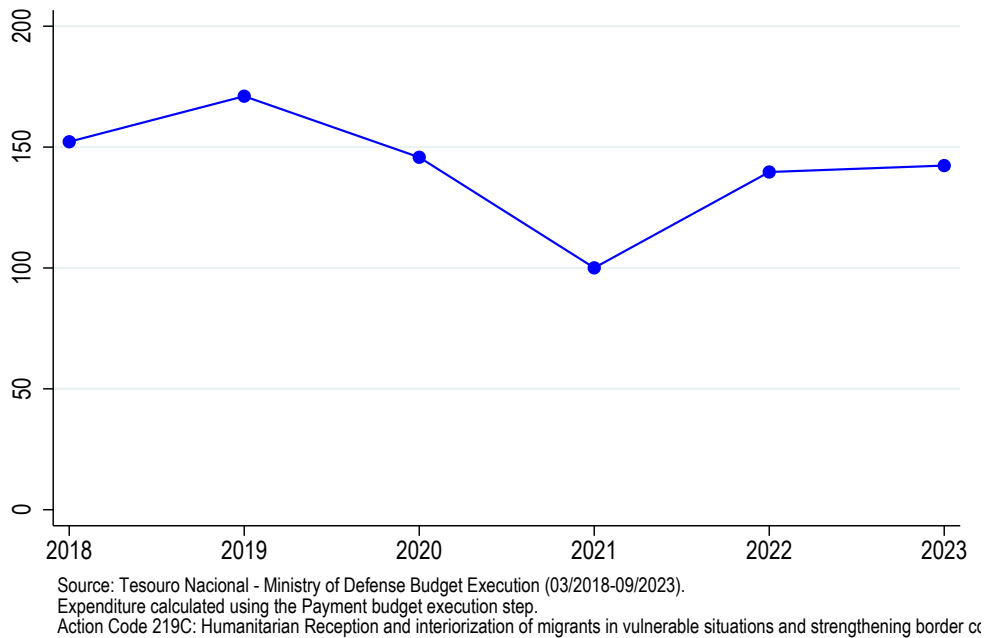


Table 10: Shelters Statistics

Name	Opening Date	Capacity (September or October 2018)	Sheltered Population (September or October 2018)	Capacity (August 2020)	Sheltered Population (September 2020)	Average Length of Stay - days (September 2020)
Pintolândia	March 2018	448	754	640	536	470
Tancredo Neves	March 2018	232	324	280	217	270
Hélio Campos	December 2017	no info	252*	closed	closed	closed
Jardim Floresta	March 2018	594	693	550	368	293
São Vicente	April 2018	378	353	300	251	270
Nova Canaã	April 2018	390	436	350	235	265
Rondon 1	July 2018	600	715	810	559	240
Latife Salomão	April 2018	no info	514*	300	195	248
Santa Tereza	May 2018	no info	531*	320	255	191
Rondon 2	September 2018	no info	453*	645	340	223
Rondon 3	October 2018	1086*	344*	1386	844	245
São Vicente 2	July 2019	did not exist	did not exist	250	110	177

Notes: (*) data not available in UNHCR reports, so obtained from "Operação Acolhida" meeting minutes. The average length of stay is not available for 2018.

C Political Background

Figure 33: Timeline Brazil's Presidents

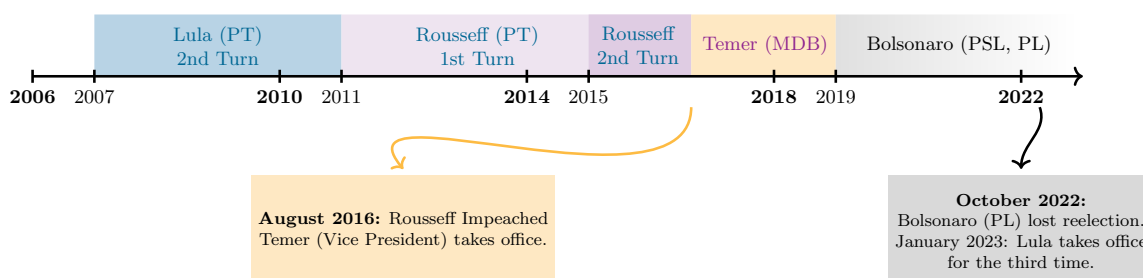
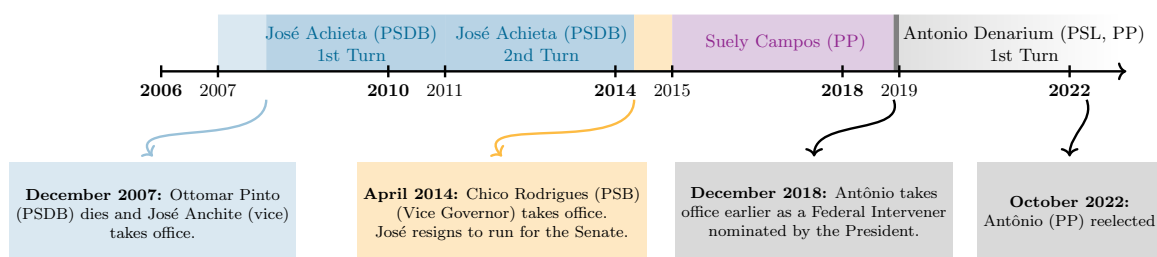


Figure 34: Timeline RR's Government



The relationship between the state and federal government was not only characterized by partnerships and cooperation. Suely (2018 incumbent governor) claimed during the 2018 campaign that the federal government's response to the Venezuelan flow in

Roraima was late and insufficient. Moreover, while Suely wanted to close the border to prevent the entrance of more Venezuelans (she even appealed to the Supreme Court), the President refused to do so, arguing it would violate humanitarian reception principles.²⁹ Finally, two months before the election, Suely also published an unconstitutional act trying to enhance deportation enforcement and to introduce a passport possession requirement for Venezuelans to access non-emergency public services.³⁰

During 2018, Roraima also suffered from a financial crisis and a surge in crime. The prison system was especially vulnerable (overcrowded and under-staffed) and mass escapes and riots were registered in 2018.³¹ During the campaign, Suely claimed the former Governor's poor financial management, the unprecedented refugee flow, and the absence of federal government assistance created "the most challenging environment a Roraima's governor ever faced".

D Electoral Outcomes

Table 11: Governor Election - Parties Classification

	2022	2018	2014	2010	2006
Incumbent		PP	PP	PP	PSDB
Far-Right	PP	PSL	PSB	-	-
Anchieta		PSDB	PSB	PSDB	PSDB

Table 12: President Election - Parties Classification

	2022	2018	2014	2010	2006
Incumbent	-	-	-	-	-
Far-Right	PL	PSL	PSB	-	PSL
Left	PT	PT	PT	PT	PT

E Latitude and Longitude of Polling Stations

[Hidalgo's code output](#) contains a polling station panel ID, the coordinates from different data sources, and also provides a predicted coordinate (useful when coordinates

²⁹ *"Governor of Roraima asks to close Brazil's border with Venezuela"*

³⁰ *"Government of Roraima signs decree that tightens foreigners access to public services"*

³¹ *"Roraima's prison system in crisis will be taken over by the federal government"*

from TSE are not available) based on a model using the TSE data as a benchmark. It also provides a predicted distance (in Km) between the chosen longitude, latitude, and "true" benchmark longitude and latitude. The following procedures were followed to use and check this data:

1. I kept only observations for Boa Vista (Roraima) municipality.
2. I used the location provided by the TSE available only for 2018 and 2020 for a given panel ID to complete the location information for the previous elections (2006 to 2016). This completed 84.68% of all pooling station-year observations. The remaining 15.32% of the sample are mostly polling stations that didn't exist anymore in 2018 and 2020.
3. I used Hidalgo's predicted location for this 15.32% of the polling station-year sample. It's predicted location searches for the address and name of the polling station in different administrative data, such as the Census and the list of public schools' locations.
4. However, some pooling stations (3.26% of the entire pooling station-year sample) end up presenting different predicted locations depending on the year. This could be because of polling stations' relocation, some error in Hidalgo's panel ID, or different data availability for different years. In those cases, I used the predicted location with the smaller predicted error (therefore, I ignored any potential relocation of polling stations).
5. Then I checked that different polling stations presented different locations. This was the case, as expected, for more than 93% of the sample, however, 6.95% of the sample consisted of different polling stations that shared the same latitude and longitude. This can be explained either by an error in Hidalgo's panel ID or because some geographic coordinate data sources were at a higher geographic level (such as at the census tract level). Therefore, in this case, I searched the address manually using Google Maps and obtained the latitude and longitude.
6. TSE provides two polling station identifiers. However, they do not work as a proper panel ID, given that they can be reused in case a polling station is

destroyed or moved. However, I can use this TSE "quasi-panel ID" to check Hidalgo's panel ID (i.e., no polling stations with different IDs that are the same). This exercise raised an alert for 12.32% of the sample. Among those, 100 observations (8.80% of the sample) were from panel stations that should have the same ID. This occurred mainly because, for some years, addresses were written in different ways (the polling station was at a corner, and each year a different street was used for its address, or the name of the street changed). For this 8.80% of the sample, the coordinate chosen follows the following priority TSE, Google Maps, and Hidalgo Predicted.

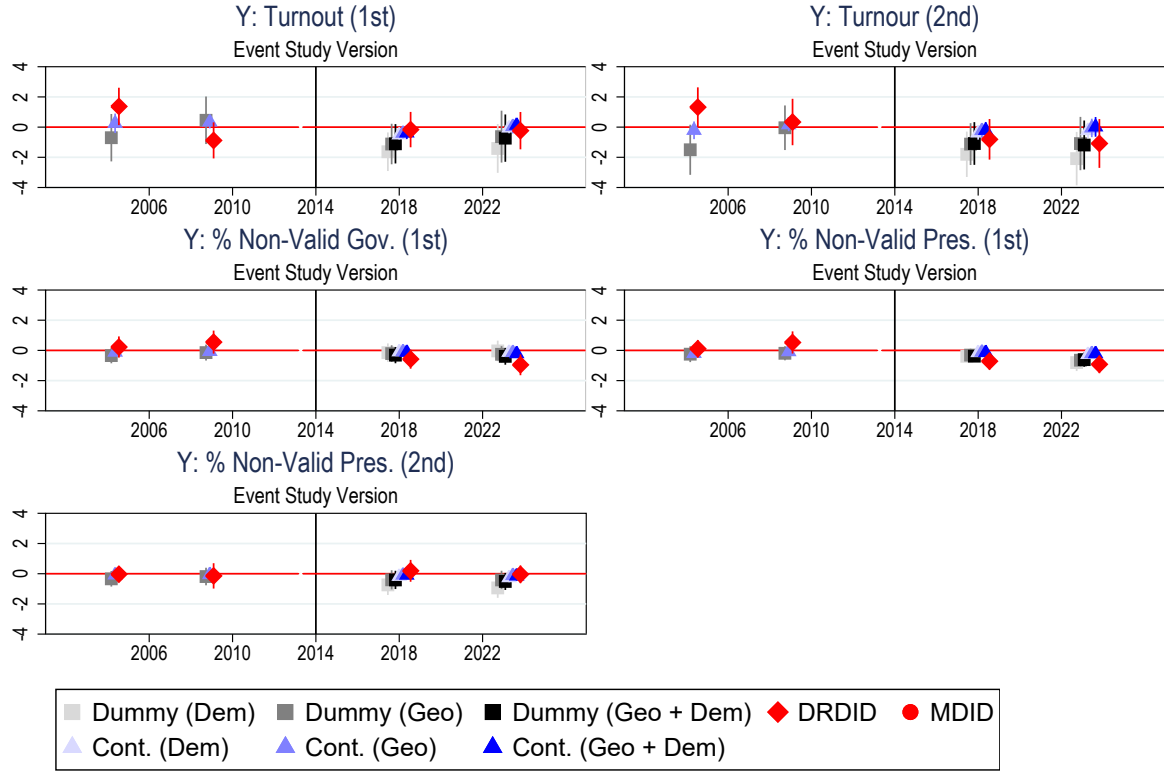
See Table 13 below for the final description of the polling stations' geographic coordinates data source.

Table 13: Polling Stations' Geographic Coordinates Data Source

Geo. Coordinate Data Source	% Sample	% Polling Stations
TSE (Supreme Court for Elections)	87.32%	76.63%
Google Maps	6.60%	10.33%
Hidalgo Predicted	5.28%	11.42%
No Latitude/Longitude	0.79%	1.63%

F Main Results

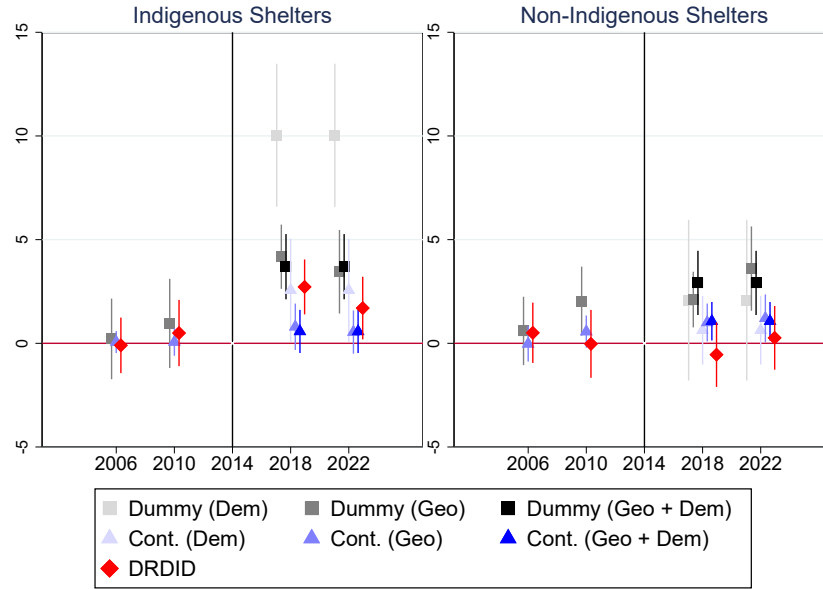
Figure 35: Turnout and Non-Valid Votes - Event Study



Notes: 2014 is the baseline year. Dependent Variable = % of valid votes for each category/candidate. *Dem* = 23 demographic (age, education, and gender) controls; *Geo* = time dummies interacted with polling station distance to downtown. DRDID = Doubly Robust DiD. MDID = Matching DiD.

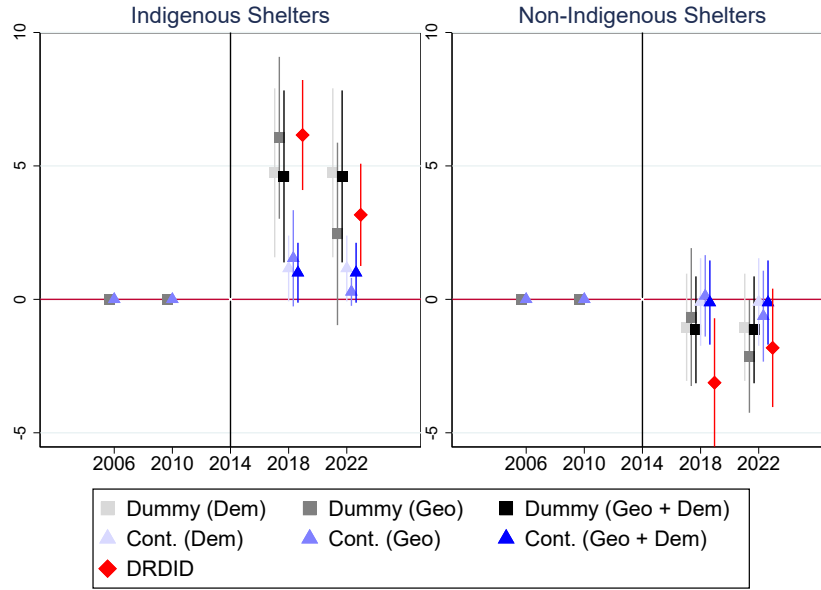
G Indigenous Vs Non-Indigenous Shelters Results

Figure 36: President Election (Challenger) Event Study - Indigenous Vs Non-Indigenous



Notes: 2014 is the baseline year. Dependent Variable = % of valid votes. *Dem* = 23 demographic (age, education, and gender) controls; *Geo* = time dummies interacted with polling station distance to downtown. DRDID = Doubly Robust DiD. MDID = Matching DiD.

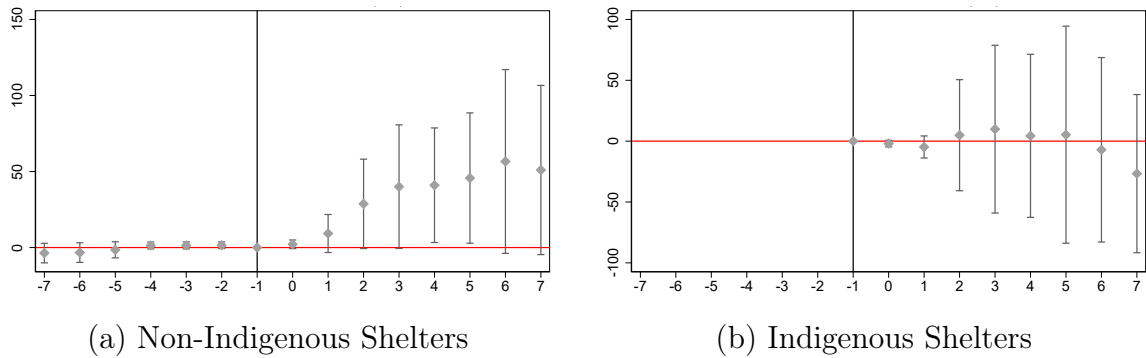
Figure 37: Governor Election (Far-Right) Event Study - Indigenous Vs Non-Indigenous



Notes: 2014 is the baseline year. PSL did not participate or support any candidate in the 2006 and 2010 state elections. Dependent Variable = % of valid votes. *Dem* = 23 demographic (age, education, and gender) controls; *Geo* = time dummies interacted with polling station distance to downtown. DRDID = Doubly Robust DiD. MDID = Matching DiD.

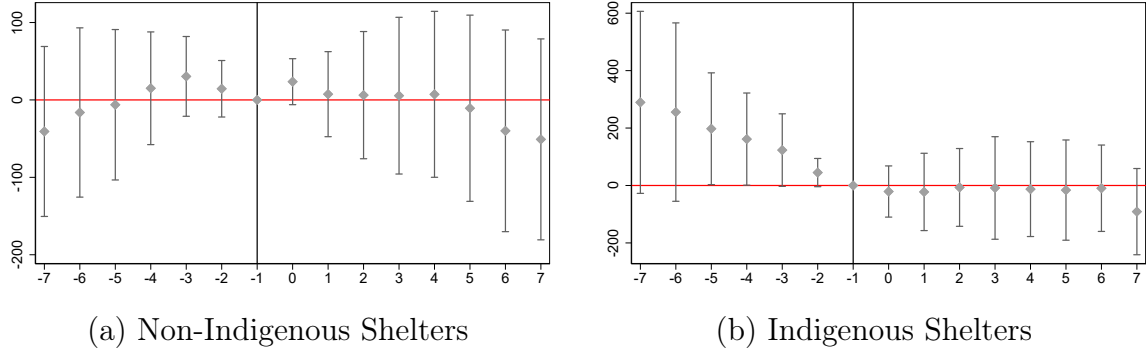
G.1 Public Education

Figure 38: Shelters' Effect on Schools' Composition - Number of Venezuelan Students



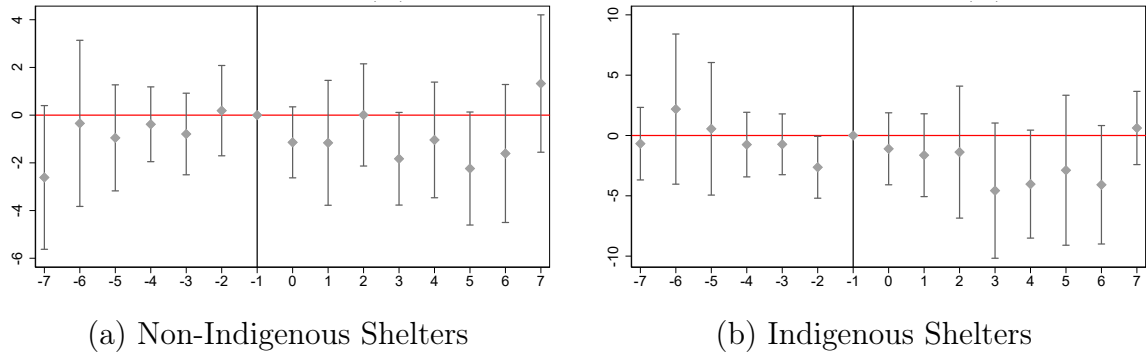
Notes: Event Study based on a "treatment" dummy equal to 1 for a school less than 1 km away from an Indigenous shelter. 2016 is the baseline year. The sample consists of all public schools in Boa Vista, including kindergarten, nursery schools, and grades 1 to 12.

Figure 39: Shelters' Effect on **Schools' Composition - Number of Brazilian Students**



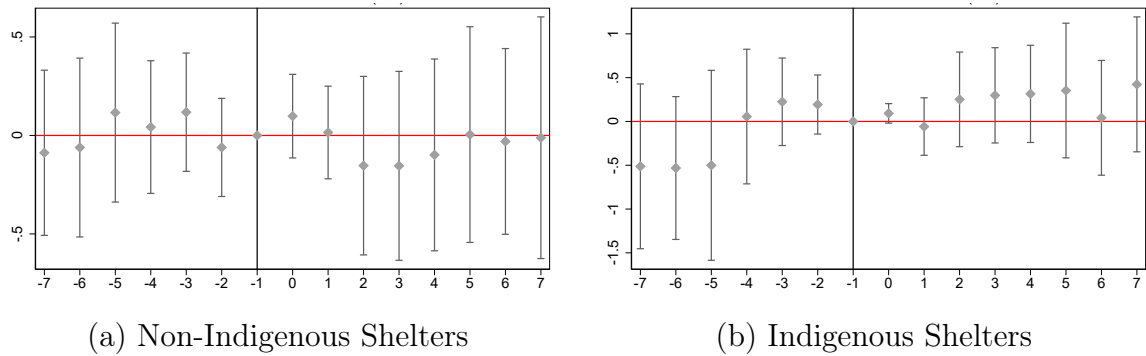
Notes: Event Study based on a "treatment" dummy equal to 1 for a school less than 1 km away from an Indigenous shelter. 2016 is the baseline year. The sample consists of all public schools in Boa Vista, including kindergarten, nursery schools, and grades 1 to 12.

Figure 40: Shelters' Effect on **Schools' Congestion - Students per Teacher**



Notes: Event Study based on a "treatment" dummy equal to 1 for a school less than 1 km away from an Indigenous shelter. 2016 is the baseline year. The sample consists of all public schools in Boa Vista, including kindergarten, nursery schools, and grades 1 to 12.

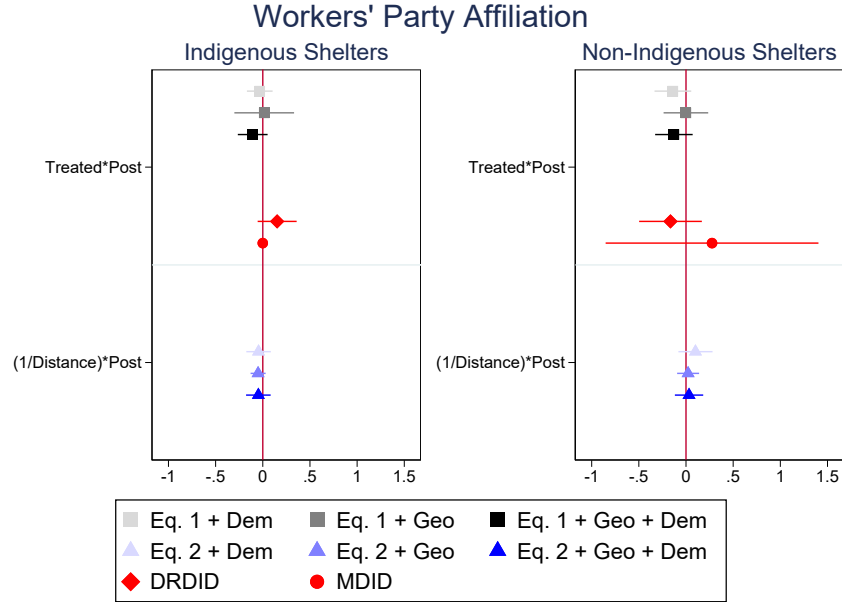
Figure 41: Shelters' Effect on Schools' **Infrastructure (number of reading rooms, libraries, labs)**



Notes: Event Study based on a "treatment" dummy equal to 1 for a school less than 1 km away from an Indigenous shelter. 2016 is the baseline year. The sample consists of all public schools in Boa Vista, including kindergarten, nursery schools, and grades 1 to 12.

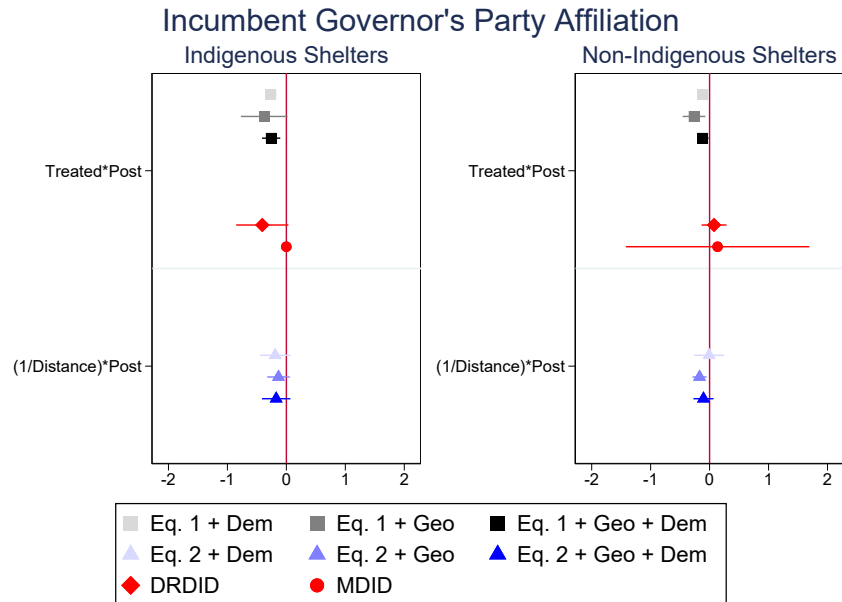
G.2 Party Affiliation

Figure 42: Party Affiliation Results



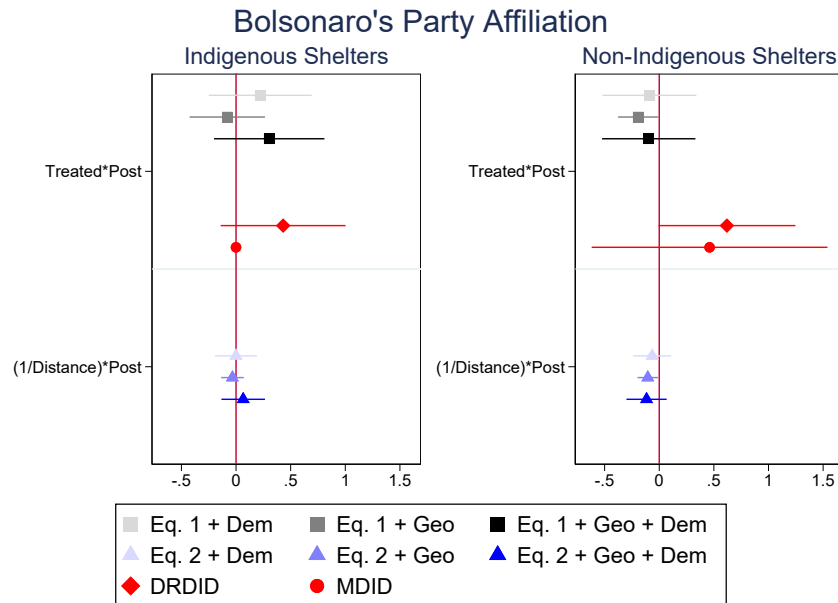
Notes: Dependent Variable = $\ln$ transformation of the number of affiliates. Dem = 23 demographic (age, education, and gender) controls; Geo = time dummies interacted with polling station distance to downtown. DRDID = Doubly Robust DiD. MDID = Matching DiD.

Figure 43: Party Affiliation Results



Notes: Dependent Variable = $\ln$ transformation of the number of affiliates. Dem = 23 demographic (age, education, and gender) controls; Geo = time dummies interacted with polling station distance to downtown. DRDID = Doubly Robust DiD. MDID = Matching DiD.

Figure 44: Party Affiliation Results



Notes: Dependent Variable = $\ln$ transformation of the number of affiliates. Dem = 23 demographic (age, education, and gender) controls; Geo = time dummies interacted with polling station distance to downtown. DRDID = Doubly Robust DiD. MDID = Matching DiD.

Figure 45: Number of New Affiliates (All Parties) - Boa Vista

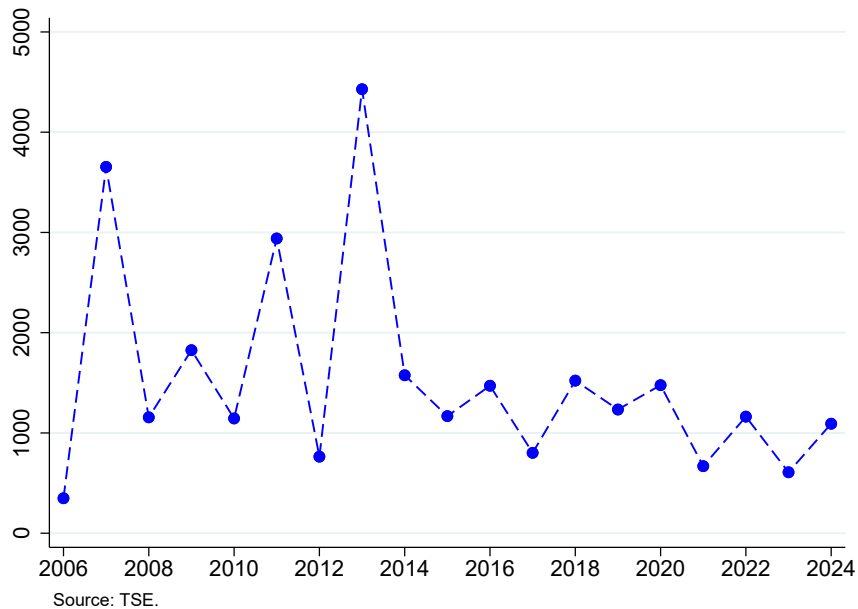


Figure 46: Incumbent Governor Party - IHS(Number of Affiliates)

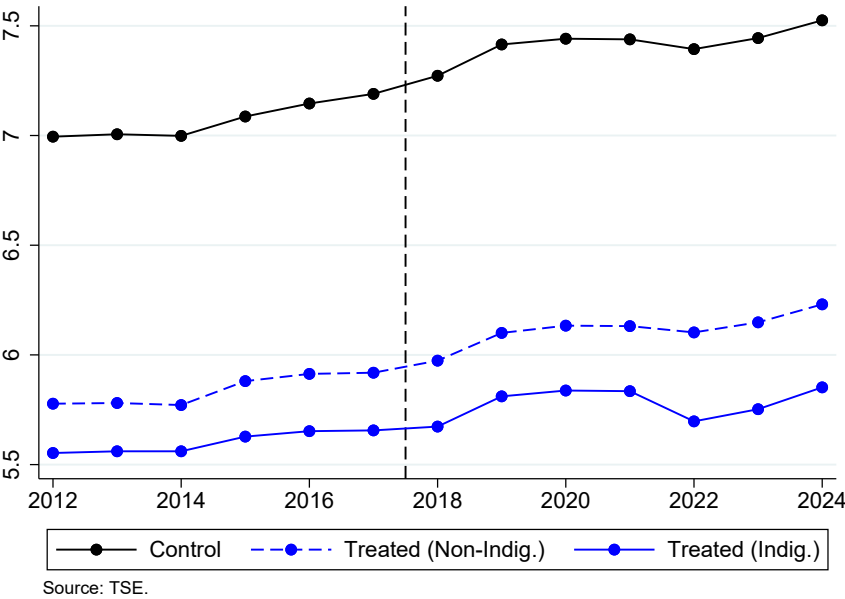


Figure 47: Workers' Party - IHS(Number of Affiliates)

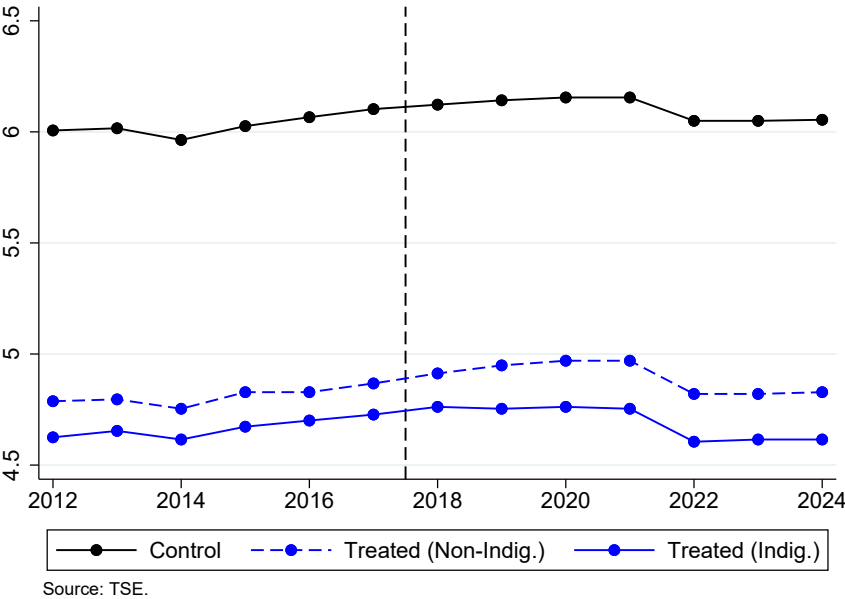
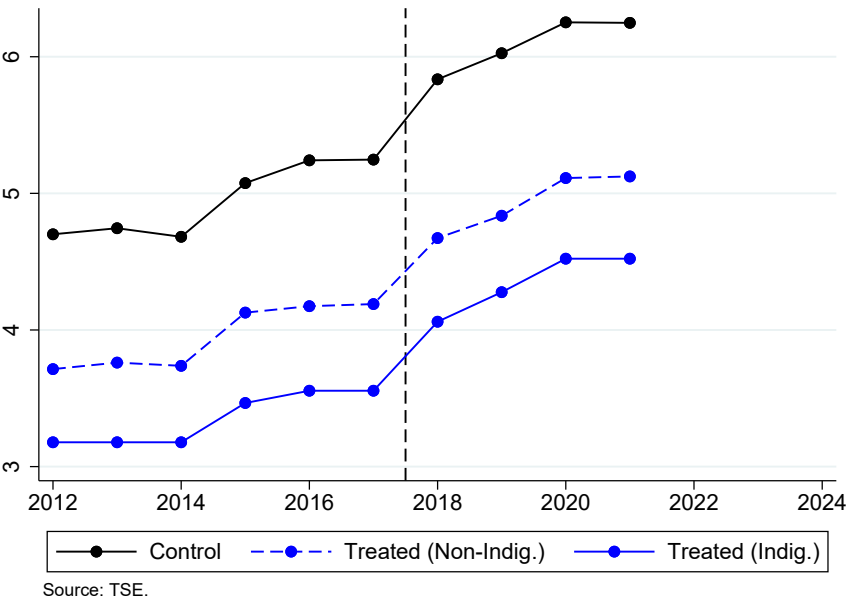
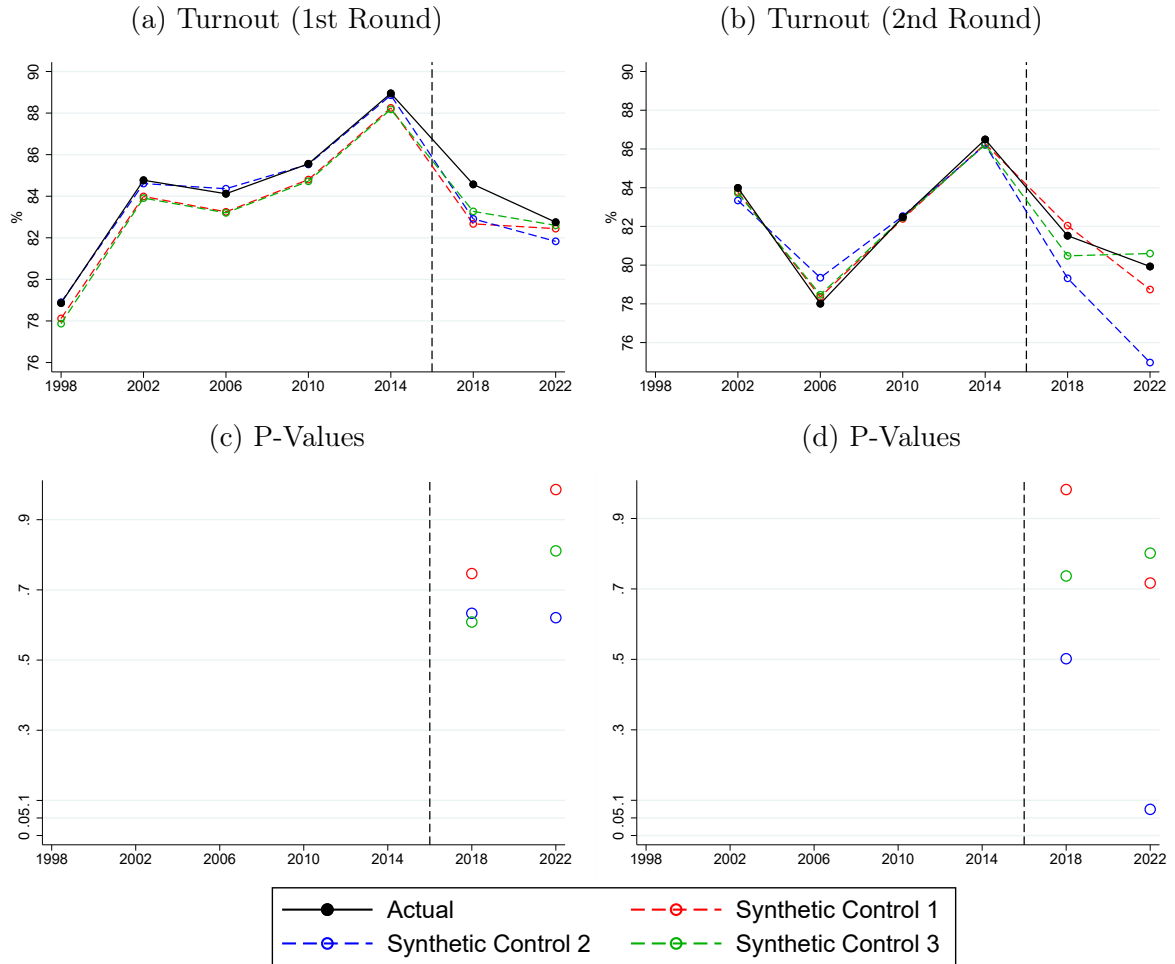


Figure 48: Bolsonaro’s Party - IHS(Number of Affiliates)



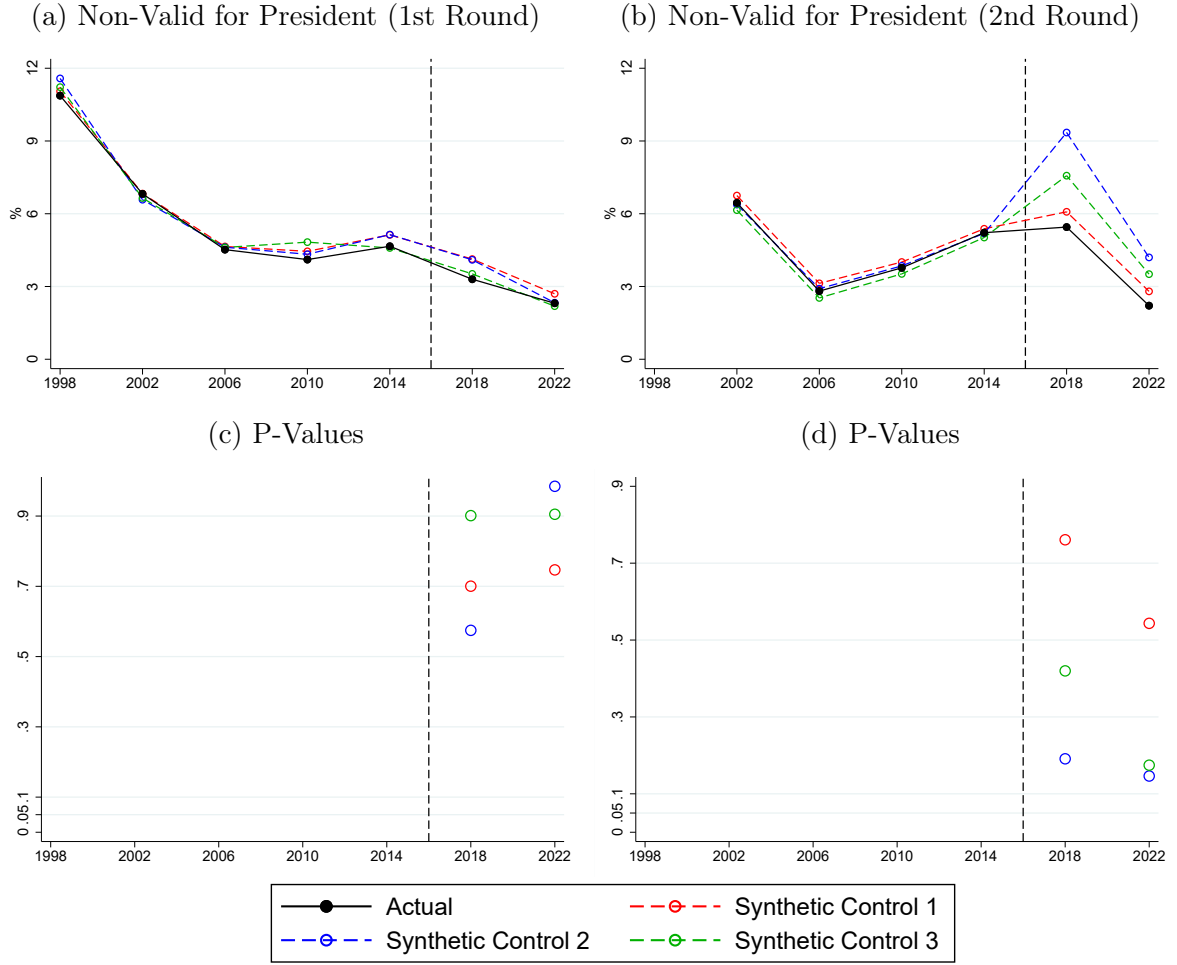
H Synthetic Control

Figure 49: Overall Effect of Reception Policy



Notes: *Synthetic Control 1*: random 5% sample of Brazilian municipalities outside Roraima. *Synthetic Control 2*: 5% sample of Brazilian municipalities outside Roraima with the closest pre-migration average population to Boa Vista. *Synthetic Control 3*: 5% sample of Brazilian municipalities outside Roraima with the closest pre-migration average GDP per capita to Boa Vista.

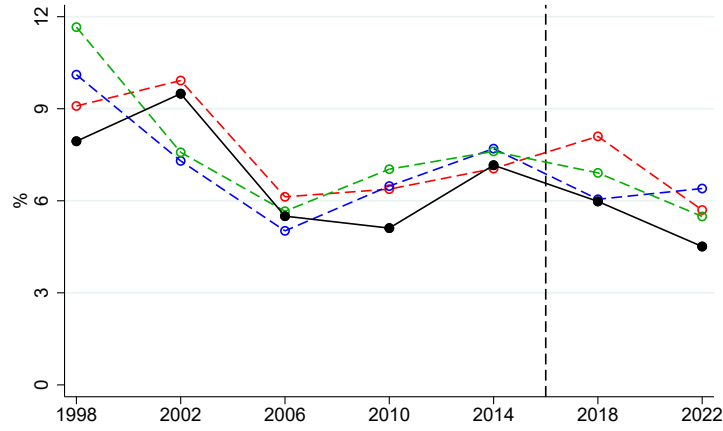
Figure 50: Overall Effect of Reception Policy



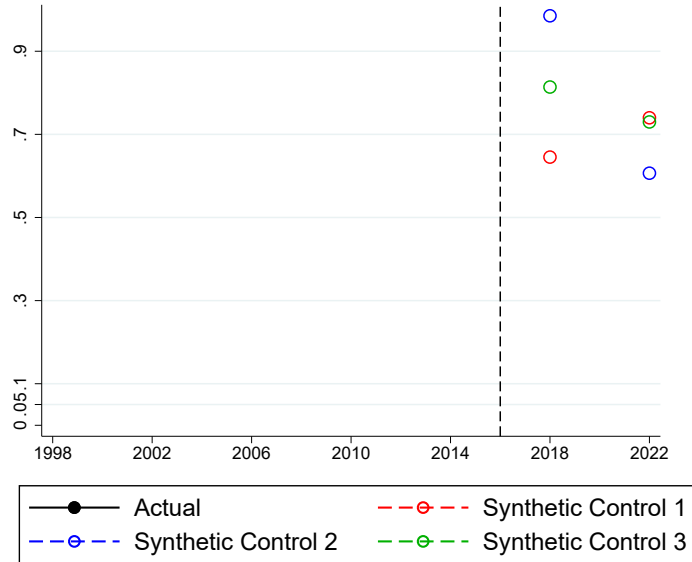
Notes: *Synthetic Control 1*: random 5% sample of Brazilian municipalities outside Roraima. *Synthetic Control 2*: 5% sample of Brazilian municipalities outside Roraima with the closest pre-migration average population to Boa Vista. *Synthetic Control 3*: 5% sample of Brazilian municipalities outside Roraima with the closest pre-migration average GDP per capita to Boa Vista.

Figure 51: Overall Effect of Reception Policy

(a) Non-Valid for Governor (1st Round)



(b) P-Values



Notes: *Synthetic Control 1*: random 5% sample of Brazilian municipalities outside Roraima. *Synthetic Control 2*: 5% sample of Brazilian municipalities outside Roraima with the closest pre-migration average population to Boa Vista. *Synthetic Control 3*: 5% sample of Brazilian municipalities outside Roraima with the closest pre-migration average GDP per capita to Boa Vista.

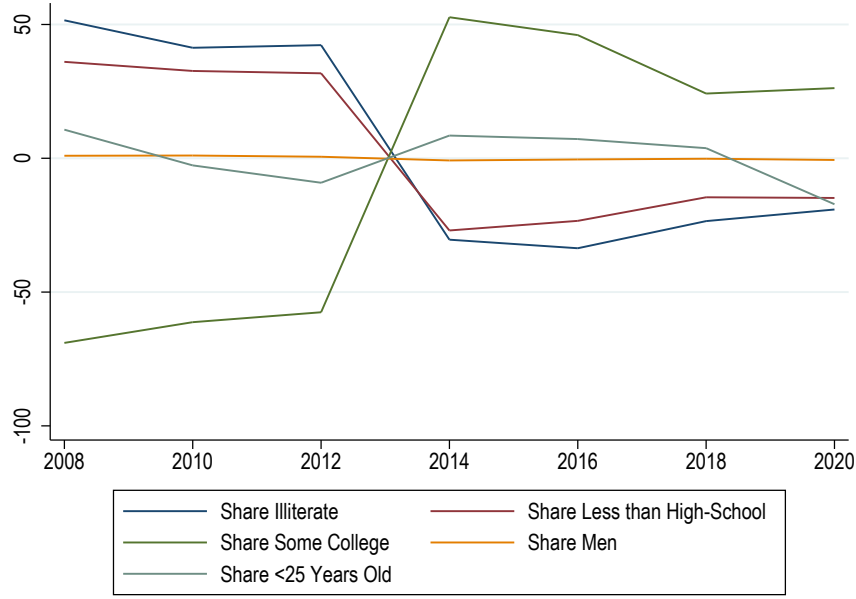
I Fingerprint scan and Voters' Demographic Info

In this appendix section, I investigate how voter fingerprint registration altered the quality of voters' demographic variables. First, I calculated the following yearly index to verify how big the update in voters' demographic variables was after the 2013 fingerprint requirement that made all voters come back to the offices.

$$ID_t = \frac{1}{N} \sum_{i=1}^N 100 \times \frac{(y_{ijt} - \bar{y}_{ij})}{\bar{y}_{ij}}$$

$\bar{y}_{ij}$ is the average across elections (2008 to 2020) of outcome y for section "i" ($\frac{\sum_t y_{ijt}}{T}$). Therefore, ID_t represents the average sections' percentage deviation from their 2008-2020 average.

Figure 52: ID_t for different variables



As we can see from Figure 52, ID_t associated with education variables are consistently above zero before 2013 and negative after. Therefore, educational information seems to have presented important updates after 2013 in the direction of more education. We don't observe this pattern for age or gender info. This could be because gender and age information don't require constant updates from the voters; on the other hand, education can change (upgrade) over time. Given that voters are registering when they are 18 years old, potential late high-school degree acquisition and college attendance were not being captured for a considerable proportion of the voter population.

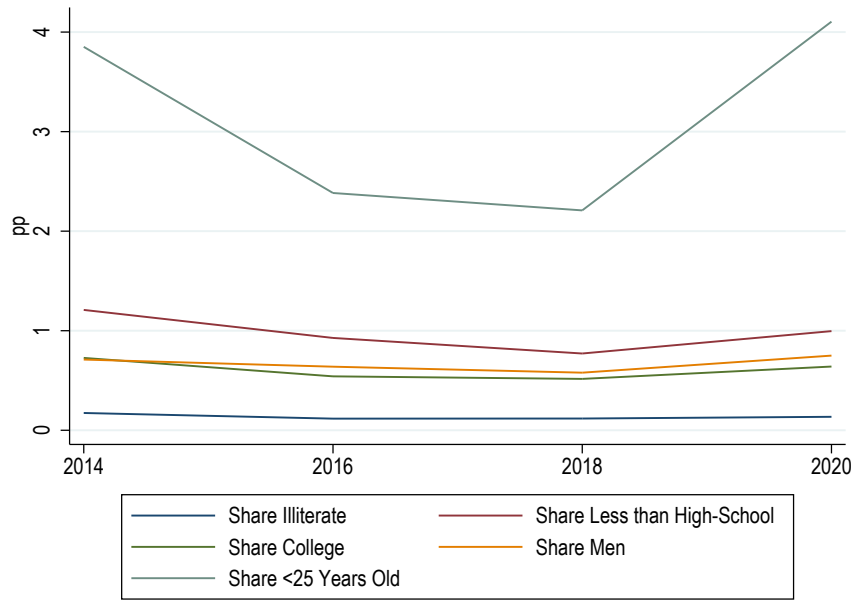
To show that after 2013 the voters' characteristics in each section were stable, i.e. people were not moving between sections or polling stations over elections, and there is an inertia in section assignment (as described by the electoral code), I calculated

the following yearly index for $t > 2013$:

$$IA_t = \frac{1}{N} \sum_{i=1}^N |y_{ijt} - \bar{y}_{ij}|$$

$\bar{y}_{ij}$ is the average across elections (2014 to 2020) of outcome y for section " i " ($\frac{\sum_t y_{ijt}}{T}$). Given that all outcomes are a share (0 to 100) the IA can be interpreted as a percentage point absolute sections' average deviation.

Figure 53: IA_t for different variables



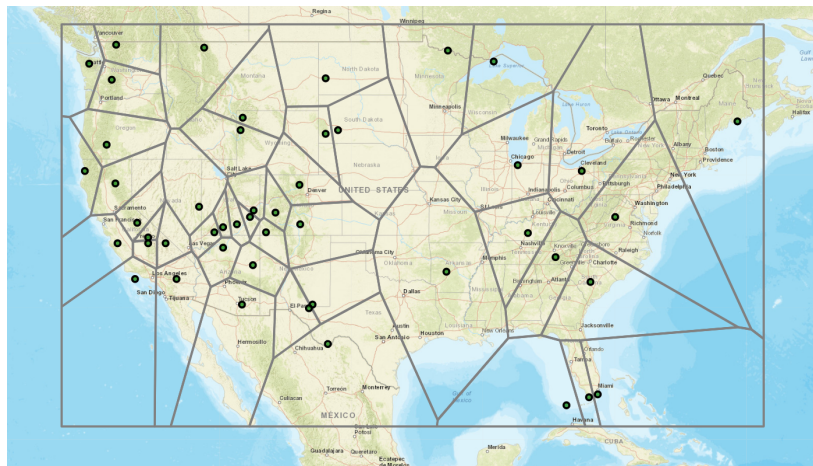
According to Figure 53, voter demographic information is stable and suffers minor deviations across elections. This goes in the direction of the National Electoral Code stating that voters will be permanently linked to their original section unless of some specific exceptions.

J Voronoi Polygons Panel

Given the desirable electoral code features, designing areas that mimic a voting district is possible. Considering that distance is an important factor during the assignment of polling stations, I will explore Voronoi Polygons (described next) to obtain "fake" voting districts for Boa Vista's urban area for robustness.

Voronoi Polygons are great at dividing the space based on the distance to reference points. The Polygon created around a certain reference point indicates that all individuals living within the Polygon "i" are closer (in terms of distance) to the reference point at the center of "i" than any other reference point. Therefore, more isolated reference points would be associated with a bigger polygon. Figure 54 below shows the Voronoi Polygons constructed using the US National Parks location as reference points. According to the map, someone living in San Francisco is closer in distance to the Pinnacles National Park than any other National Parks (Yosemite and Yellowstone, for example).

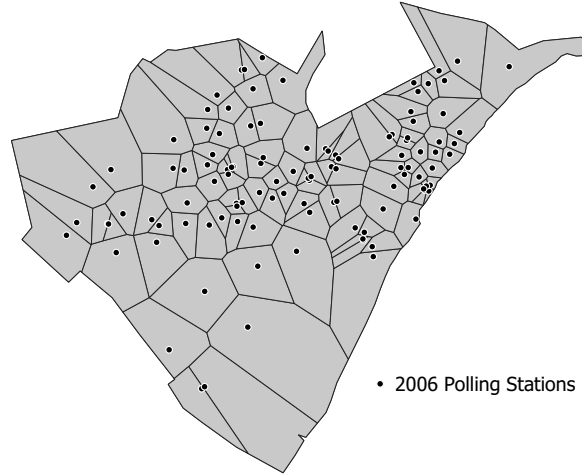
Figure 54: Voronoi Polygons using US National Parks



Note: [Image Source.](#)

I used the 2006 polling stations as reference points to obtain the Voronoi Polygons for the entire urban area of Boa Vista (there were no shelters in the municipality's rural part). Boa Vista's urban limit was drawn based on the 2010 Map of streets and avenues by the National Statistics Institute (IBGE). Figure 55 shows all the 111 polygons constructed based on the 2006 polling stations.

Figure 55: Voronoi Polygons using 2006 Polling Stations (Urban Area of Boa Vista)



By construction, the political outcome of observation "i" in 2006 will be measured using the single 2006 polling station data that generated that polygon "i". However, after 2006, there was destruction and the creation of new polling stations. Therefore, a weighting strategy will be necessary, given that more than one polling station might be located within the same polygon after 2006. To get the weights, I will first overlap the Voronoi patterns of 2006 and year "t" for $t > 2006/2008$ (see Figure 56 for the 2006 and 2010 polygons overlap example). The weight that a certain polling station "j" will receive when calculating the outcome in a year "t" for observation/polygon "i" will be equal to the share of j's Voronoi area in the year "t" that lies within observation/polygon "i". The same weighting strategy will be used to obtain "i" covariates (voters' characteristics) over time.

Figure 56: Overlapping the Voronoi Diagrams of 2006 and 2010 Polling Stations

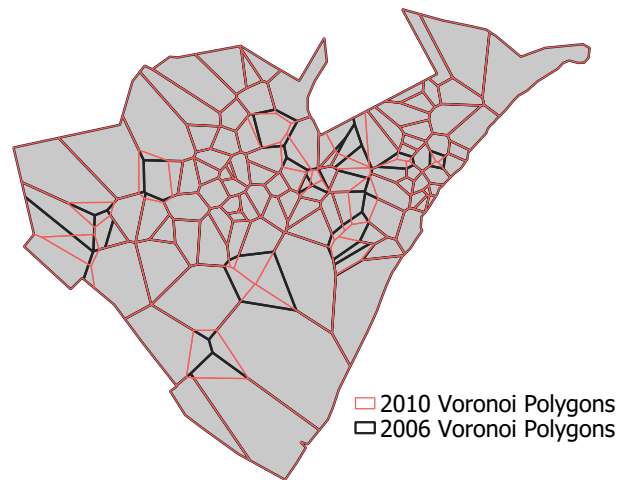
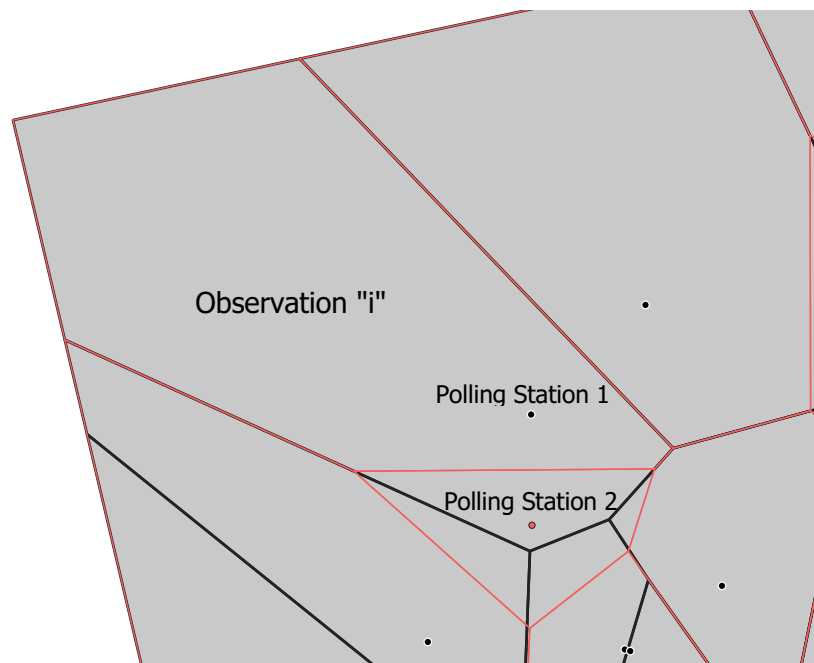


Figure 57 describes an example of how the weighting strategy works. Take observation "i" (the striped polygon). In 2006, its votes were entirely made out of Polling Station "1". Polling Station "2" was opened in 2010, which shrank Polling Station 1 Voronoi borders. Now, 100% of Polling Station "1" Voronoi Polygon and 50% of Polling Station "2" lie within observation "i".

Figure 57: Example of Weighting to get 2010 Political Outcome



The number of votes a certain candidate "13" had in 2010 for observation "i" equals

100% the number of votes for "13" at polling station "1" summed with 50% polling station "2" votes for "13". Using the same strategy for the total number of votes, I will get the observation "i" share of votes for a candidate "13" in 2010. Treated Polygons will be the ones for which its center is less than one kilometer away from the closest shelter.

K Robustness

Figure 58: President Election (2nd Round) - Challenger - Selected Control (unlikely treated)

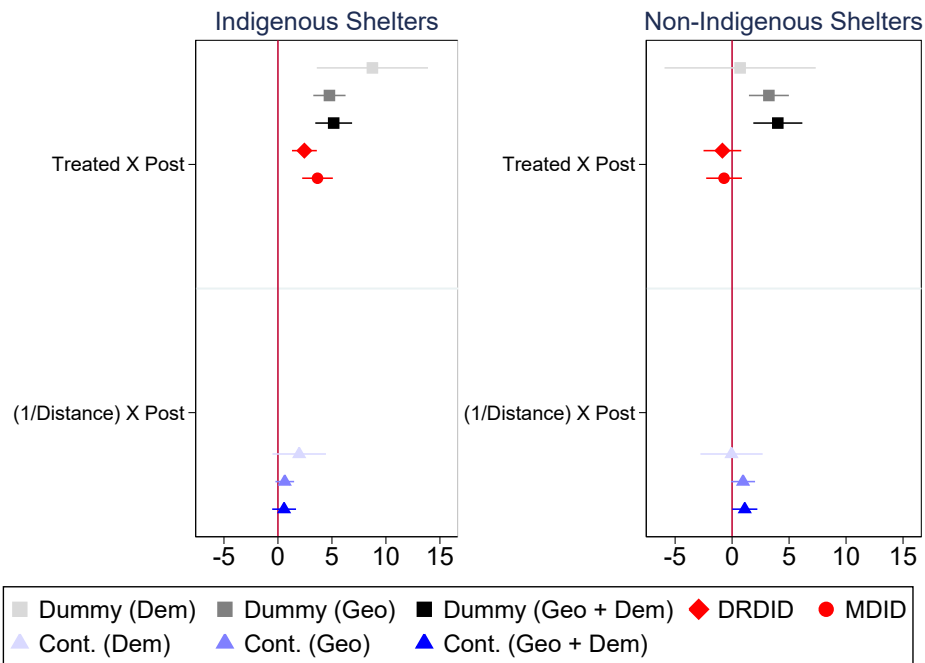


Figure 60: President Election 2nd Round - Challenger- Ind. Vs Random 2 Non-Ind.

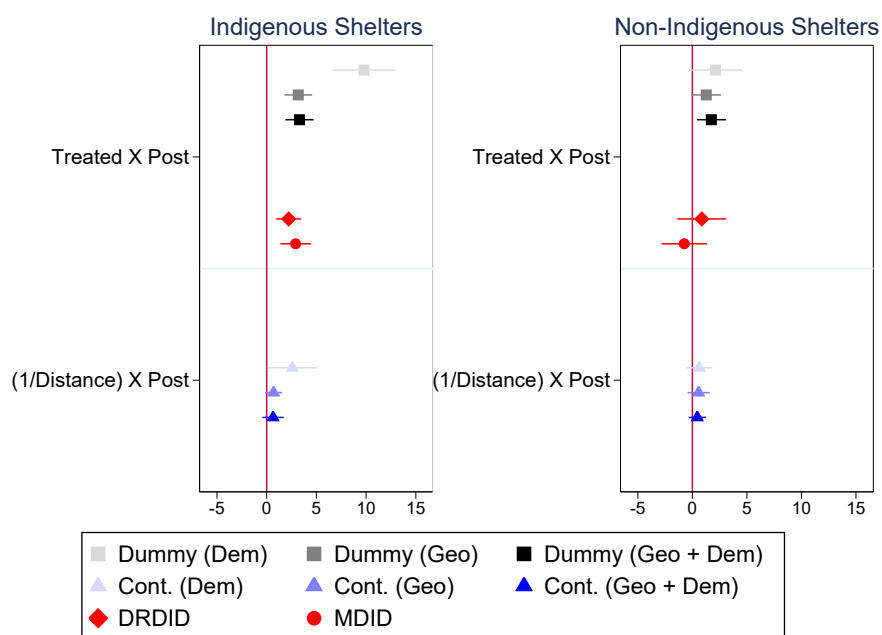


Figure 59: President Election 2nd Round - Challenger -Errors Clustered at Neighborhood Level

