Refugee Urban Shelters and Locals' Electoral Outcomes: Evidence from the Venezuelan Refugee Crisis in Northern Brazil

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Abstract

Since 2014, over one million Venezuelans have entered Brazil, mostly through Roraima state. Unlike many developing countries that rely on isolated camps, Brazil granted broad rights and established urban shelters in Roraima's capital. By increasing visibility, contact, and competition for resources, this reception model risks provoking local backlash. This paper studies the impacts of this modern refugee reception policy on crime, public service congestion, and ultimately, voting. I leverage the quasi-random placement of shelters and granular within-city data to estimate a DiD comparing areas close and further away from them. According to the results, shelters did not affect crime activity or public schools' congestion and infrastructure. However, they shaped the city's voting patterns. Shelters hosting Indigenous Venezuelans boosted support for far-right candidates while reducing votes for the incumbent. Analysis using public school data and UN reports suggests that locals' exposure to poverty and vulnerability, such as children outside of school, child labor, and homelessness, can be behind the results. Therefore, political backlash depends less on the presence of shelters than on who is housed, particularly their ethnicity and integration.

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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, reaching 41 million in 2023.[1] The majority (75%) are hosted by low- and middle-income countries, where reception policies typically combine refugee camps and substantial rights restrictions.[2] Camps, currently house 6.6 million people worldwide, are intended for immediate protection and are usually located in rural areas, away from major urban centers.[3]

This logic assumes refugees can go home relatively soon and, therefore, efforts to integrate them into the host community are secondary. However, modern displacement is increasingly defined by prolonged periods of exile, and most refugees (78%) now live in cities. Therefore, scholars and the UNHCR (United Nations agency for refugees) have advocated for a shift from the camp-centric and short-term logic to a local integration model by broadening refugees' rights and adapting assistance to urban contexts - see Betts (2021), Parekh (2020), Collier and Betts (2017), and UNHCR Global Survey Report (2012).

This modernized approach potentially increases everyday interaction and contact between locals and migrants, and it can also shape neighborhood amenities and trigger competition in labor markets and public services. These dynamics can, on one hand, fuel resentment, intensify social tensions, and translate into political backlash; on the other, closer interactions can foster empathy, reduce prejudice, and ultimately generate support for refugee reception. A large body of literature examines how migration flows shape attitudes toward migrants, particularly in electoral behavior. However, most studies rely on municipality-level data that are too aggregated, while the few recent contributions employing granular contact measures report mixed findings and lack comparable mechanism data.

In that sense, this paper studies how the introduction of a modern refugee reception policy shapes host communities' crime incidence, public service congestion, and,

[1] See UNHCR Statistics for more.

[2] For example, refugees in Tanzania and Bangladesh cannot work legally outside the camps, and Kenya imposes restrictions on leaving the camps.

[3] Some of the world's largest refugee camps are Kutupalong-Balukhali (Bangladesh), Bidi Bidi (Uganda), Dadaab and Kakuma (Kenya), Azraq and Zaatari (Jordan), Nyarugusu, Nduta, and Mtendeli (Tanzania).

consequently, voting. I leverage granular within-municipality data on election results, crime reports, and public schools. Additionally, I use novel data on the refugee population, especially differences in refugees' ethnicity (indigenous and non-indigenous), to assess how migrants' characteristics influence the results.

This study focuses on one of the world's largest and fastest-growing displacement flows in the last decade. The deepening of Venezuela's political and economic crises after 2014 has driven almost 8 million of its citizens to emigrate, the majority (84%) to neighboring countries. In 2018 alone, more than 150,000 Venezuelans entered Brazil through the border state of Roraima. Contrasting the standard refugee reception in developing countries, the Brazilian response was to establish urban shelters in Roraima's capital and grant Venezuelans documentation, freedom of movement, and access to public services, welfare, and work permits.

The empirical strategy leverages two features of the Venezuelan displacement and reception policy in Brazil. First, the migrant flows and reception efforts were concentrated in Roraima, with less salience in the rest of the country. Second, refugee assistance was implemented rapidly and with quasi-experimental spatial variation, as shelters were established in different neighborhoods of Roraima's capital. Therefore, I employ a difference-in-differences design comparing areas closer to farther away from urban Venezuelan refugee shelters.

According to the results, shelters did not increase crime in surrounding areas and had no impact on schools' congestion and infrastructure. With respect to election results, this modern reception policy reshaped within-city voting patterns. In particular, proximity to shelters boosted support for far-right candidates (3 to 4 p.p) while reducing votes for the incumbent governor. However, by estimating a synthetic control, I verified that the city's overall far-right voting trends mirrored those observed in other non-affected municipalities. Therefore, shelter effects were limited and not big enough to increase the overall performance of far-right populist candidates.

Importantly, political backlash was only caused by facilities hosting Indigenous Venezuelans. According to UNHCR reports, Indigenous refugees were especially vulnerable (higher illiteracy among adults and lower vaccination rates) and had lower measures of integration (access to documentation). Moreover, though Indigenous shelters housed considerably more children, surrounding schools experienced higher Venezuelan enrollment. This indicates that the salience of refugees' presence and locals' exposure to poverty and vulnerability, such as children outside school and child labor, can be behind the effects. Therefore, ethnic-specific contact triggered political backlash even when we don't observe worsening crime and public goods congestion.

Most papers in the literature of the political economy of migration also find that migrant flows increase support for populist far-right and anti-migration candidates and parties.[4] However, they mainly rely on county or municipality-level data and overlook key within-city variation, given that migrants are unevenly distributed.[5] A smaller and more recent group of studies uses more granular data exploring refugee reception centers' location within German cities - see Fremerey, Hörnig, and Schaffner (2024), Endrich (2024), Pettrachin et al. (2023), Schmidt, Jacobsen, and Iglauer (2024). The evidence, however, remains mixed, and they lack granular mechanism data. This paper contributes to the literature by using granular data on public services and crime, which are important potential mediators, especially in a developing and limited state capacity setting. Moreover, I explore a unique feature of the reception policy to separate refugees' ethnicity to reveal whether sheltered population characteristics play a role.

In addition, despite hosting the majority of the world's displaced population, the literature on the political economy of migration in developing countries remains limited.[6] The Brazilian reception policy 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. Notably, determinants of host communities' attitudes might differ from those of developed countries, given the differences in state capacity, public services quality, and prevalence of crime.

By studying the effects on voting for an incumbent involved in the reception policy,

[4] See Alesina and Tabellini (2024) for a review of the literature.

[5] For example: Edo et al. (2019), Vertier, Viskanic, and Gamalerio (2023) (French cantons and municipalities); Barone et al. (2016), Campo, Giunti, and Mendola (2021) (Italian municipalities); Mendez and Cutillas (2014) (Spanish provinces); Moriconi, Peri, and Turati (2022) (regions of 12 European countries); Mayda, Peri, and Steingress (2022) (USA counties); Halla, Wagner, and Zweimüller (2017) (Austrian communities) and Steinmayr (2021) (Austrian municipalities); Brunner and Kuhn (2018) (Swiss communities); Dinas et al. (2019)(Greek islands); Harmon (2018) (Danish municipalities)

[6] Rozo and Vargas (2021) and Lebow et al. (2024) look at Venezuelan migration in Colombia, and Ajzenman, Dominguez, and Undurraga (2022) explores immigration in Chile.

this paper also speaks with the literature studying political accountability and how voters associate policies with policymakers.[7] Considering that in most contexts migrants have limited to no voting rights, locals' voting behavior can be consequential for the implementation and maintenance of policies targeting immigrants. In fact, the results suggest that voters indeed react once ethnic diversity and exposure to vulnerability reach their neighborhoods.

Finally, this paper expands the outcomes studied by the literature on the effects of refugee camps and shelters on host communities by looking at public education and crime while existing work has focused on protests, rents, earnings, employment, and consumption of local families - see Coniglio, Peragine, and Vurchio (2023), Batut and Schneider-Strawczynski (2022), Hennig (2021), Sanghi, Onder, and Vemuru (2016), Alix-Garcia, Walker, et al. (2018), and Alix-Garcia and Saah (2010).

The rest of the paper is organized as follows. First, I provide the background descriptions of the Venezuelan refugee crisis, the reception policy, Brazilian election logistics, and the political environment. 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 describe and discuss the results. Finally, Section 6 concludes.

2 Background

2.1 Venezuelan Refugee Crisis in 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%.[8] 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

[7] Ferraz and Finan (2008), for example, found that voters punished politicians when corruption was revealed in Brazilian municipalities. Ajzenman and Durante (2023) shows that the infrastructure quality of the polling stations in Argentina (usually public schools) worked as a signal for the incumbent's education policies and shifted voters' decisions. Also see Bobonis, Cámara Fuertes, and Schwabe (2016) and Weitz-Shapiro and Winters (2017).

[8] IMF statistics.

Latin America and the Caribbean.[9]

Between January 2017 and April 2024, more than 1 million Venezuelans entered Brazil, and around half left to go to other South American countries.[10] According to Baeninger, Demétrio, and Domeniconi (2022), Venezuelan immigration to Brazil can be organized in three waves. The first wave occurred between 2012 and 2014 and consisted of highly qualified immigrants who arrived at the main international airports. The second wave, between 2015 and 2017, was made up of middle-class Venezuelans, such as engineers, technicians, and professors.

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.

The entrance of Venezuelan Indigenous groups was also registered at the 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%).[11] They relied on fishing, agriculture, and crafts, and mentioned the

[9]See R4V Platform for statistics by hosting country.

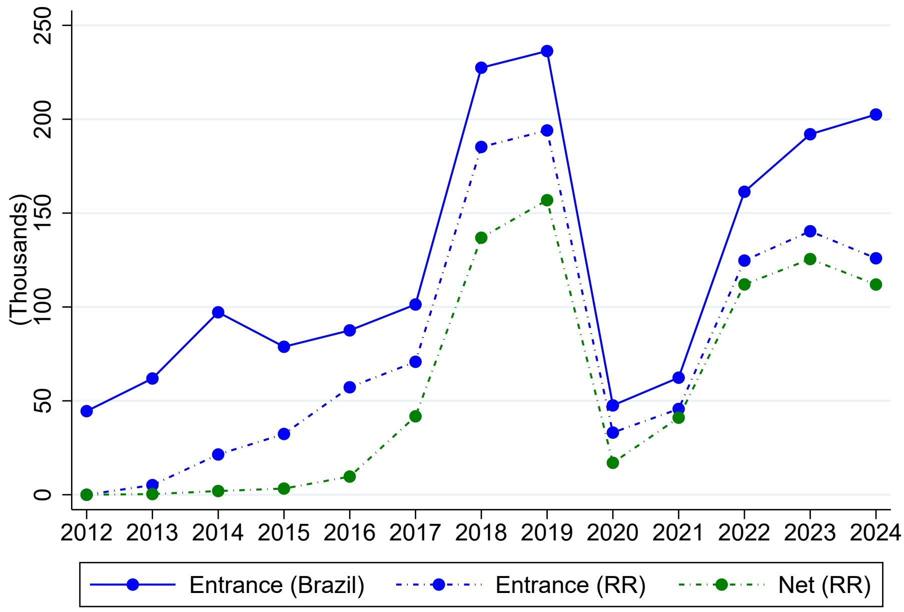
[10]Source: Ministry of Justice and Public Security report on Venezuelan Migration for April 2024.

[11]Other 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

political and economic crisis and environmental and climate-related reasons (flooding, water contamination, and heavy rains) for leaving their territories in Venezuela. [12]

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 drop in 2020 and 2021, when the border was closed due to the COVID-19 pandemic, entries surged again in 2023 and 2024, indicating that the situation continues to evolve in the region.[13]

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



Source: Sistema de Tráfego Internacional (STI).

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.[14]. 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 Venezuelans; on the other hand, the proportion of refugees without a high-school degree is larger. In other words, refugees' education distribution is less

[12]For more see IOM Report.

[13]See Figures 26 and 27 in the Appendix A for more details about the gender and age composition of the inflow.

[14]See newspaper article

polarized than the Brazilian one. Finally, the two populations present a similar gender composition.[15] [16]

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.[17]

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 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.[18]

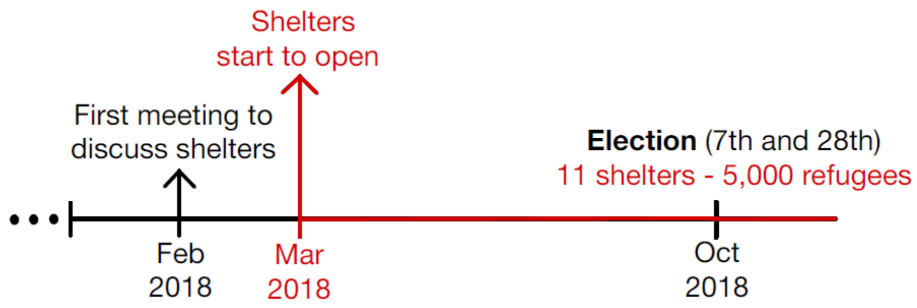
[15] For more details, see Figure 28, 29, and 30 in the Appendix.

[16] PNAD 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.

[17] This 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).

[18] Since April 2018, more than 140,000 Venezuelans have participated in the voluntary dispersal

Figure 3: 2018 Timeline - Shelters and Election



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 to control entrance.[19] 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.[20]

policy and moved to more than 750 Brazilian municipalities. For updated statistics about the dispersal policy access: Dispersal Strategy Statistics Platform.

[19]For more details about the shelters' logistics and the discussion behind the militarization of the reception policy, see Machado and Vasconcelos (2022).

[20]See Table 9 in the Appendix Section **??** for 2018 and 2020 shelter-specific statistics.

Figure 4: Shelters' Photos

(a) Inside Photos

(a.1) Tancredo Neves Shelter

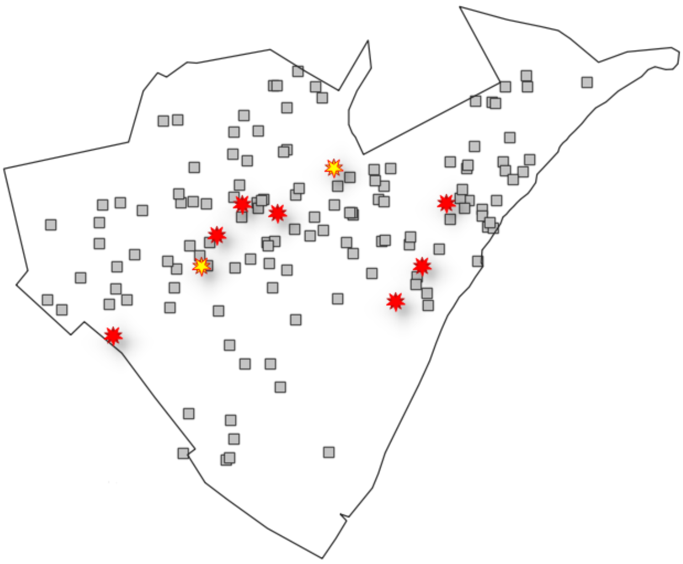
(a.2) Rondon 1 Shelter

(b) "Operação Acolhida" logo and shelters' name on outside signs

(b.1) Jardim Floresta Shelter

(b.2) Santa Teresa Shelter

Figure 5: Indigenous (2) and Non-Indigenous (7) Shelters Map



Finally, 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 5. Table 1 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 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 (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 1: 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 18-59 Years Old	50,2%	58,2%
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%

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). *Source*: UNHCR and Federal Emergency Assistance Committee reports for October 2018.

2.3 Brazilian Elections

Voting Right

Voting is mandatory for 18- to 65-year-old Brazilians living in the country and optional for 16- and 17-year-olds. To get a voter's ID, citizens must go to the electoral registry office, bringing an official identification document and proof of residence (utility bills, for example). Voting is restricted to citizens, and the naturalization of individuals without specific family ties with Brazilians can take up to 180 days and 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.[21]

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.

Political Environment - Presidential Election

"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.[22] He decided not to run for reelection; therefore, there was no incumbent candidate in the 2018 presidential election.[23] The main national left party, the Workers Party (PT), launched Fernando Haddad, who lost the election to Jair Bolsonaro (55.10% 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 polemic statements and ideas.

[21] Information about the number of naturalized citizens among the voters is unavailable; however, naturalized citizens represent less than 0.1% of the total population according to the 2022 Census.

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

[23] His party launched the finance minister as a candidate, but he got less than 1.3% of the valid votes nationally.

"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 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 11 in Appendix D for a complete description of the parties used in each presidential election.

Political Environment - Governor Election

Figure 6: 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.[24] 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.[25]

[24] Roraima's Governor Candidates Interview.

[25] For more details on political context, see Appendix C and Table 10.

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, 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 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 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 2.

Table 2: Crime Data

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.

3.3 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.

Table 3: Public Schools - 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 School Census.

3.4 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.[26]

I use data on the geographic coordinates of polling stations from F. Daniel Hidalgo. 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).[27] 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.

4 Empirical Strategy

4.1 Crime

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 7 for a map visualization. Then I estimate a Diff-in-Diff using the following TWFE specification:

$$\text{Crime}_{jt} = \beta_1 \; \textit{Treat-Ind.}_j \times \textit{Post}_t + \beta_2 \; \textit{Treat-Non-Ind.}_j \times \textit{Post}_t + \textit{FE} + \textit{Controls} + \nu_{jt} \quad (1)$$

Crime_{jt} represents the inverse hyperbolic sine (IHS) of the total number of crimes registered in grid j in quarter t. *Treated-Ind*$_j$ and *Treated-Non-Ind*$_j$ are dummy variables indicating whether grid "j" is less than 1 kilometer away from the closest indigenous and non-indigenous Venezuelan refugee shelter, respectively. *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*). In addition, I explore a quarter number (1, 2, 3, or

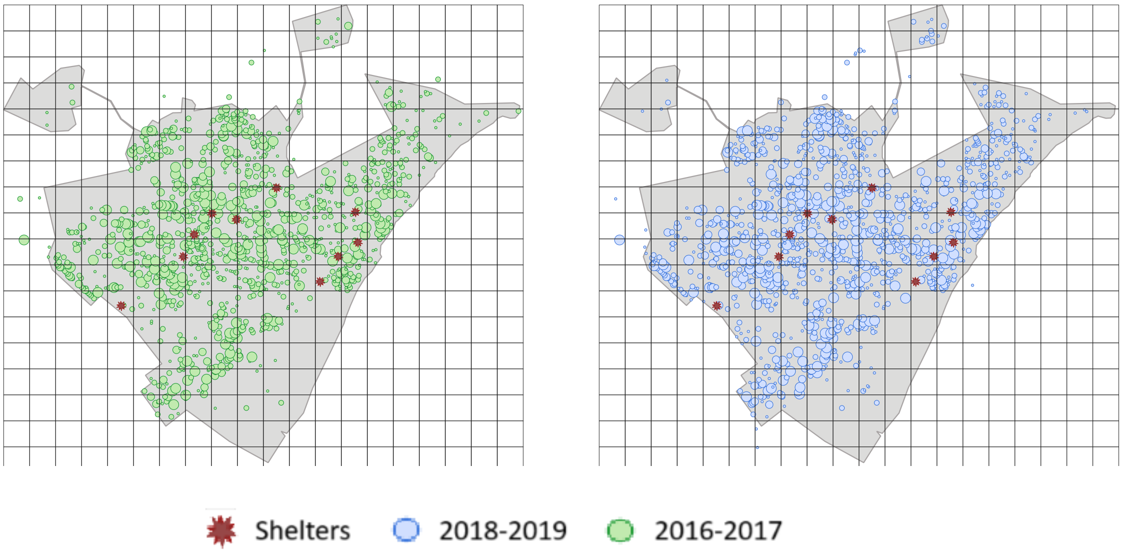
[26] The marital status information contains a considerable amount of missing; therefore, only voters' education, gender, and age were used.

[27] Hidalgo's code and some of its input data are publicly available.

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 7: Crime Map Before and After Shelters

(a) 2016-2017 (b) 2018-2019



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.

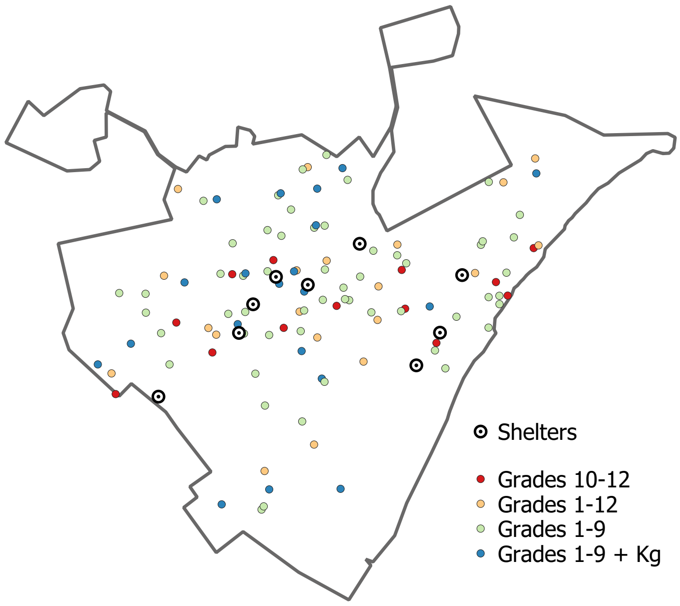
4.2 Public Education

I use 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:

$$Y_{st} = \alpha + \sum_{\tau=2010}^{2023} \beta_1 \tau \, \textit{Treat-Ind.}_s + \sum_{\tau=2010}^{2023} \beta_2 \tau \, \textit{Treat-Non-Ind.}_s + \gamma_s + \gamma_t + \varepsilon_{st} \quad (2)$$

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. *Treat-Ind.*$_s$ and *Treat-Non-Ind.*$_s$ are dummies for whether the school is less than 1 kilometer away from an Indigenous and Non-Indigenous shelter, respectively. γ_s and γ_t are the school and year fixed effects. See the schools and shelters' location in Figure 9.

Figure 9: Schools and Refugee Shelters - Boa Vista (2019)



4.3 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.

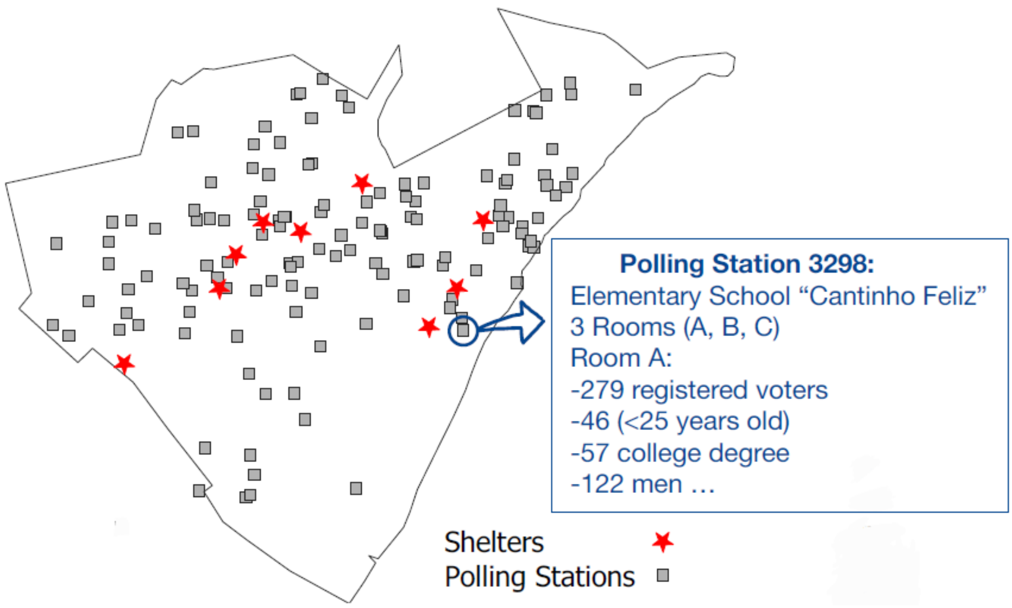
Brazilian election logistics doesn't use voting districts to allocate voters; instead, it works at two different allocation levels. First, voters are assigned to a polling station (i.e., a building, usually a public school). Then, they are separated into different sections (i.e., rooms) within that building. 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 municipality 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 10 for an example of how the data looks.

Figure 10: Election Results 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:

$$Y_{ijt} = \beta \text{ Treated}_j \times I(t \geq 2018) + \gamma_i + \mu_t + Controls + \epsilon_{ijt} \tag{3}$$

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 4: 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 Education 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
Section-Level Age Variables (2014):					
Share 16 and 17 Years Old	714	1.687	2.062	0	22.22
Share 18 Year Old	714	1.612	1.566	0	7.194
Share <25 Years Old	714	16.87	8.911	0	58.11
Share less than 30 years old	714	29.58	12.75	0	69.47
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
Section-Level Gender-Educ. Variables (2014):					
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

Notes: Differences in sample sizes come from voters' education, age, and gender available after 2013, and numbers of voters and turnout rates available for all elections.

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.[28]

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 (3):

$$Y_{ijt} = \beta_1 \; \textit{Treat-Ind.}_j \times Post_t + \beta_2 \; \textit{Treat-Non-Ind.}_j \times Post_t + \gamma_i + \mu_t + Controls + \nu_{ijt} \quad (4)$$

$$Y_{ijt} = \beta_1 \; \frac{1}{\textit{Dist. Ind.}_j} \times Post_t + \beta_2 \; \frac{1}{\textit{Dist. Non-Ind.}_j} \times Post_t + \gamma_i + \mu_t + Controls + \nu_{ijt} \quad (5)$$

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. *Dist. Non-Ind.*$_j$ and *Dist. Ind.*$_j$ are the distances in kilometers from polling station "j" to each type of shelter, respectively. Given that there are only 2 Indigenous shelters compared with nine non-indigenous, for robustness, 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 (results are similar and not reported in this draft).

Data Quality and Identification Assumptions Tests

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

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

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).

Table 5: Balance Table on Pre-Migration Variables

	Treatment			Control			
	n	mean	sd	n	mean	sd	Diff
Section Constant Variables:							
Distance (Km) to Boa-Vista center/downtown	81	5.62	2.85	157	4.27	3.23	1.352***
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***
Section Variables Measured in 2014:							
Share Men	81	47.27	3.26	157	47.09	3.89	0.178
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 <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
% Votes Incumbent Governor	81	43.61	5.89	157	41.17	5.59	2.440***
% Votes Worker‘s Party President (1st Round)	81	26.67	6.54	157	21.99	8.22	4.688***
% Votes Worker‘s Party President (2nd Round)	81	36.41	7.04	157	31.13	8.42	5.283***

Notes: Sample includes only balanced sections. Results are similar for the unbalanced panel.

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 5 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 4.3, 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.[29] 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 J 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. Distance_j is the distance in kilometers between polling station "j" and the closest refugee shelter.

[29]According 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."

$$Y_{ijt} = \beta \, \frac{1}{\text{Distance}_j} \times I(t = 2018) + \gamma_i + \mu_t + Controls + \nu_{ijt} \tag{6}$$

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 a misleading zero or even wrong sign results.

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 6.

Table 6: DiD Results - Control Variables as Outcome

	Eq. (3)		**Eq. (6)**	
Outcomes	**Treated*Post**	**R2**	**(1/Distance)*Post**	**R2**
Share Men	-0.876 (0.674)	0.002	0.118 (0.330)	0.001
Share Illiterate	-0.135 (0.118)	0.025	0.023 (0.035)	0.023
Share Less than High School	0.495 (0.894)	0.029	-0.503 (0.349)	0.031
Share Some College	0.302 (0.715)	0.008	0.404 (0.257)	0.009
Share 16-17 Years Old	-0.331 (0.587)	0.042	-0.349* (0.181)	0.050
Share 18 Years Old	-0.247 (0.536)	0.146	-0.295* (0.166)	0.156
Share <25 Years Old	1.317 (1.355)	0.087	-0.924 (0.761)	0.090
Share <40 Years Old	-1.418 (1.169)	0.294	-0.110 (0.687)	0.293
Share >65 Years Old	0.083 (0.361)	0.336	-0.022 (0.155)	0.336
Share Men Illiterate	-0.006 (0.060)	0.003	-0.007 (0.013)	0.003
Share Men Less than High School	-0.099 (0.685)	0.015	-0.610*** (0.215)	0.020
Share Working-Age Men	-0.504 (0.786)	0.022	0.375 (0.311)	0.022
Share Women Illiterate	-0.129* (0.076)	0.048	0.030 (0.028)	0.045
Share Women Less than High School	0.594 (0.644)	0.009	0.108 (0.213)	0.008
Share 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 7, there was no differential logistic capacity between treated and control units. Therefore, it is unlikely that the election organization explains the results.

Table 7: DiD Results - Election Logistics Variables as Outcome

	Eq. (3)		**Eq. (6)**	
Outcomes	**Treated*Post**	**R2**	**(1/Distance)*Post**	**R2**
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: standard errors in parentheses and standard errors clustered at the polling station level in brackets.

5 Results

5.1 Crime

According to the results (see Table 8), 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 12) also reassures parallel trends.

Figure 11: Quarterly Number of Crimes - Boa Vista

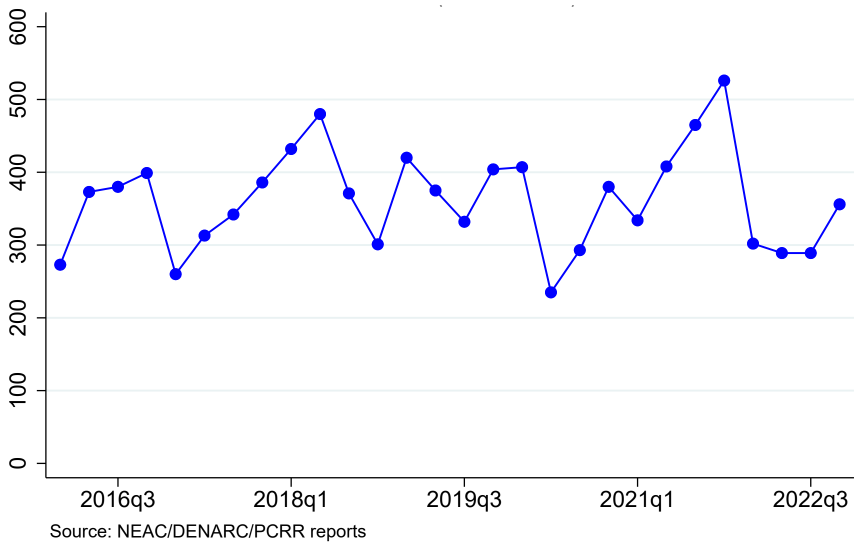


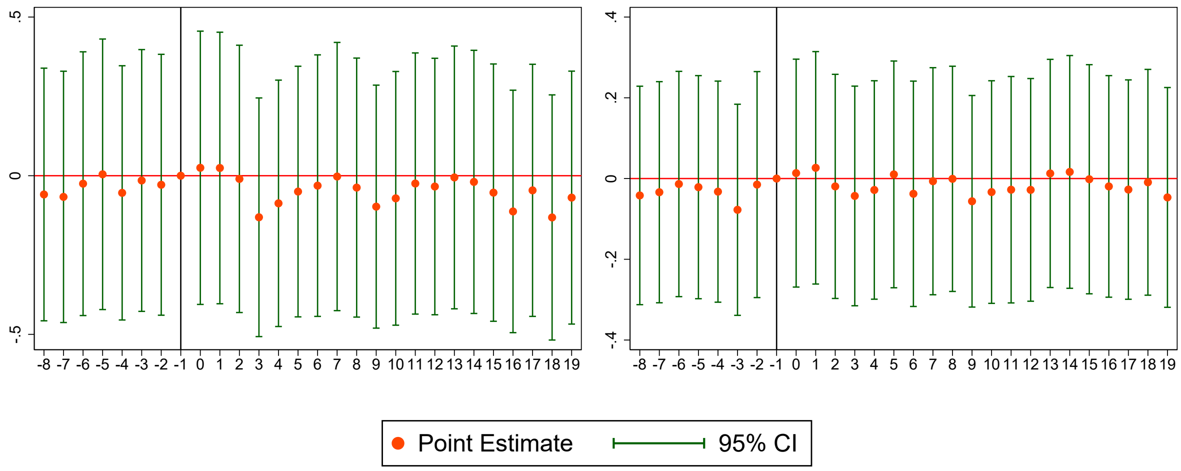
Table 8: Shelters' Effect on Total Number of Crimes

	OLS				Poisson
	(1)	(2)	(3)	(4)	(5)
Treated (Ind. Shelter) × Post	-0.028	-0.028	-0.030	-0.030	-0.140
	(0.057)	(0.057)	(0.058)	(0.058)	(0.174)
Treated (Non-Ind. Shelter) × Post	0.008	0.008	0.008	0.008	-0.001
	(0.039)	(0.039)	(0.039)	(0.039)	(0.128)
Observations	30,968	30,968	30,968	30,968	27,489
R-squared	0.052	0.052	0.053	0.053	
Fixed-effects					
Time FE	Y	Y	Y	Y	Y
Grid FE	Y	Y	N	N	N
Dist. Downtown-Time 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 (all types combined), and for column (5) is the number of crimes (all types combined). All models include a constant term. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Figure 12: Shelters' Effect on Total Number of Crimes - Event Study

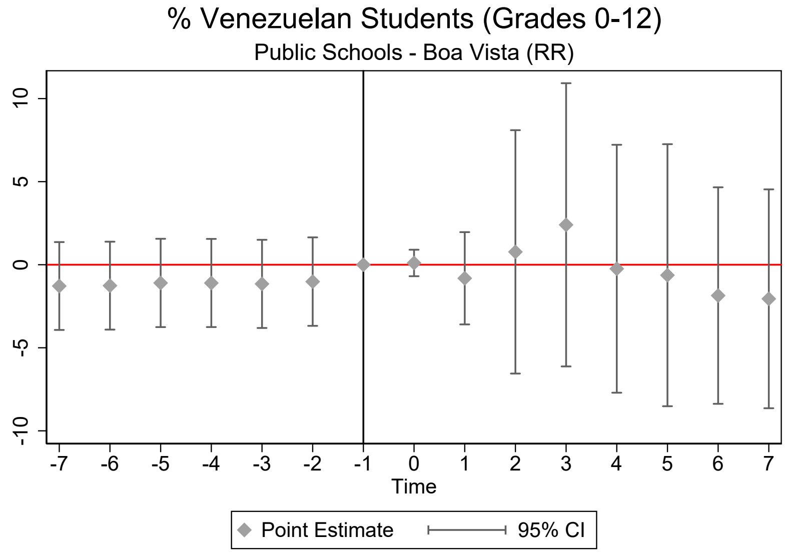
(a) Indigenous Shelters (b) Non-Indigenous Shelters



5.2 Public Education

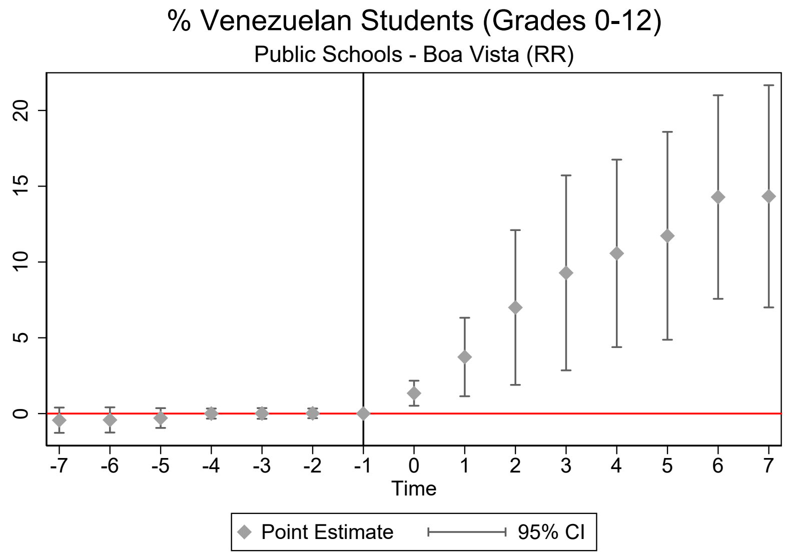
The values for $\beta_1\tau$ and $\beta_2\tau$ are plotted in the Figure 14 and 15, respectively. Despite hosting a larger share of school-age Venezuelans, Indigenous shelters do not affect the surrounding schools' share or number of Venezuelan students. Contrastingly, non-indigenous shelters increased Venezuelan enrollment in schools less than one kilometer away. Moreover, neither shelter had an effect on different measures of school congestion or infrastructure: number of students per teacher, classroom sizes, or number of infrastructure amenities such as libraries and laboratories - see Figure 39, 40, and 41 in the Appendix G.

Figure 14: **Indigenous shelters** effect on schools' composition - Event Study



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.

Figure 15: **Non-Indigenous shelters** effect on schools' composition - Event Study



Notes: Event Study based on a "treatment" dummy equal to 1 for a school less than 1 km away from a Non-Indigenous shelter. 2016 is the baseline year.

5.3 Voting

Presidential Election

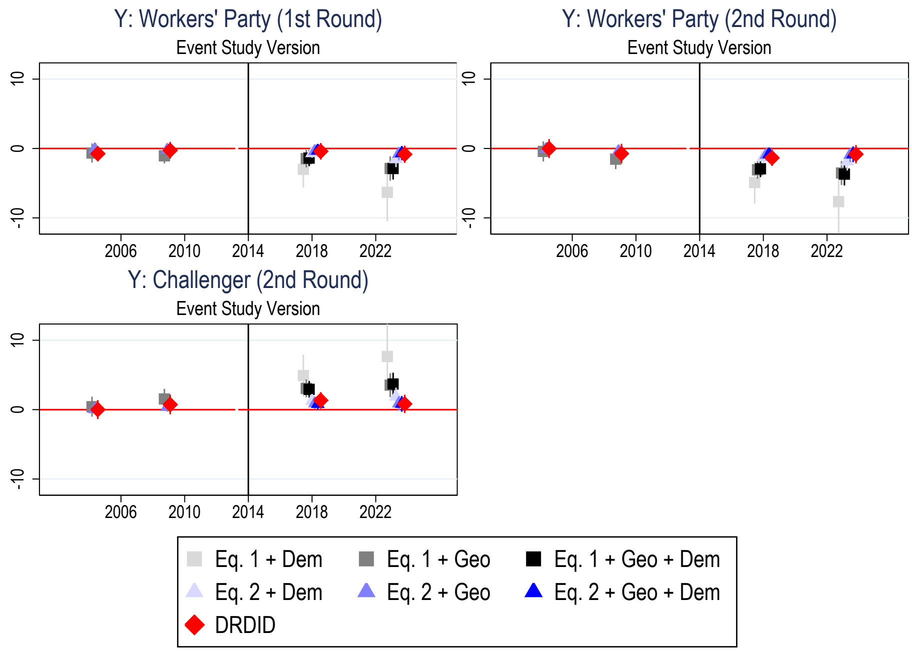
Figure 16: President Election Results (β) - Eq.(1) and (2)

Notes: 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. *Challenger (2nd Round)* = voting for the party not PT. Given that PT participated in every second round, *Challenger (2nd Round)* = 100- *Workers' Party (2nd Round)*.

According to Figure 16, 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).[30]. Additionally, from Figure 17, the results persist for the 2022 election.

[30]The results for the other candidates were not statistically significant

Figure 17: President Election Event Study Results

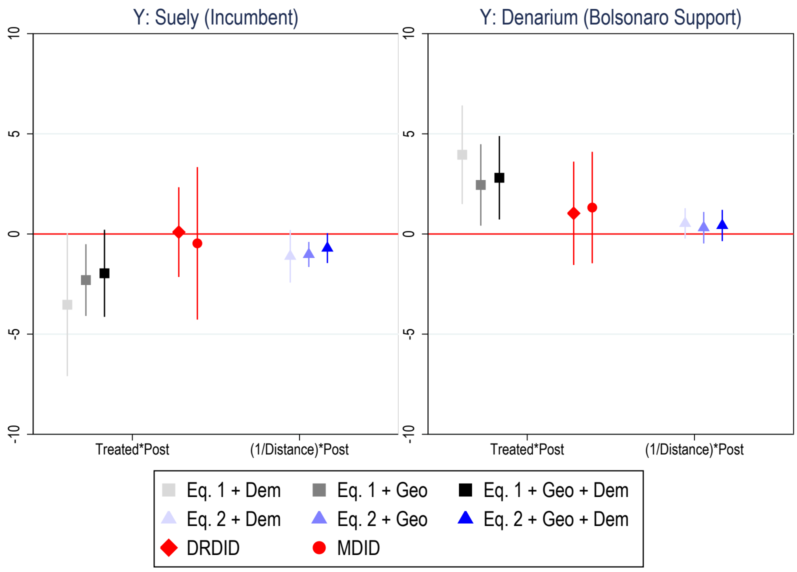


Notes: 2014 is the baseline year. Dependent Variable = % of valid votes for each category/candidate. *Dem* = 23 demographic (age, education, and gender) controls; *Geo* = time dummies interacted with polling station distance to downtown. DRDID = Doubly Robust DiD. MDID = Matching DiD.

Governor Election

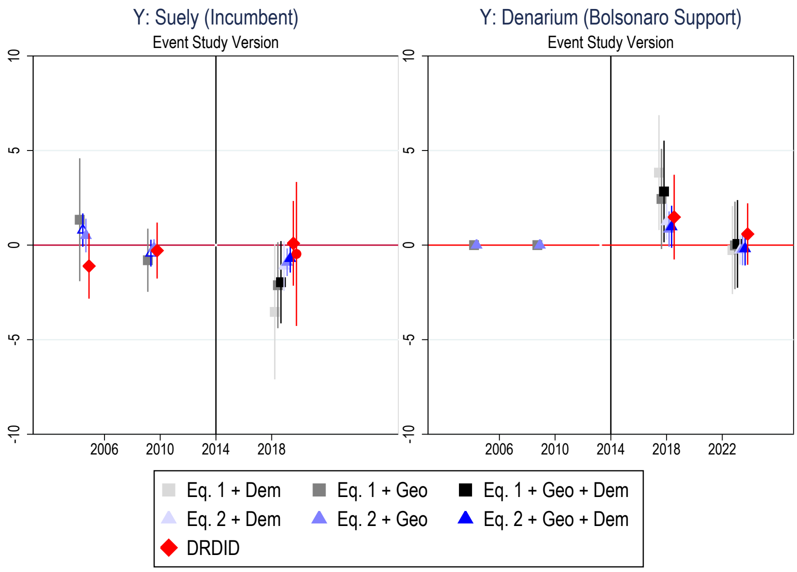
Figure 18 summarizes the main results of the Governor's election. According to the estimates, there is suggestive evidence that the incumbent governor (Suely) lost between 2 and 4 percentage points of the valid votes in sections within treated polling stations. This incumbent "punishment" accountability 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 18: Governor Election Results (β) - Eq.(1) and (2)



Notes: 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.

Figure 19: Governor Election Event Study Results



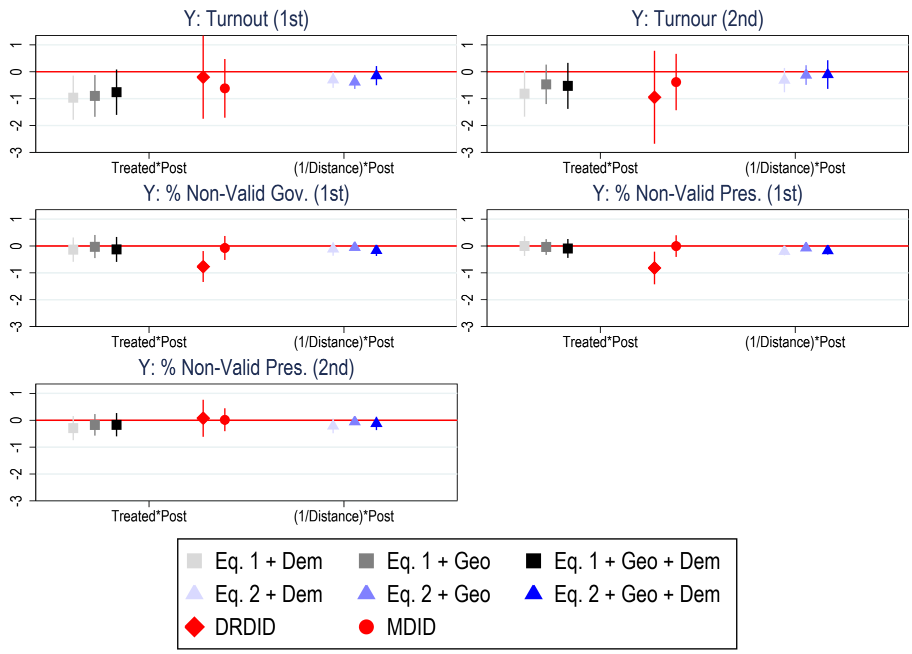
Notes: 2014 is the baseline year. PSL did not participate or support any candidate in the 2006 and 2010 state elections. Dependent Variable = % of valid votes for each category/candidate. *Dem* = 23 demographic (age, education, and gender) controls; *Geo* = time dummies interacted with polling station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

Additionally, the voting loss suffered by Suely translated into increased support for Antônio Denarium. This is more evident in the event study version (see Figure 19), given it only lasts for the 2018 election and is no longer statistically different than 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 20, 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 20: Turnout and Non Valid Votes Results (β) - Eq.(1) and (2)

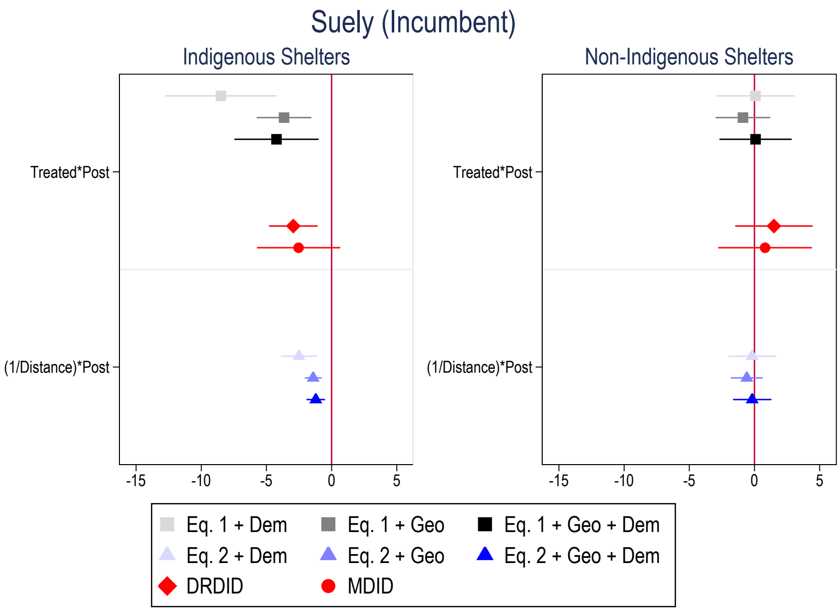


Notes: Dependent Variable = % of valid votes for each category/candidate. *Dem* = 23 demographic (age, education, and gender) controls; *Geo* = time dummies interacted with polling station distance to downtown. DRDID = Doubly Robust DiD. MDID = Matching DiD.

Indigenous Shelters

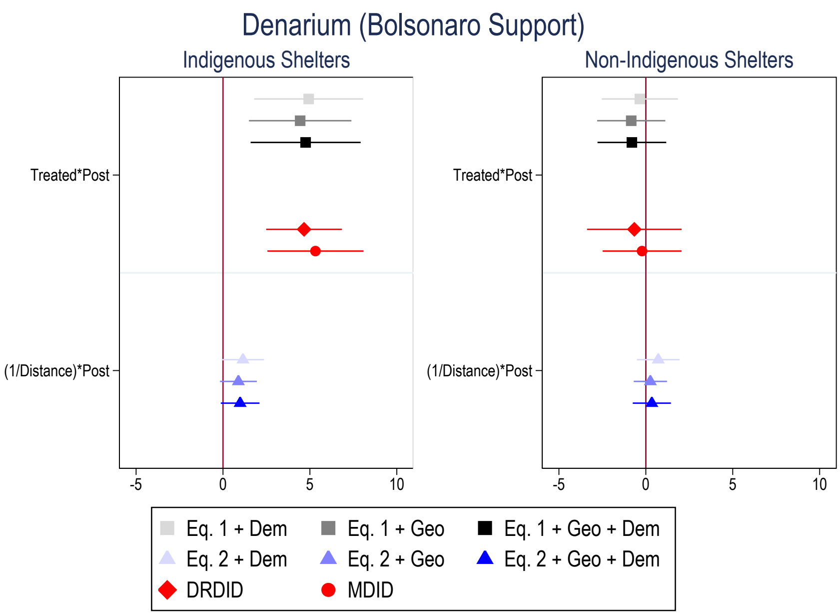
According to the results in Figures 21, to 24, the indigenous shelters are the ones driving the results for both the governor and presidential elections. It highlights that establishing an urban refugee shelter might be less important for political backlash than the cultural, socioeconomic, and integration features of the housed population.

Figure 21: Governor Election Incumbent Results (β_1 and β_2) - Eq. (4) and (5)



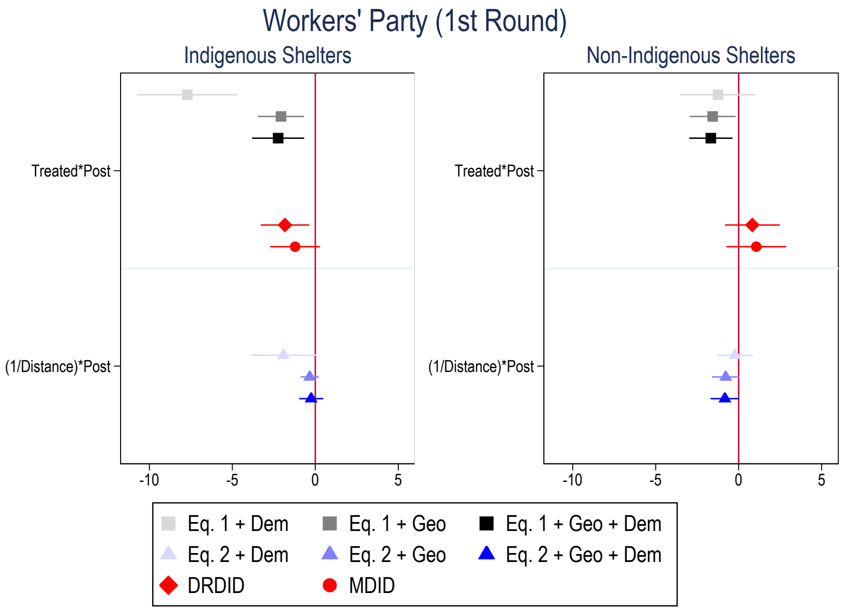
Notes: Dependent Variable = % of valid votes for each category/candidate. Dem = 23 demographic (age, education, and gender) controls; Geo = time dummies interacted with polling station distance to downtown. DRDID = Doubly Robust DiD. MDID = Matching DiD.

Figure 22: Governor Election Far-Right Results (β_1 and β_2) - Eq. (4) and (5)



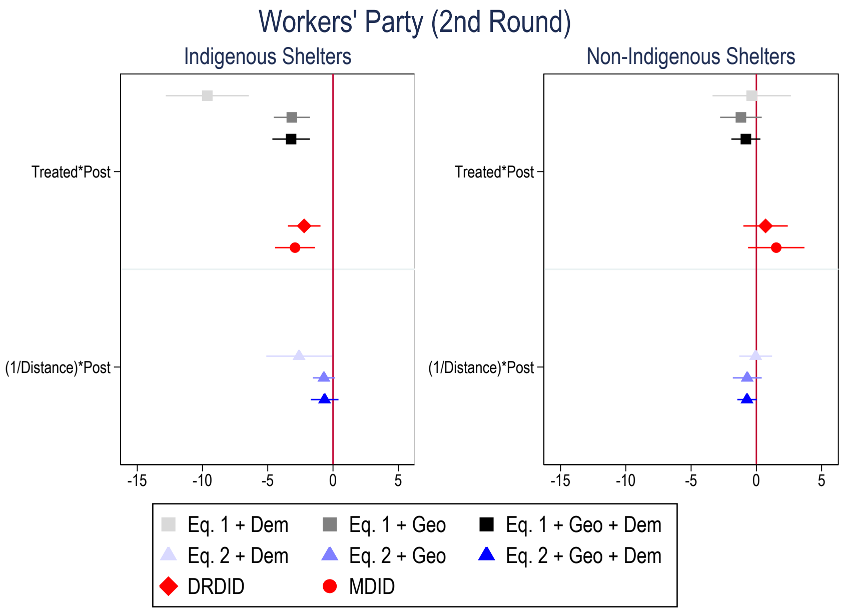
Notes: Dependent Variable = % of valid votes for each category/candidate. Dem = 23 demographic (age, education, and gender) controls; Geo = time dummies interacted with polling station distance to downtown. DRDID = Doubly Robust DiD. MDID = Matching DiD.

Figure 23: President Election Results (β_1 and β_2) - Eq. (4) and (5)



Notes: 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.

Figure 24: President Election Results (β_1 and β_2) - Eq. (4) and (5)



Notes: 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.

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 primary 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 46, 47, and 48 in the Appendix H) reveal a 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.

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 25 below and Figures 49, 50, and 51 in the Appendix I), 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 25: 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.

5.4 Robustness Checks

Polling Stations and Voronoi Polygons Panels

For robustness, 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. [31] 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).

Others

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). This group of controls is more likely to not have been treated by the shelters. The results (not reported in this draft) go in the same direction as the main findings. However, as expected, they present larger standard errors given the smaller sample size.

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.

6 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 crisis. 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. This modernized reception, by triggering competition for

[31] See Appendix K for details.

resources and higher exposure to migrants, potentially increases social tensions and steers political decisions, ultimately threatening both the effectiveness and long-term political sustainability of the reception model.

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 neighborhoods 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 policy. The results are robust to different definitions of treatment and data aggregation (polling stations and Voronoi polygons) and weighting observations by the number of registered voters or clustering errors at the neighborhood level.

Using a synthetic control, I verified that the city's overall far-right voting trends mirrored those observed in other municipalities not affected by the migration flow and the reception policy. Therefore, the effects of shelters were not significant enough to produce a citywide rise in populist far-right voting. In addition, there is no evidence of changes in party affiliation, suggesting that the political reaction, though present, did not escalate to more extreme or enduring forms of political engagement.

Importantly, the results are driven only 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. They present lower integration measures. This indicates that the salience of refugees' presence and locals' exposure to poverty and vulnerability, such as children outside school and child labor, 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 indicate that implementing a modernized refugee reception had a limited impact on voting. Moreover, the results reveal that establishing an urban refugee shelter might be less important for political backlash than who is housed, especially their ethnicity. Consequently, when policies are absent or ineffective in addressing the integration challenges of specific subgroups, they can reinforce support for candidates who are less likely to promote inclusion, leading to a vicious cycle.

References

Accetturo, Antonio et al. (2014). “Don’t Stand so close to me: the urban impact of immigration”. In: *Regional Science and Urban Economics* 45, pp. 45–56.

Adler, David and Ben Ansell (2020). “Housing and populism”. In: *West European Politics* 43(2), pp. 344–365.

Ajzenman, Nicolás, Patricio Dominguez, and Raimundo Undurraga (2022). “Immigration and labor market (mis) perceptions”. In: *AEA Papers and Proceedings*. Vol. 112. American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203, pp. 402–408.

Ajzenman, Nicolás and Ruben Durante (2023). “Salience and accountability: School infrastructure and last-minute electoral punishment”. In: *The Economic Journal* 133(649), pp. 460–476.

Alabrese, Eleonora et al. (2024). “Levelling up by levelling down: The economic and political cost of Brexit”. In.

Albu, Daniela (2023). “World Development Report 2023: Migrants, Refugees, and Societies”. In: *Drepturile Omului*, p. 81.

Alesina, Alberto and Marco Tabellini (2024). “The political effects of immigration: Culture or economics?” In: *Journal of Economic Literature* 62(1), pp. 5–46.

Alix-Garcia, Jennifer and David Saah (2010). “The effect of refugee inflows on host communities: Evidence from Tanzania”. In: *The World Bank Economic Review* 24(1), pp. 148–170.

Alix-Garcia, Jennifer, Sarah Walker, et al. (2018). “Do refugee camps help or hurt hosts? The case of Kakuma, Kenya”. In: *Journal of Development Economics* 130, pp. 66–83.

Baeninger, Rosana, Natália Belmonte Demétrio, and Jóice de Oliveira Santos Domeniconi (2022). “Migrações dirigidas: estado e migrações venezuelanas no Brasil”. In: *Revista Latinoamericana de Población* 16, p. 5.

Barone, Guglielmo et al. (2016). “Mr. Rossi, Mr. Hu and politics. The role of immigration in shaping natives’ voting behavior”. In: *Journal of Public Economics* 136, pp. 1–13.

Batut, Cyprien and Sarah Schneider-Strawczynski (2022). "Rival guests or defiant hosts? The local economic impact of hosting refugees". In: *Journal of Economic Geography* 22(2), pp. 327–350.

Becker, Sascha O, Thiemo Fetzer, et al. (2016). "Does migration cause extreme voting?" In: *Center for Competitive Advantage in the Global Economy and The Economic & Social Research Council*, pp. 1–54.

Betts, Alexander (2021). *The wealth of refugees: how displaced people can build economies*. Oxford University Press.

Betts, Alexander and Paul Collier (2018). "Sustainable migration framework". In: *EMN Norway Occasional Papers, University of Oxford.*

Bobonis, Gustavo J, Luis R Cámara Fuertes, and Rainer Schwabe (2016). "Monitoring corruptible politicians". In: *American Economic Review* 106(8), pp. 2371–2405.

Bolet, Diane (2021). "Drinking alone: local socio-cultural degradation and radical right support—the case of British pub closures". In: *Comparative Political Studies* 54(9), pp. 1653–1692.

Bolognesi, Bruno, Ednaldo Ribeiro, and Adriano Codato (2022). "Uma nova classificação ideológica dos partidos políticos brasileiros". In: *Dados* 66.

Bredtmann, Julia (2022). "Immigration and electoral outcomes: Evidence from the 2015 refugee inflow to Germany". In: *Regional Science and Urban Economics* 96, p. 103807.

Brunner, Beatrice and Andreas Kuhn (2018). "Immigration, cultural distance and natives' attitudes towards immigrants: Evidence from Swiss voting results". In: *Kyklos* 71(1), pp. 28–58.

Butts, Kyle (2021). "Difference-in-differences estimation with spatial spillovers". In: *arXiv preprint arXiv:2105.03737.*

Callaway, Brantly, Andrew Goodman-Bacon, and Pedro HC Sant'Anna (2021). "Difference-in-differences with a continuous treatment". In: *arXiv preprint arXiv:2107.02637.*

Callaway, Brantly and Pedro HC Sant'Anna (2021). "Difference-in-differences with multiple time periods". In: *Journal of Econometrics* 225(2), pp. 200–230.

Campo, Francesco, Sara Giunti, and Mariapia Mendola (2021). "The refugee crisis and right-wing populism: Evidence from the Italian dispersal policy". In.

Collier, Paul and Alexander Betts (2017). *Refuge: Rethinking refugee policy in a changing world.* Oxford University Press.

Coniglio, Nicola Daniele, Vitorocco Peragine, and Davide Vurchio (2023). "The effects of refugees' camps on hosting areas: Social conflicts and economic growth". In: *World Development* 168, p. 106273.

Cremaschi, Simone et al. (2024). "Geographies of discontent: Public service deprivation and the rise of the far right in Italy". In: *American Journal of Political Science.*

Dinas, Elias et al. (2019). "Waking up the golden dawn: does exposure to the refugee crisis increase support for extreme-right parties?" In: *Political analysis* 27(2), pp. 244–254.

Dustmann, Christian, Kristine Vasiljeva, and Anna Piil Damm (2019). "Refugee migration and electoral outcomes". In: *The Review of Economic Studies* 86(5), pp. 2035–2091.

Edo, Anthony et al. (2019). "Immigration and electoral support for the far-left and the far-right". In: *European Economic Review* 115, pp. 99–143.

Endrich, Marek (2024). "A gate to the world for all? The reaction of neighborhoods in Hamburg to refugee housing". In: *European Journal of Political Economy* 84, p. 102455.

Erdal, Marta Bivand et al. (2018). "Defining sustainable migration". In: *EMN Norway occasional papers, PRIO paper. Oslo: PRIO.*

Fernández-Villaverde, Jesús and Carlos Sanz (2024). *Classical Right, New Right, and Voting Behavior: Evidence from a Quasi-Natural Experiment.* Tech. rep. National Bureau of Economic Research.

Ferraz, Claudio and Frederico Finan (2008). "Exposing corrupt politicians: the effects of Brazil's publicly released audits on electoral outcomes". In: *The Quarterly journal of economics* 123(2), pp. 703–745.

Fetzer, Thiemo, Jacob Edenhofer, and Prashant Garg (2024). "Local decline and populism". In.

Fremerey, Melinda, Lukas Hörnig, and Sandra Schaffner (2024). "Becoming neighbors with refugees and voting for the far-right? The impact of refugee inflows at the small-scale level". In: *Labour Economics* 86, p. 102467.

Gerdes, Christer and Eskil Wadensjö (2008). *The impact of immigration on election outcomes in Danish municipalities*. Tech. rep. IZA Discussion Papers.

Ginn, Thomas et al. (2022). “2022 Global Refugee Work Rights Report”. In: *Center for Global Development, Refugees International, and Asylum Access*.

Hager, Anselm and Miguel M Pereira (2023). “Holocaust Memorials Reduce Xenophobic Voting”. In.

Halla, Martin, Alexander F Wagner, and Josef Zweimüller (2017). “Immigration and voting for the far right”. In: *Journal of the European Economic Association* 15(6), pp. 1341–1385.

Harmon, Nikolaj A (2018). “Immigration, ethnic diversity, and political outcomes: Evidence from Denmark”. In: *The Scandinavian Journal of Economics* 120(4), pp. 1043–1074.

Hennig, Jakob (2021). “Neighborhood quality and opposition to immigration: Evidence from German refugee shelters”. In: *Journal of Development Economics* 150, p. 102604.

Lebow, Jeremy et al. (2024). “Migrant exposure and anti-migrant sentiment: The case of the Venezuelan exodus”. In: *Journal of Public Economics* 236, p. 105169.

Machado, Igor José de Renó and Iana dos Santos Vasconcelos (2022). “Military Reception and Venezuelan Migrants in Brazilian far North: New Policies of Securitisation and Hybrid Refugee Camps”. In: *Journal of International Migration and Integration* 23(3), pp. 1217–1234.

Mayda, Anna Maria (2006). “Who is against immigration? A cross-country investigation of individual attitudes toward immigrants”. In: *The review of Economics and Statistics* 88(3), pp. 510–530.

Mayda, Anna Maria, Giovanni Peri, and Walter Steingress (2022). “The political impact of immigration: Evidence from the United States”. In: *American Economic Journal: Applied Economics* 14(1), pp. 358–389.

Mendez, Ildefonso and Isabel M Cutillas (2014). “Has immigration affected Spanish presidential elections results?” In: *Journal of Population Economics* 27, pp. 135–171.

Moriconi, Simone, Giovanni Peri, and Riccardo Turati (2022). "Skill of the immigrants and vote of the natives: Immigration and nationalism in European elections 2007–2016". In: *European Economic Review* 141, p. 103986.

Oliveira Tavares, Natalia Cintra de and Vinicus Pureza Cabral (2020). "The application of the Cartagena Declaration on Refugees to Venezuelans in Brazil: An analysis of the decision-making process by the National Committee for Refugees". In: *Latin American Law Review.*

Otto, Alkis Henri and Max Friedrich Steinhardt (2014). "Immigration and election outcomes—Evidence from city districts in Hamburg". In: *Regional Science and Urban Economics* 45, pp. 67–79.

Parekh, Serena (2020). *No refuge: Ethics and the global refugee crisis.* Oxford University Press.

Pettrachin, Andrea et al. (2023). "Did exposure to asylum seeking migration affect the electoral outcome of the 'Alternative für Deutschland'in Berlin? Evidence from the 2019 European elections". In: *Journal of Ethnic and Migration Studies* 49(2), pp. 576–600.

Raffoul, Jacqueline Salmen (2018). "Crisis in Venezuela: The Brazilian response to the massive flow of Venezuelan in Roraima". In: *Revista de Direito Internacional* 15(2).

Rozo, Sandra V and Juan F Vargas (2021). "Brothers or invaders? How crisis-driven migrants shape voting behavior". In: *Journal of Development Economics* 150, p. 102636.

Sanghi, Apurva, Harun Onder, and Varalakshmi Vemuru (2016). "" Yes" in My Backyard?" In.

Sant'Anna, Pedro HC and Jun Zhao (2020). "Doubly robust difference-in-differences estimators". In: *Journal of Econometrics* 219(1), pp. 101–122.

Schmidt, Katja, Jannes Jacobsen, and Theresa Iglauer (2024). "Proximity to refugee accommodations does not affect locals' attitudes toward refugees: evidence from Germany". In: *European Sociological Review* 40(4), pp. 615–638.

Silva, João Carlos Jarochinski and Liliana Lyra Jubilut (2018). "Venezuelans in Brazil: Challenges of Protection". In: *E-International Relations* 12.

Steinmayr, Andreas (2021). "Contact versus exposure: Refugee presence and voting for the far right". In: *Review of Economics and Statistics* 103(2), pp. 310–327.

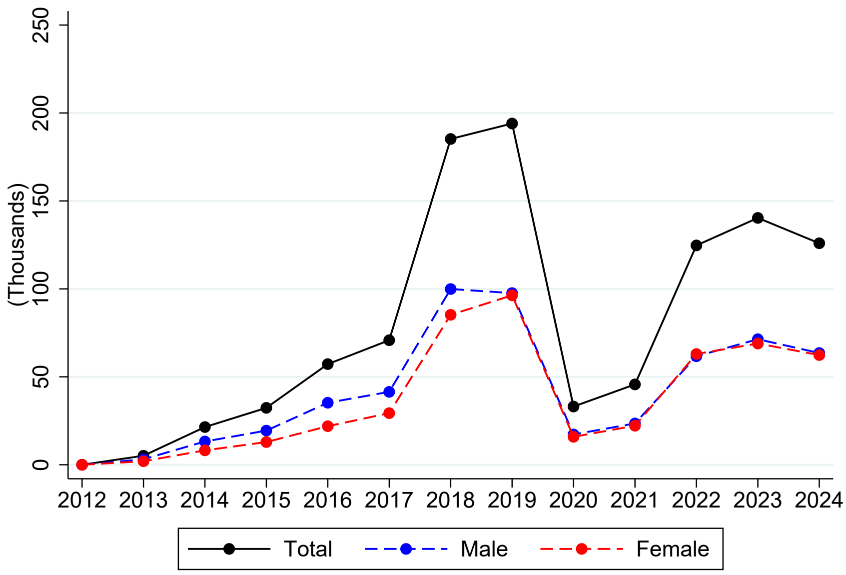
Vertier, Paul, Max Viskanic, and Matteo Gamalerio (2023). "Dismantling the "Jungle": Migrant relocation and extreme voting in France". In: *Political Science Research and Methods* 11(1), pp. 129–143.

Weitz-Shapiro, Rebecca and Matthew S Winters (2017). "Can citizens discern? Information credibility, political sophistication, and the punishment of corruption in Brazil". In: *The Journal of Politics* 79(1), pp. 60–74.

Appendix

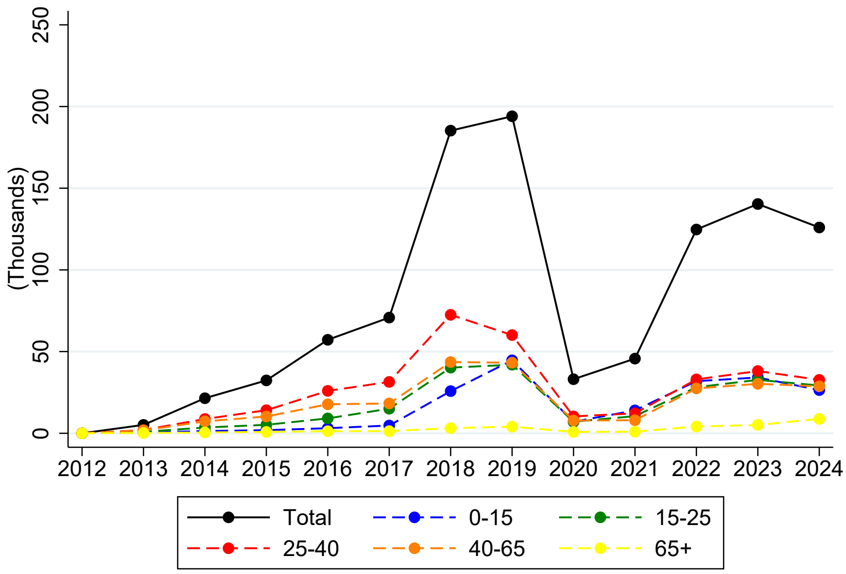
A Venezuelan Refugee Flow

Figure 26: Venezuelan Entrance Flows to Roraima



Source: Sistema de Tráfego Internacional (STI).

Figure 27: Venezuelan Entrance Flows to Roraima



Source: Sistema de Tráfego Internacional (STI).

Figure 28: Sheltered Refugees Vs Roraima's Population - Age

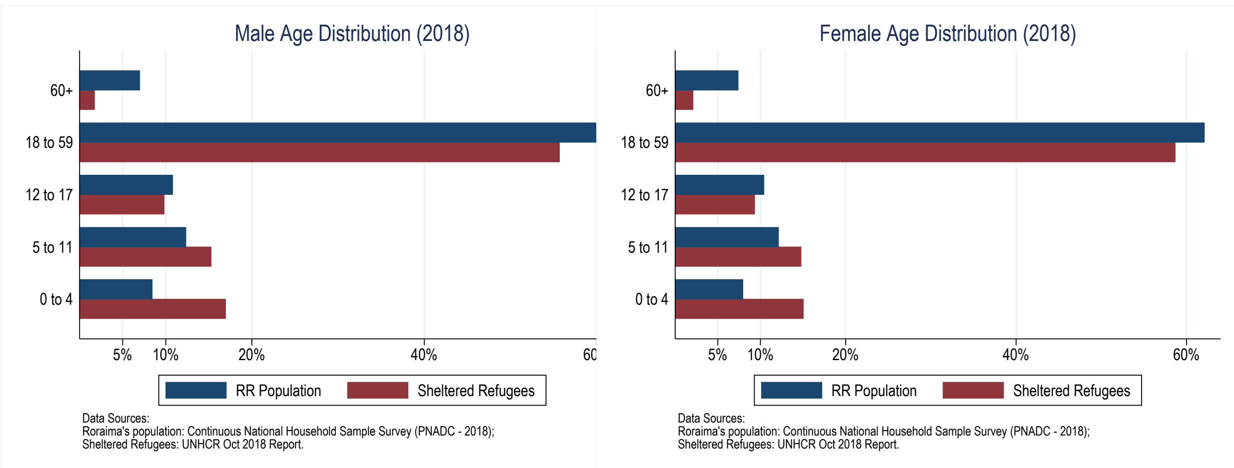


Figure 29: Sheltered Refugees Vs Roraima's Population - Education

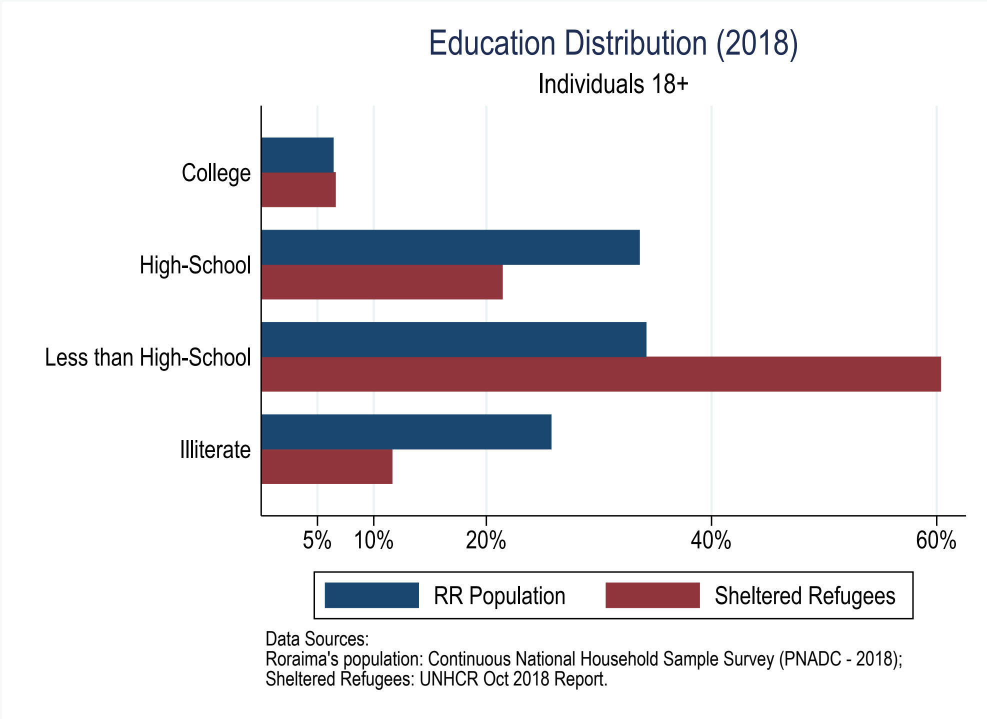
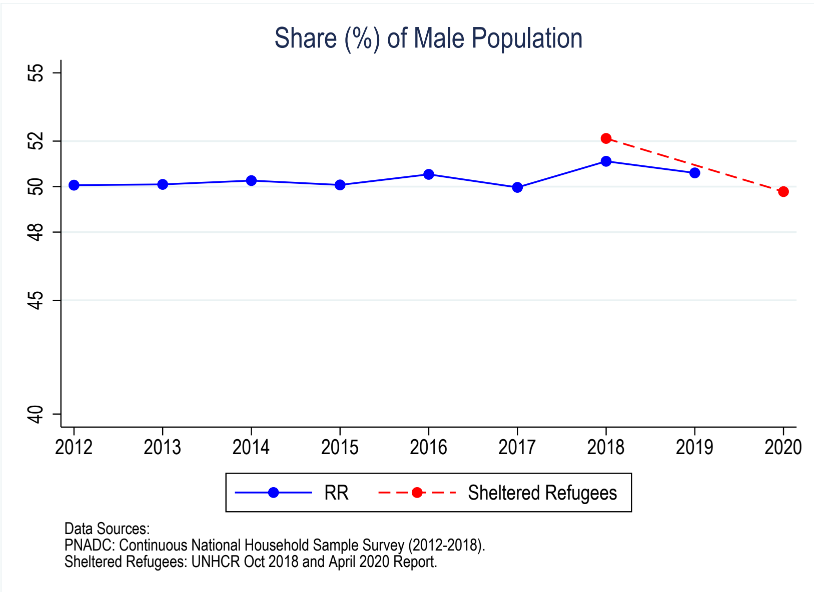


Figure 30: Sheltered Refugees Vs Roraima's Population - Gender



B Reception Policy Details

Figure 31: "Operação Acolhida" Anual Budget

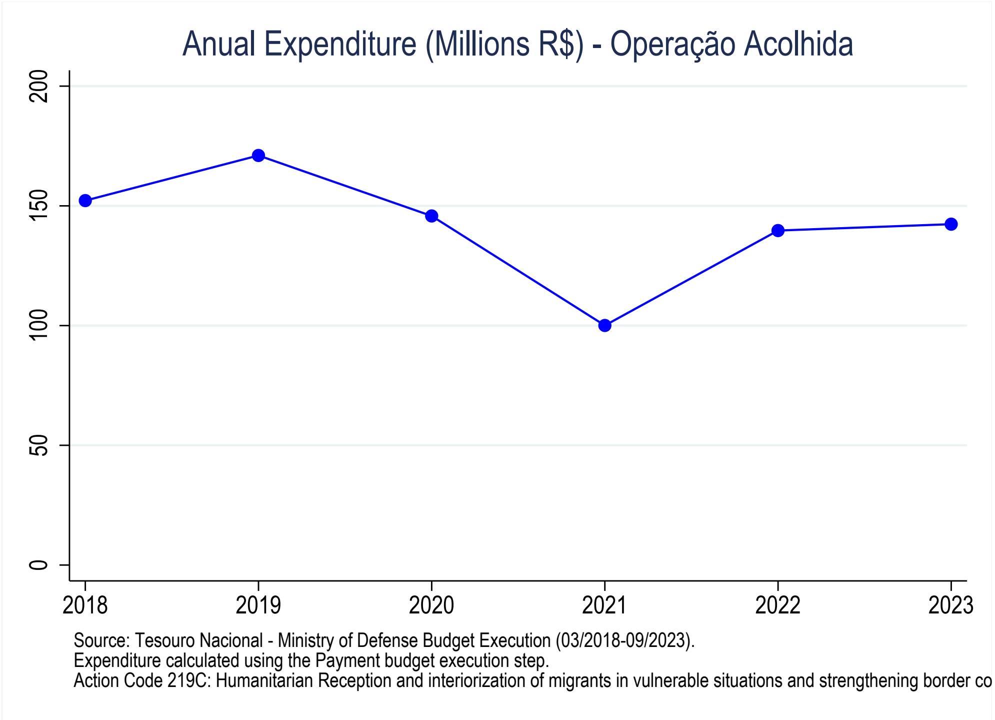


Figure 32: "Operação Acolhida" Monthly Budget

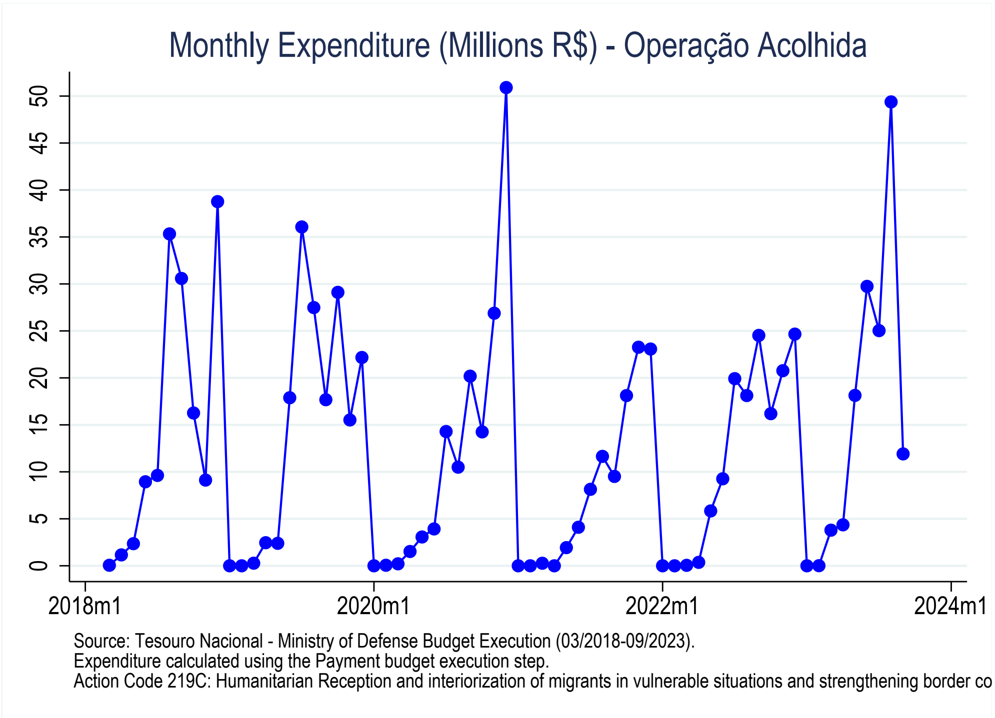


Table 9: Shelters Statistics

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

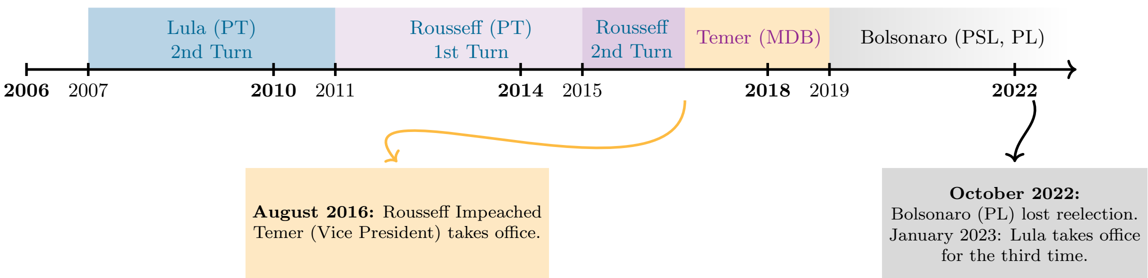
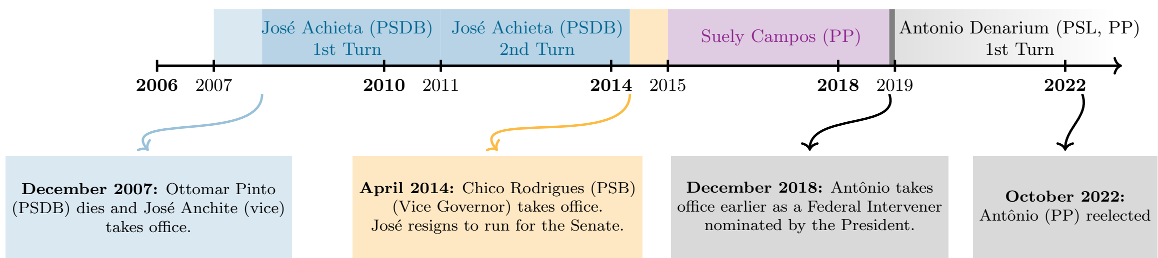


Figure 34: Timeline RR's Government



The relationship between the state and federal government was not only characterized by partnerships and cooperation. Suely 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.[32] 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.[33]

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.[34] 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 10: Governor Election - Parties Classification

	2018	**2014**	**2010**	**2006**
Suely (2018 Incumbent Candidate)	PP	PP	PP	PSDB
Denarium (Supported by Bolsonaro)	PSL	PSB	-	-
Anchieta	PSDB	PSB	PSDB	PSDB

Table 11: President Election - Parties Classification

	2018	**2014**	**2010**	**2006**
2018 Incumbent Candidate	-	-	-	-
Jair Bolsonaro (Far-Right Candidate)	PSL	PSB	-	PSL
Haddad (Worker's Party Candidate)	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

32 *"Governor of Roraima asks to close Brazil's border with Venezuela"*
33 *"Government of Roraima signs decree that tightens foreigners access to public services"*
34 *"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.

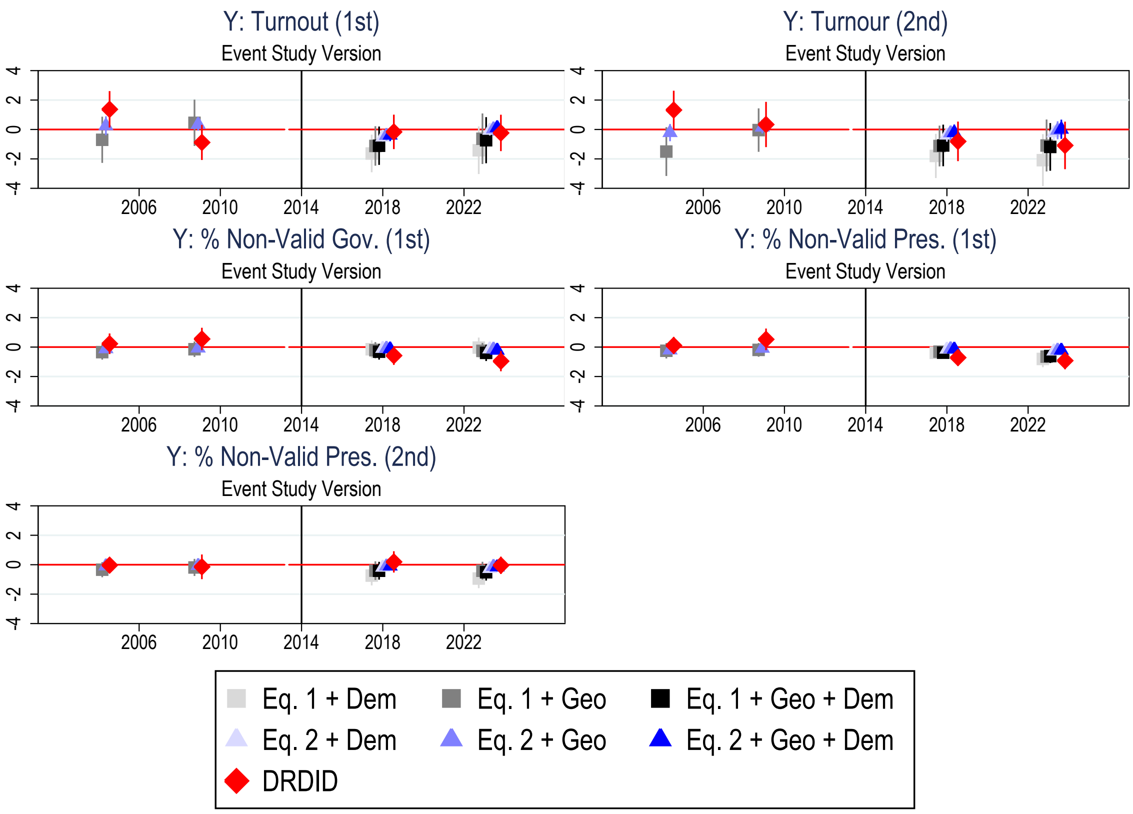
See Table 12 below for the final description of the polling stations' geographic coordinates data source.

Table 12: 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

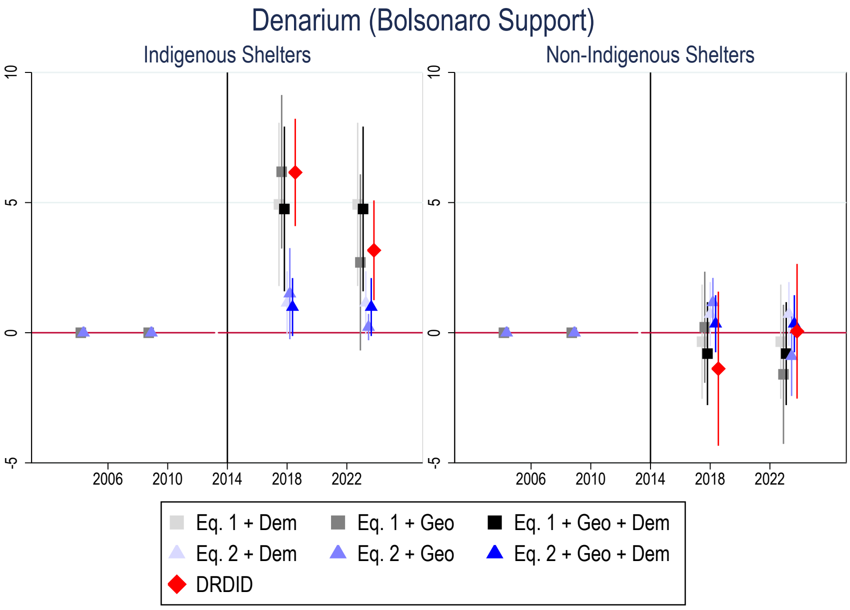
Figure 35: Turnout and Non-Valid Votes Event Study Results



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.

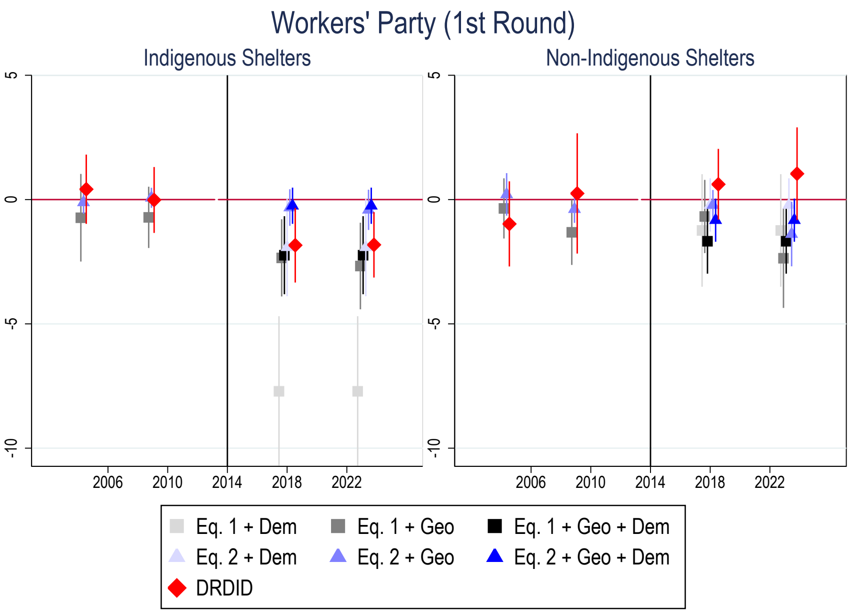
G Mechanisms

Figure 36: Governor Election Event Study Results - Indigenous Vs Non-Indigenous



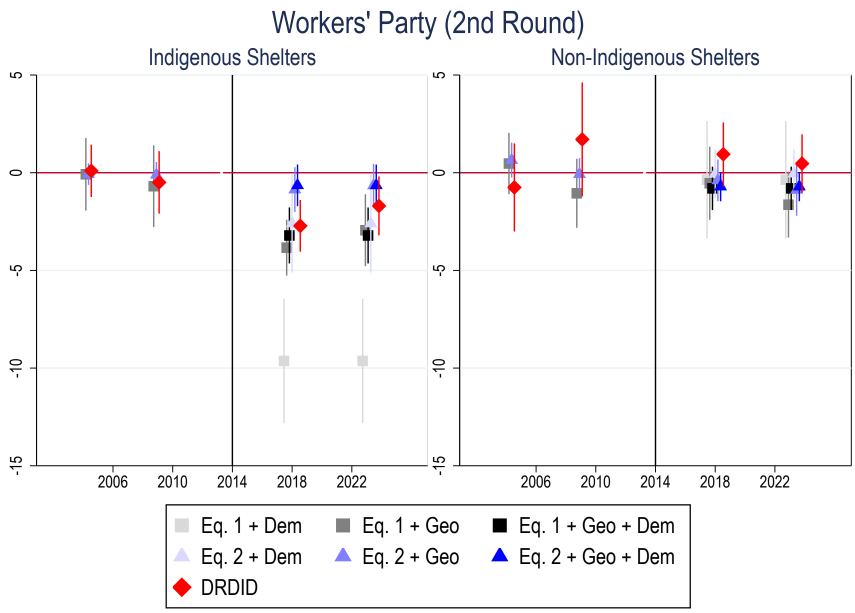
Notes: 2014 is the baseline year. PSL did not participate or support any candidate in the 2006 and 2010 state elections. Dependent Variable = % of valid votes for each category/candidate. *Dem* = 23 demographic (age, education, and gender) controls; *Geo* = time dummies interacted with polling station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

Figure 37: President Election Event Study Results - Indigenous Vs Non-Indigenous



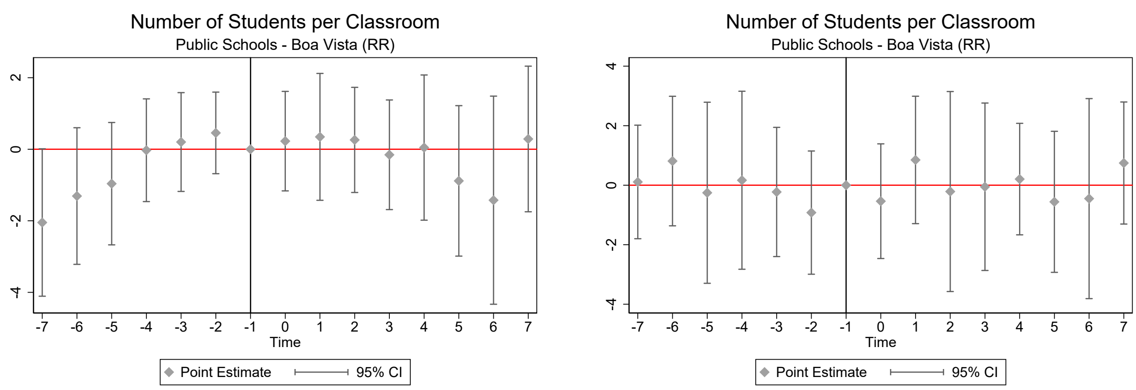
Notes: 2014 is the baseline year. Dependent Variable = % of valid votes for each category/candidate. *Dem* = 23 demographic (age, education, and gender) controls; *Geo* = time dummies interacted with polling station distance to downtown. DRDID = Doubly Robust DiD. MDID = Matching DiD.

Figure 38: President Election Event Study Results - Indigenous Vs Non-Indigenous



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.

Figure 39: Shelters' effect on schools' congestion - Classroom Size

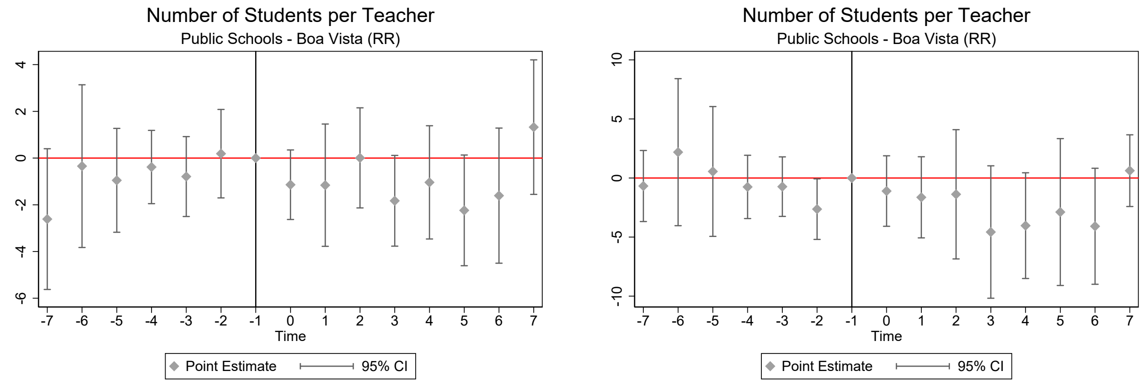


(a) Non-Indigenous Shelters

(b) Indigenous Shelters

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. Data source: administrative data from the Ministry of Education (2010 to 2024).

Figure 40: Shelters' effect on schools' congestion - Students per teacher

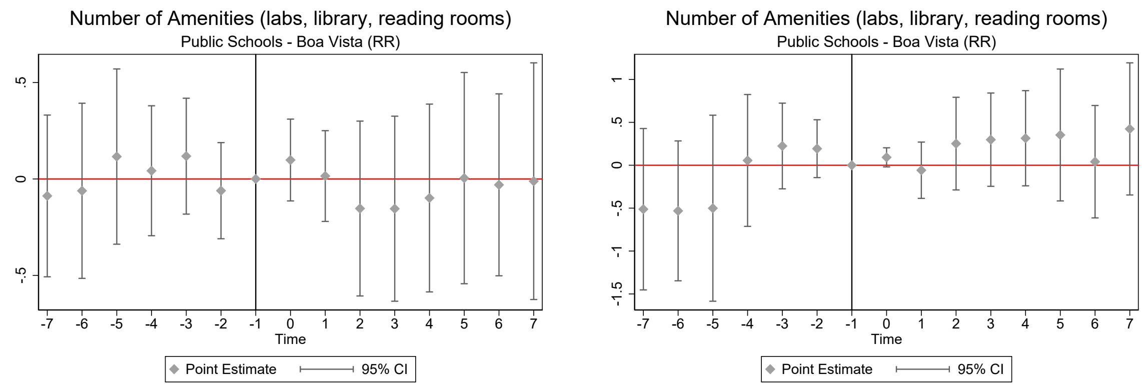


(a) Non-Indigenous Shelters

(b) Indigenous Shelters

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. Data source: administrative data from the Ministry of Education (2010 to 2024).

Figure 41: Shelters' effect on schools' amenities - Number of reading rooms, libraries and labs



(a) Non-Indigenous Shelters

(b) Indigenous Shelters

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. Data source: administrative data from the Ministry of Education (2010 to 2024).

H Party Affiliation

Figure 42: Number of New Affiliates (All Parties) - Boa Vista

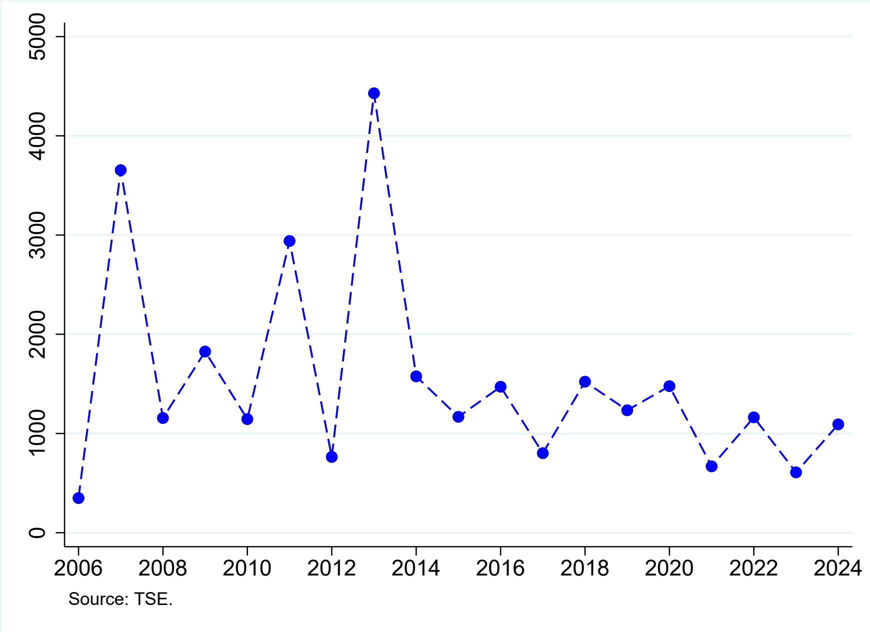


Figure 43: Incumbent Governor Party - log(Number of Affiliates)

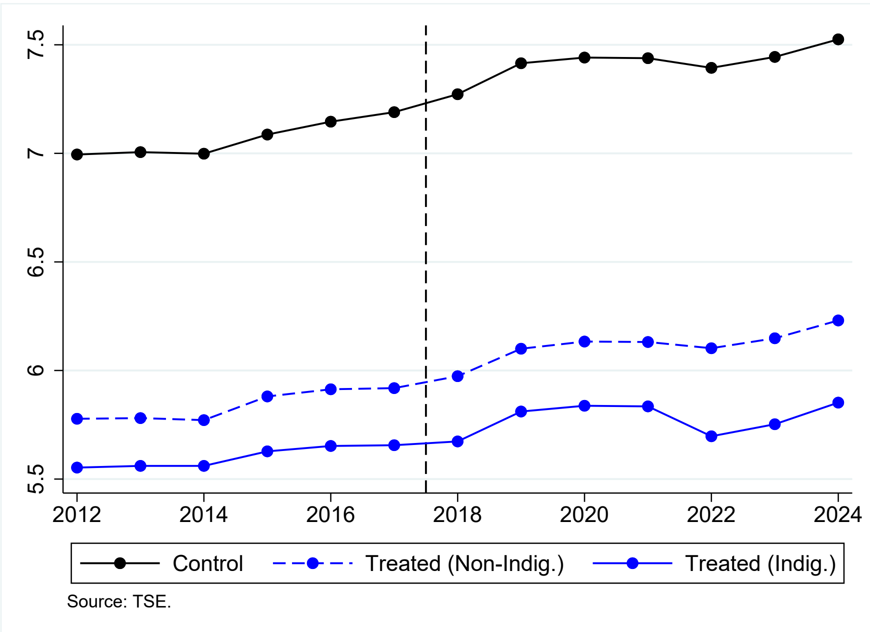


Figure 44: Workers' Party - log(Number of Affiliates)

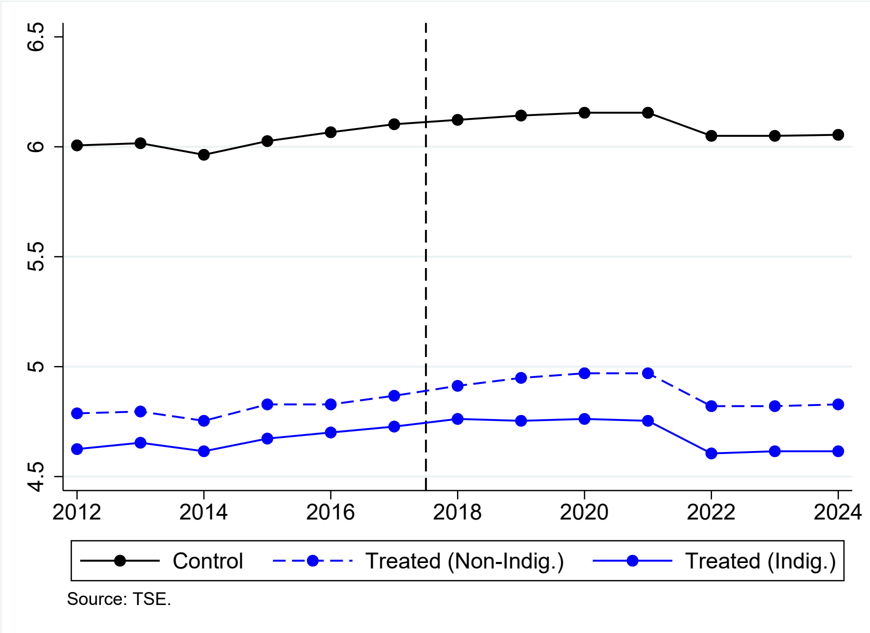


Figure 45: Bolsonaro's Party - log(Number of Affiliates)

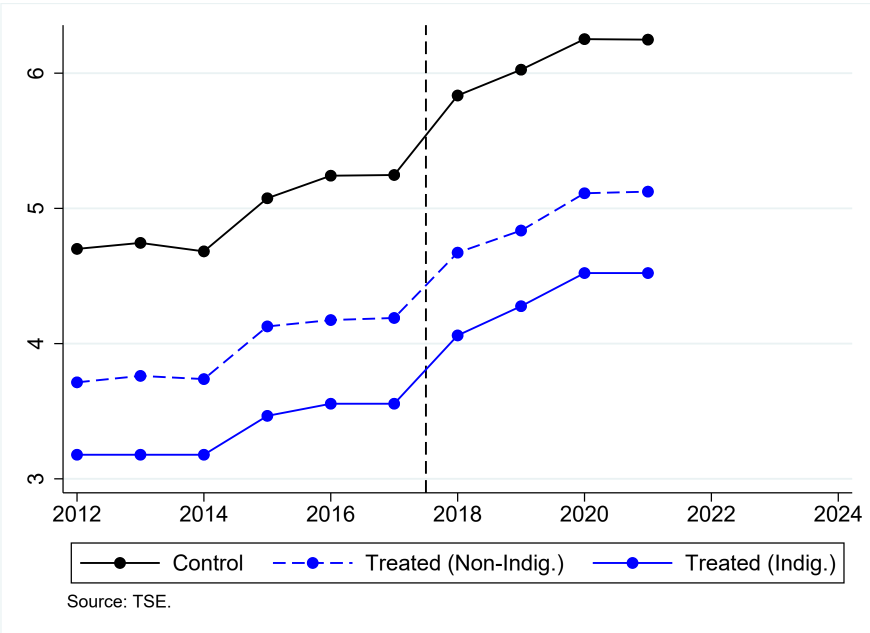
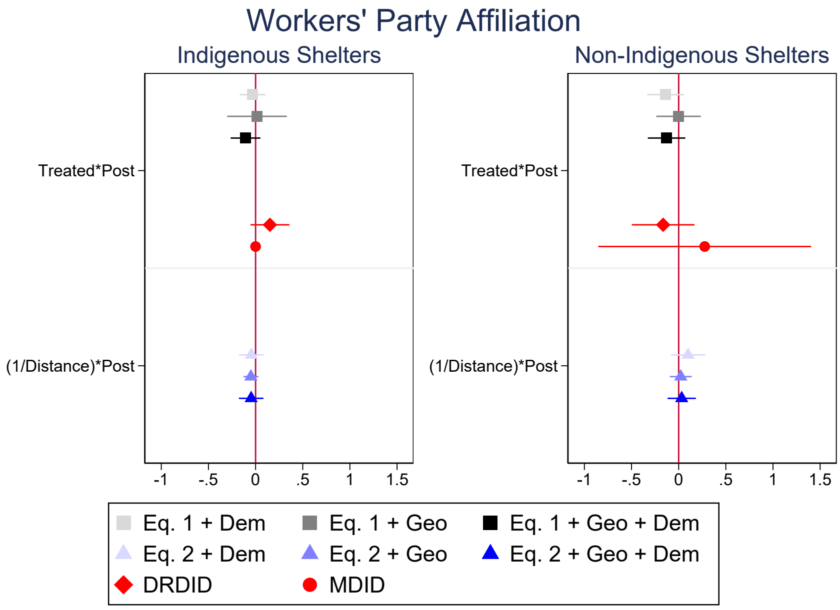
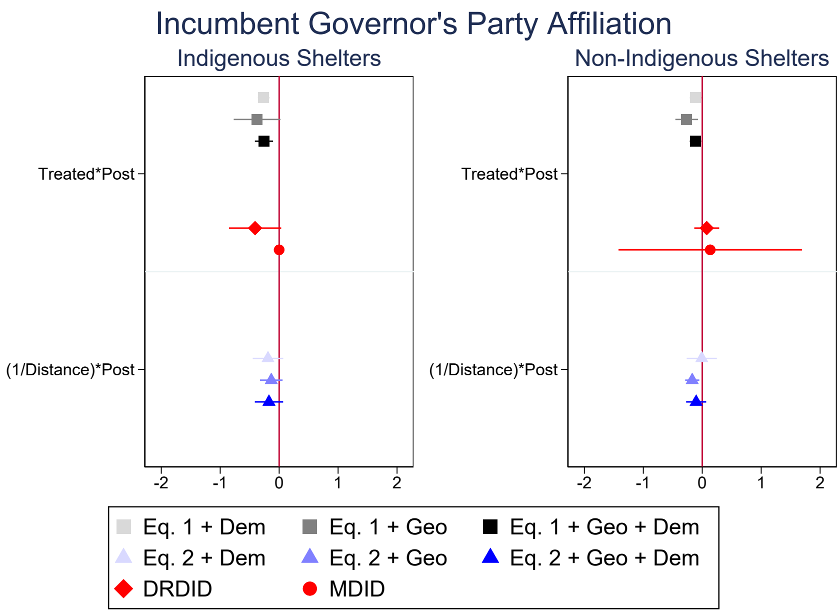


Figure 46: Party Affiliation Results



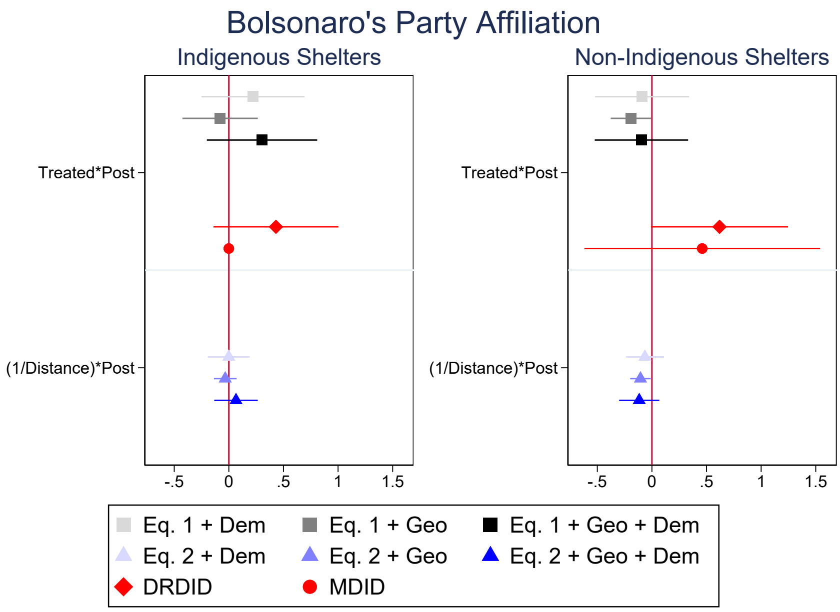
Notes: Dependent Variable = ihs transformation of the number of affiliates. Dem = 23 demographic (age, education, and gender) controls; Geo = time dummies interacted with polling station distance to downtown. DRDID = Doubly Robust DiD. MDID = Matching DiD.

Figure 47: Party Affiliation Results



Notes: Dependent Variable = ihs 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.

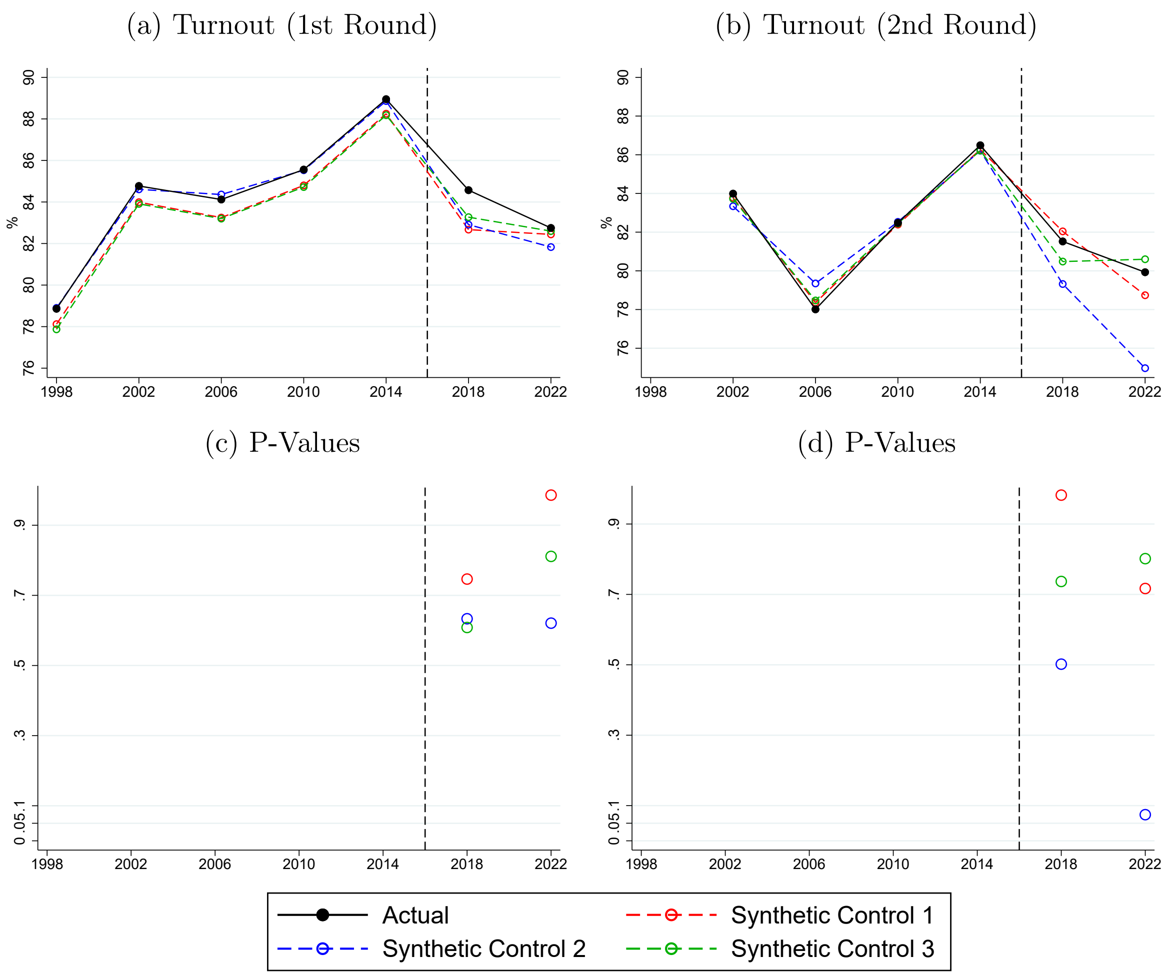
Figure 48: Party Affiliation Results



Notes: Dependent Variable = ihs 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.

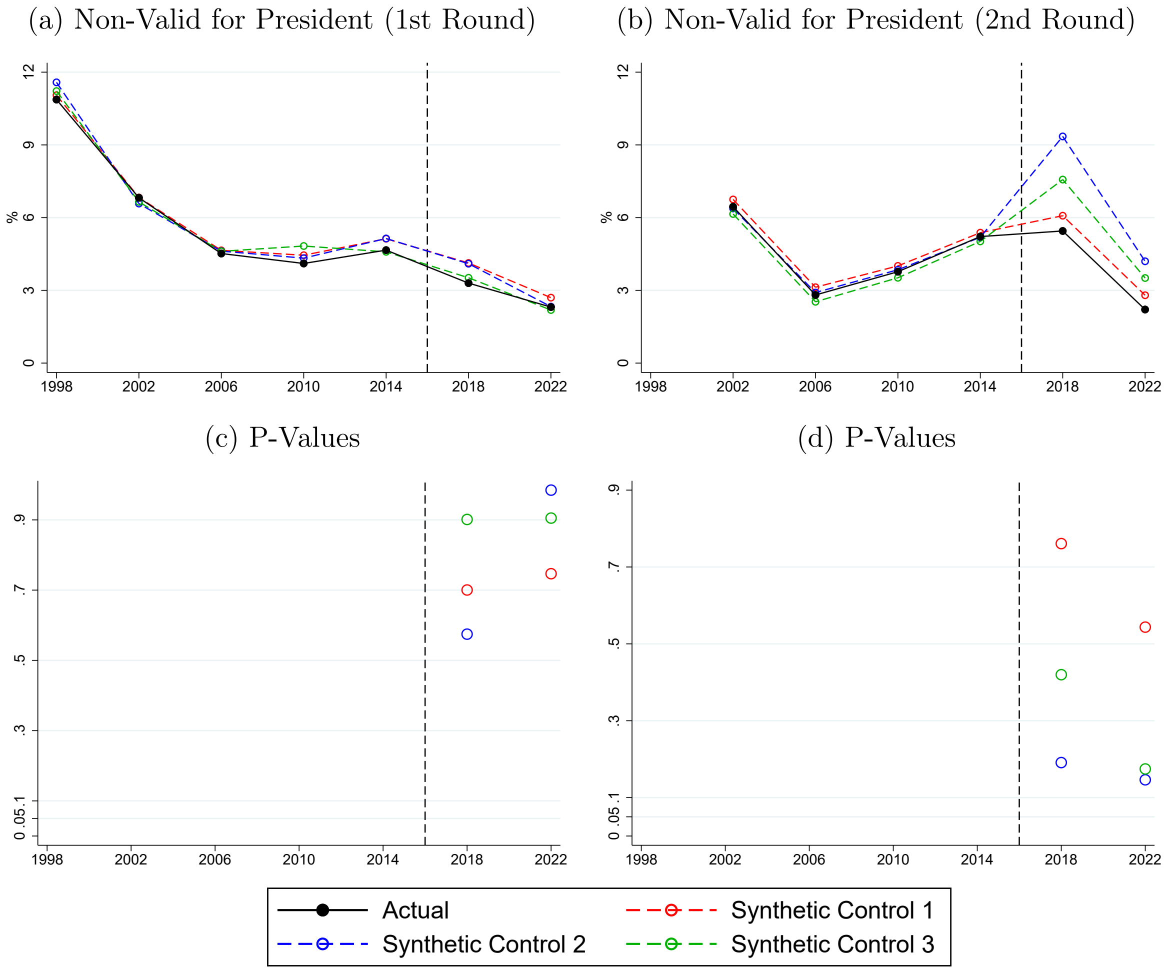
I Synthetic Control

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.

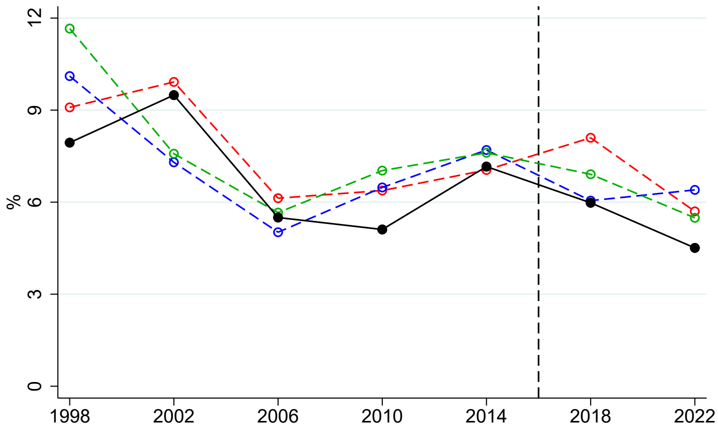
Figure 50: Overall Effect of Reception Policy



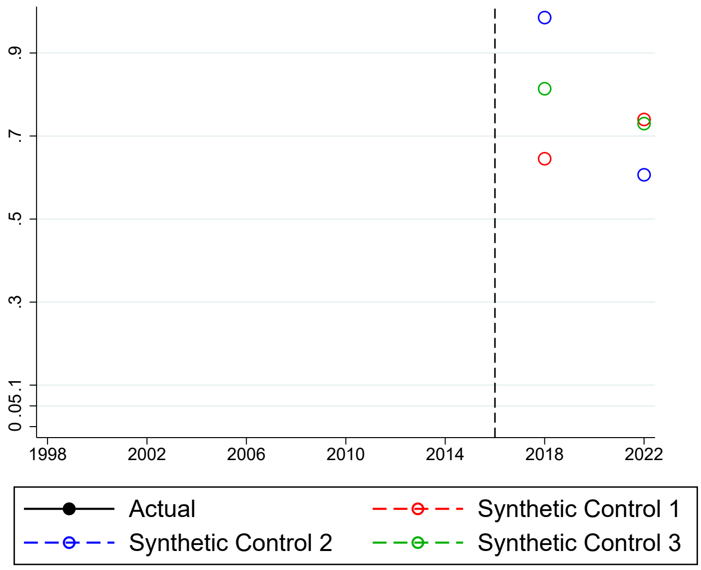
Notes: Synthetic Control 1: random 5% sample of Brazilian municipalities outside Roraima. *Synthetic Control 2*: 5% sample of Brazilian municipalities outside Roraima with the closest pre-migration average population to Boa Vista. *Synthetic Control 3*: 5% sample of Brazilian municipalities outside Roraima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

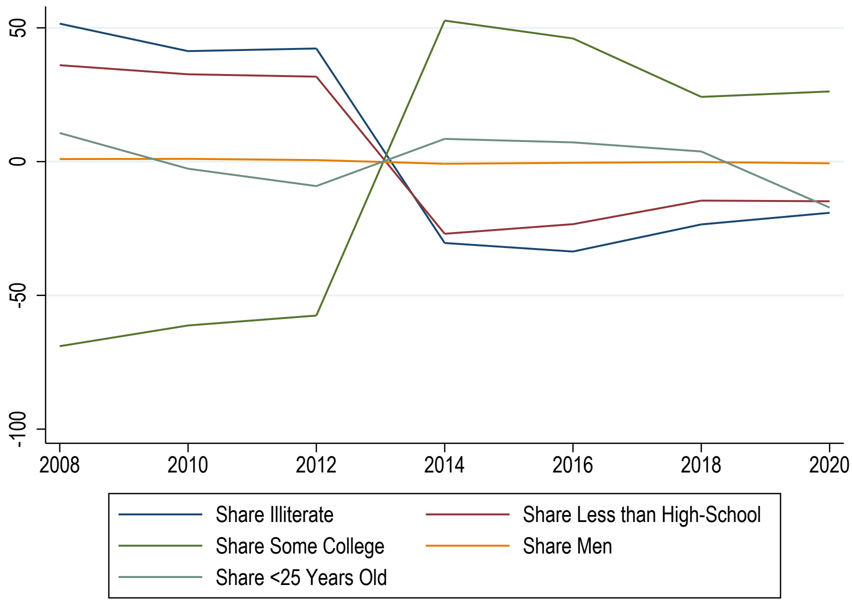
J Fingerprint scan and Voters' Demographic Info

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



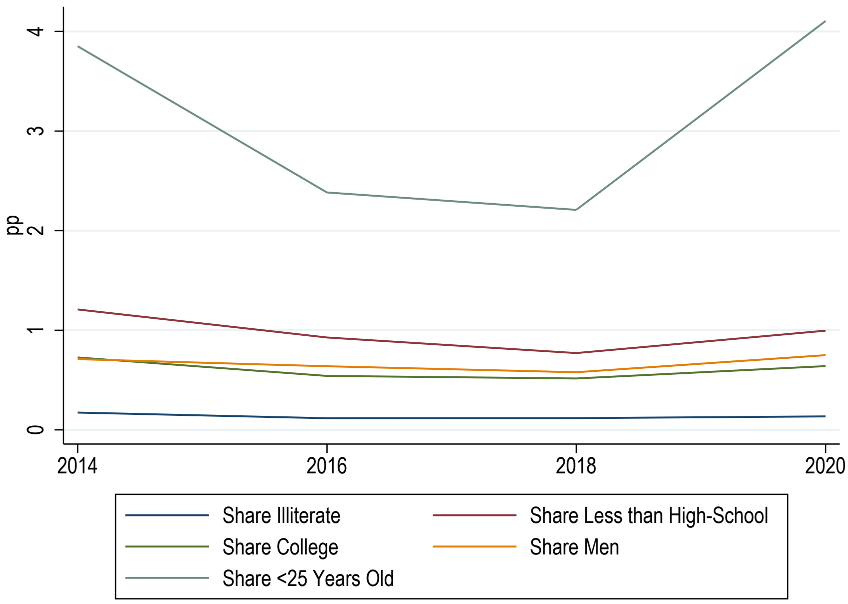
As we can see from Figure 52, ID_t associated with education variables are consistently above zero before 2013 and negative after. Therefore, educational information seems to have presented important updates after 2013 in the direction of more education. We don't observe this pattern for age or gender 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



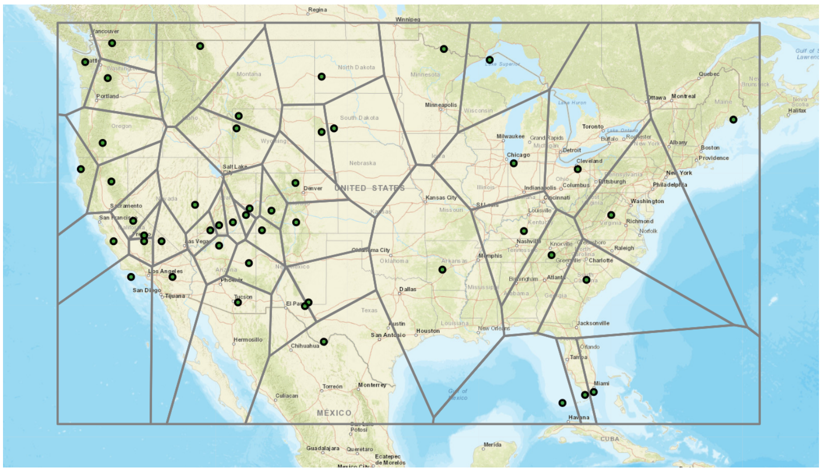
According to Figure 53, voter demographic information is stable and suffers minor deviations across elections. This goes in the direction of the National Electoral Code stating that voters will be permanently linked to their original section unless of some specific exceptions.

K 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).

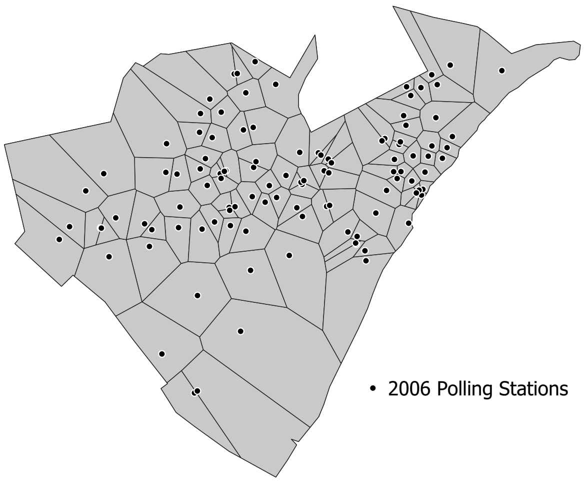
Figure 54: Voronoi Polygons using US National Parks



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: Overlaping the Voronoi Diagrams of 2006 and 2010 Polling Stations

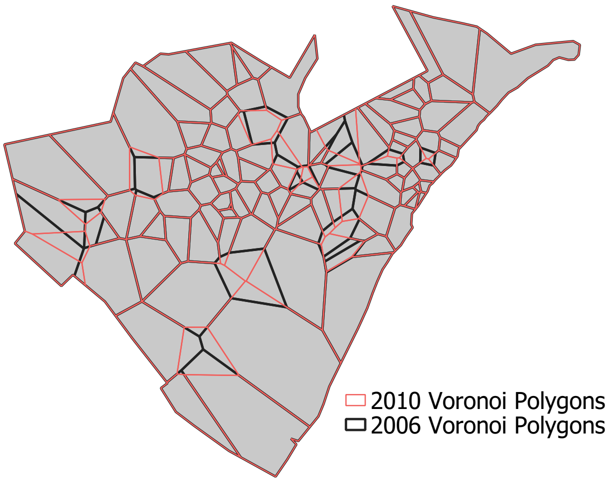
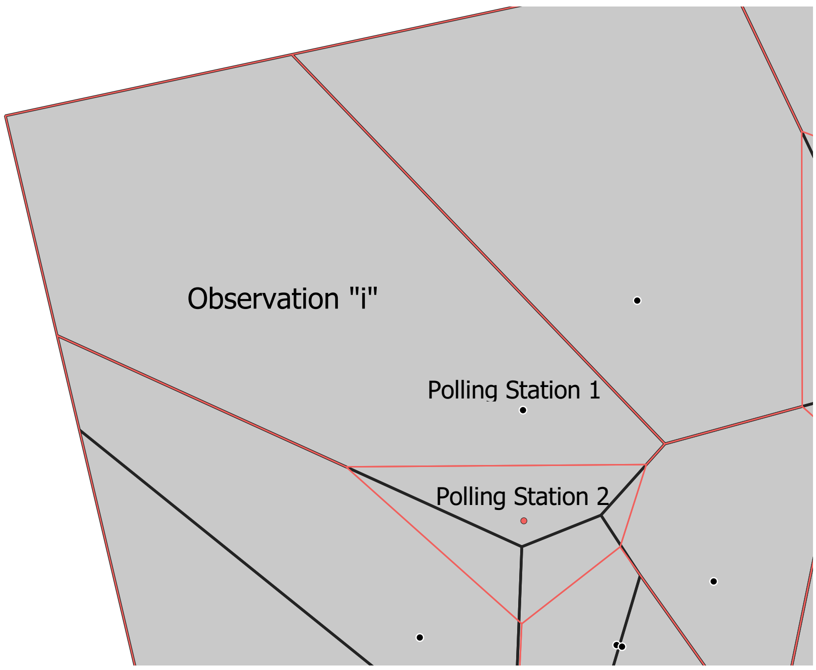


Figure 57 describes an example of how the weighting strategy works. Take observation "i" (the striped polygon). In 2006, its votes were entirely made out of Polling Station "1". Polling Station "2" was opened in 2010, which shrank Polling Station 1 Voronoi borders. Now, 100% of Polling Station "1" Voronoi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