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

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Abstract

Refugee camps and shelters in rural/secluded areas (often combined with restrictions on rights) remain the predominant form of aid provided by developing host countries, even though 78% of refugees worldwide reside in urban areas. Since 2014, one million Venezuelans have entered Brazil, and the border between the two countries in Roraima (the smallest Brazilian state in terms of GDP and population) has become the main entry point of an unprecedented migration flow. Diverging from this "standard" reception strategy, the Brazilian government granted comprehensive rights to Venezuelans and opened 11 urban refugee shelters in different neighborhoods of Roraima's capital. Leveraging the quasi-random placement of these shelters, I investigate how this "refined" reception policy affected locals' political choices. According to the results, Brazilians living closer to shelters increased their support for far-right presidential and gubernatorial candidates, at the expense of the incumbent governor involved in the shelter policy efforts. Therefore, urban shelters triggered an accountability effect combined with a shift towards far-right populist candidates. The results are mainly driven by shelters hosting Venezuelan indigenous people (an especially vulnerable and culturally distinct subgroup of the refugee population). This potentially reveals that cultural differences and competition for government resources and services can play an important role. Finally, the estimated results were small in magnitude and the shelters' absence wouldn't change the elected politicians' composition.

1 Introduction

The number of refugees and people in need of international protection worldwide has more than tripled in the last decade reaching around 41 million in 2023. Most of them (75%) are hosted by low and middle-income countries (mostly in Africa and Asia).[1]

Shelters and camps (currently hosting 6.6 million people) remain the dominant mode of aid for refugees and displaced populations in developing countries.[2] They in principle serve as temporary immediate protection and are usually in rural areas and outside the main urban centers. Additionally, most humanitarian assistance (food and services) is concentrated within camps, and sheltered refugees can face restrictions to accessing public services, welfare, and the labor market and even exit the camp and own property.[3]

However, this commonly offered reception approach contrasts with the reality that the vast majority (78%) of refugees live in cities, usually in non-functional public buildings, collective centers, slums, and informal settlements. Moreover, UNHCR recognizes that "unlike a camp, cities allow refugees to live autonomously, make money, and build a better future".

The potential urban shelters' benefits of improving targeting and fostering immigrants'; integration can come with political backlash. According to a vast literature, migration increases support for populist far-right and anti-migration candidates and parties.[4] And urban shelters will likely increase exposure and contact between locals and immigrants besides affecting neighborhood amenities, the local labor market, and shared public services.

Betts (2021) includes political support ("acceptable to political elites at the global,

[1]The forcibly displaced population worldwide (refugees, asylum seekers, people in need of international protection, and internally displaced) is around 110 million - see UNHCR Statistics for more.

[2]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).

[3]For example, refugees in Tanzania and Bangladesh cannot work legally outside the camps, and Kenya imposes restrictions to leave camps.

[4]See Alesina and Tabellini (2024)

national, and local levels") as one of the three foundations for a "sustainable" (capable of enduring) refugee policy. Erdal et al. (2018) also highlights the importance of not only understanding the economic and social effects of a migration flow into a host community but also how those effects are assessed politically.

The deepening of Venezuela's political and economic crises after 2014 made almost 8 million of its citizens emigrate, the majority (84%) to neighboring countries (mostly Colombia, Peru, Ecuador, Chile, and Brazil). During 2018, more than 150,000 entrances of Venezuelans were registered at the border of Brazil and Venezuela in the smallest Brazilian state of Roraima (population of 500,000). Contrasting the "traditional" camps, the Brazilian response to the unprecedented Venezuelan flow at its border was to grant Venezuelans extensive rights (freedom of movement, access to public services, welfare, and labor market) and establish urban shelters in Roraima's capital (Boa Vista). In that sense, Venezuelan shelters could have influenced locals' political preferences through economic (labor-market and welfare resources competition, for example) and cultural (such as tradition preservation) mechanisms.

Most of the literature on the causal electoral effects of migration focuses on developed countries (especially Europe) and mainly concludes that higher exposure to migrants increases the voting for right and far-right candidates and parties.[5] The main causal estimation challenge is the non-random spatial allocation of immigrants (they might self-select based on economic and political conditions). It is possible to divide the literature into two groups depending on how the paper deals with the endogenous immigrants' location. The first group of papers explores a shift-share instrument approach.[6] For example, Otto and Steinhardt (2014) show that far-right parties benefited from migration flows by capturing pro-immigration parties' votes in Hamburg (Germany) districts during the '80s and '90s national and regional elections. Rozo and Vargas (2021) show that exposure to Venezuelan immigrants induced higher turnout and votes for right-wing candidates in Colombian municipalities.[7]

[5]Two important exceptions explore Venezuelan refugee inflow in Colombia: Rozo and Vargas (2021) and Woldemikael (2022). Ajzenman, Dominguez, and Undurraga (2022) explore Chilean data.

[6]Some papers explore other instrument variables. Brunner and Kuhn (2018) use migrant concentrations at higher spatial aggregations as IV for Swiss communities. Harmon (2018) uses Danish municipalities' housing stock as an instrument given refugee settlement was highly dependent on rental housing availability.

[7]Other examples: Edo et al. (2019) (French Cantons); Barone et al. (2016) (Italian municipal-

The second group of papers explores an exogenous variation in migrant spatial dispersion. Dustmann, Vasiljeva, and Piil Damm (2019) take advantage of the Danish dispersal policy that quasi-randomly assigned refugees to municipalities. They found positive effects over right-leaning parties' performance in rural areas and potential small negative effects in urban areas in the 90's national and local elections.[8] According to Woldemikael (2022), the Venezuelan migration flow induced higher party fragmentation (number of contenders and independent candidates) in Colombian municipalities. Finally, Dinas et al. (2019) compare Greek islands closer and further from Turkey that experienced different inflows of Syrian refugees and concluded that refugee exposure increased the far-right party vote share.[9]

This paper belongs to the second group since I explored the quasi-random shelter locations across the different neighborhoods of Boa Vista set up in 2018. I explore the state (governor) and national (president) elections from 2006 to 2022.

This paper contributes to the literature by focusing on an "improved" refugee reception policy adopted in a developing country in a newly refugee-hosting area (South America). Moreover, in my setting, shelters could also have induced an accountability effect, making it hard for politicians who participated in the shelter policy to get reelected. Therefore, to some extent, this paper also speaks to the literature studying political accountability and how voters associate policies with policymakers.[10]

Finally, this paper also contributes to the literature studying the effects of refugee camps and shelters on host communities. Hennig (2021) focused on shelters' effect on the neighborhood quality (rents and ratings of amenities) in Berlin (Germany) and looked at political outcomes as a potential side effect (didn't find any effect on votes for anti-migration parties). Other papers studied how camps in Africa affected earnings, employment, and consumption of families in surrounding villages - see Sanghi,

ities); Mendez and Cutillas (2014) (Spanish Provinces); Moriconi, Peri, and Turati (2022) (regions of 12 European countries); Mayda, Peri, and Steingress (2016) (USA states); Halla, Wagner, and Zweimüller (2017) (Austrian communities) and Steinmayr (2021) (Austrian municipalities).

[8] Dustmann, Vasiljeva, and Piil Damm (2019) also found refugee dispersion affected parties' decision whether or not to run at the municipality level.

[9] Other examples: Vertier, Viskanic, and Gamalerio (2023) (reception centers in France), Brunner and Kuhn (2018) (Switzerland); Harmon (2018) (Denmark); Becker, Fetzer, et al. (2016) (UK); Mayda (2006) (cross-country individual level surveys data); Campo, Giunti, and Mendola (2021) (Italian refugee dispersal policy).

[10] Ferraz and Finan (2008), for example, found that voters punished politicians when corruption is revealed in Brazilian municipalities.

Onder, and Vemuru (2016), Alix-Garcia, Walker, et al. (2018), and Alix-Garcia and Saah (2010). The literature on shelters' causal public policy analysis and "political sustainability" strength is very limited.

The rest of the paper is organized as follows. First, I provide the background descriptions of the Venezuelan refugee crisis and the Brazilian elections and political environment. The third section describes the data. Section 4 presents the regression equations, the estimation methods, and the 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 suffers from a deep economic crisis that led to a 65% decrease in its GDP between 2014 and 2019 and yearly inflation rates above 1000%.[11] 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, the majority (more than 84%) to other countries in Latin America and the Caribbean.[12]

Between January 2017 and April 2024, more than 1 million Venezuelans entered Brazil, most trying to get to other South American Countries (over 450,000 stayed).[13] According to Baeninger, Demétrio, and Domeniconi (2022), Venezuelan immigration to Brazil can be organized in three waves. The first wave happened between 2012 and 2014; it consisted of highly qualified immigrants who arrived at the main international airports and chose Brazil (especially the southeast) because of restrictions imposed by developed countries, such as the US and Spain. The second wave took place between 2015 and 2017. It was also made up of middle-class Venezuelans, such as engineers, technicians, and professors, but some were already seeking other Brazilian cities on their own.

[11] IMF statistics.

[12] See R4V Platform for statistics by destination country.

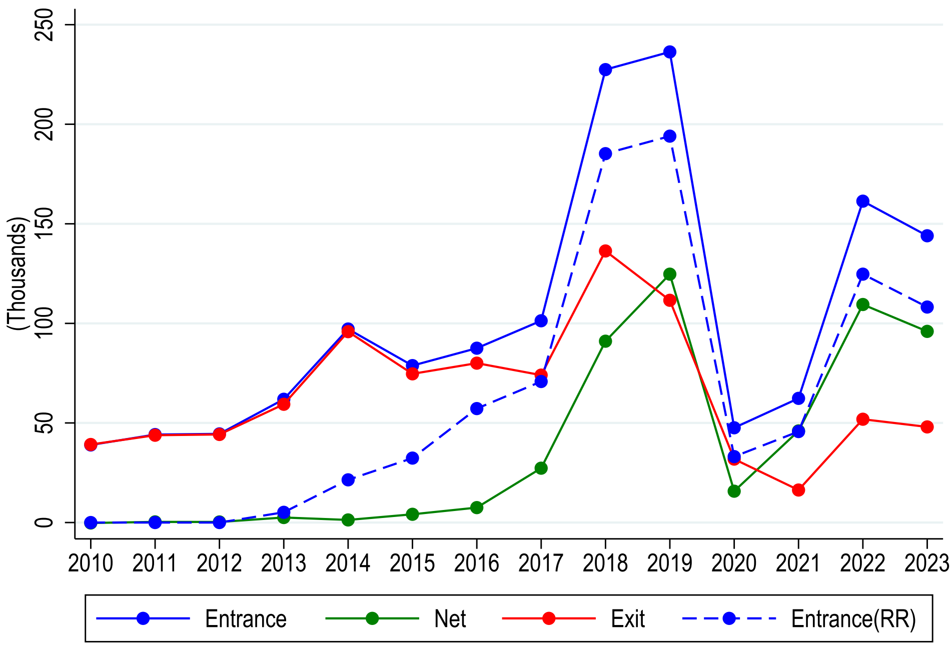
[13] Source: Ministry of Justice and Public Security report on Venezuelan Migration for April 2024.

Figure 1: Brazil-Venezula 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 (especially at the city of Pacaraima - see Figure 1). Refugees then go to Boa Vista, the state capital and Roraima's biggest city (more than 400,000 people in 2020), and from there, they can go to other parts of the country. The entrance flows the border picked up in 2019 and sharply decreased during 2020 and 2021 when the border was closed due to the COVID-19 pandemic (see Figure 2).[14]

[14]See Figures 24 and 25 in the Appendix for more details about the gender and age composition of the refugee flow.

Figure 2: Venezuelan Migration Flows to Brazil and RR



Source: STI. For 2023 data includes January to September.

In Brazil, immigrants, disregarding their legal status, can access public schools and the national health care system (which is free and covers ERs and medical appointments to more complex treatments). Once documented, immigrants can access the formal labor market and welfare programs (most importantly, the national cash transfer to poor households). Unlike some European countries, where the government places all arriving refugees in specific municipalities, refugees in Brazil have free movement within the country.[15]

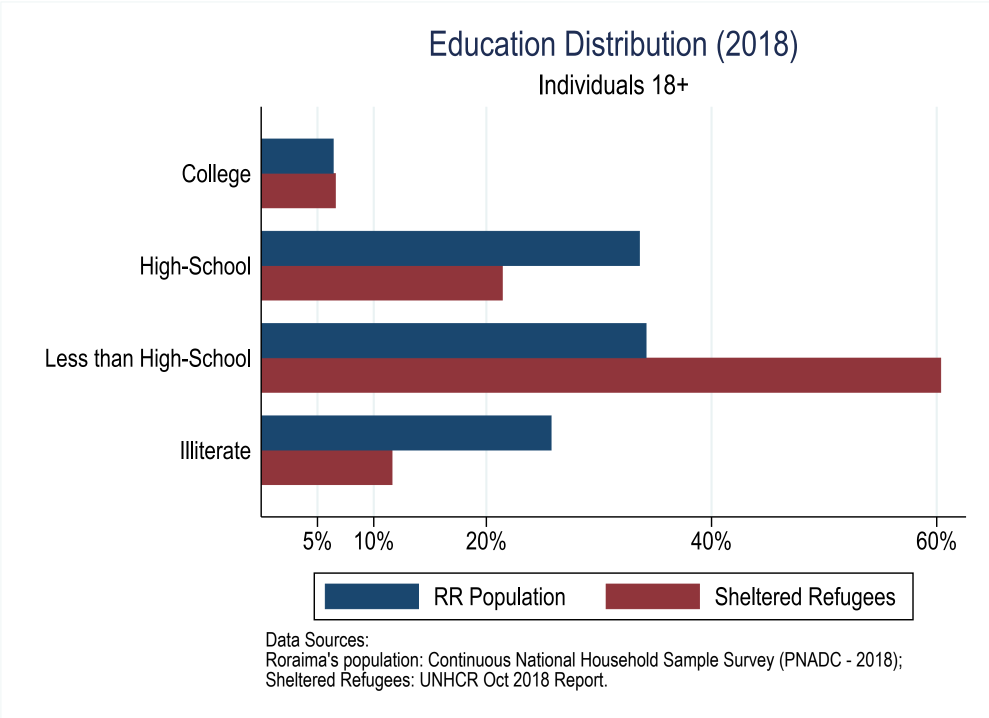
To obtain a refugee status (one of the options for regularization) the foreigner must first fill out forms online and schedule an appointment at one of the Federal Police offices to present the required documents and get a temporary ID. The refugee status grant decision can take several months, however, 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. Refugees and refugee status seekers must request a travel permit to visit their home country and regular trips or long stays outside Brazil can terminate the process

[15]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).

or cancel the status. Another option for regularization is through residency permits, which follow a similar process, but it is not free and requires different documents.

By April 2024, more than 480,000 Venezuelans possessed residency (either temporary or permanent), around 15,000 refugee status requests were being analyzed, and more than 130,000 Venezuelans were granted refugee status.[16] Therefore, those numbers compared with the estimated size of the Venezuelan community in the country and the existence of straightforward legal pathways for documentation, indicate a documentation rate close to 100%.

Figure 3: Sheltered Refugees Vs Roraima's Population - Education

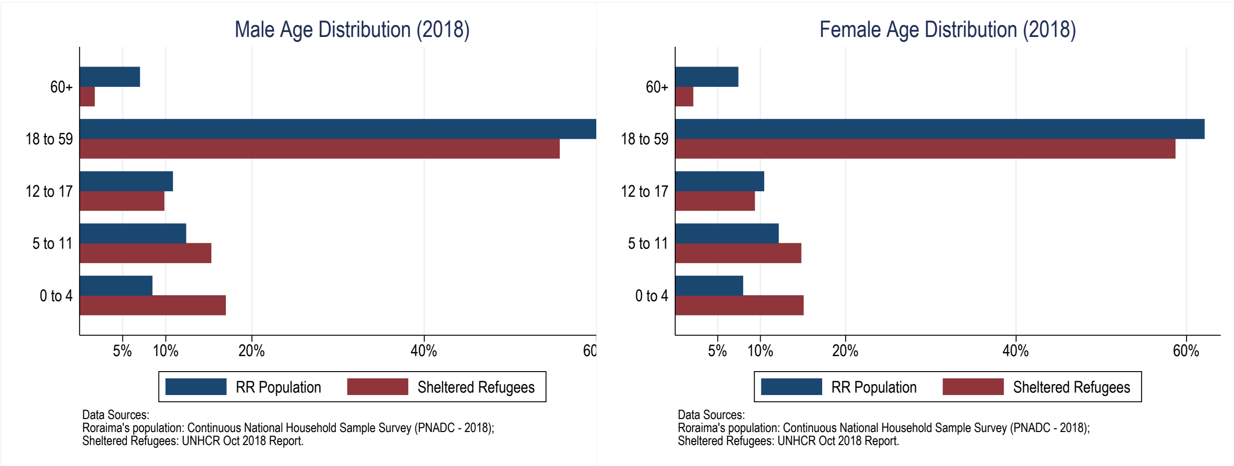


According to a survey conducted by the Boa Vista (Roraima's capital) government in June 2018, 25,000 refugees were living in the city (7.5% of its population), and around 10% were homeless.[17] The availability of data about the refugee population in Roraima is limited to UNHCR monthly reports containing some demographic and socioeconomic characteristics of the sheltered Venezuelan population. Therefore, I used these reports and the Brazilian household survey (PNAD) available at the state level to compare Roraima's population and sheltered refugees. The refugees are younger

[16]Source: Ministry of Justice and Public Security report on Venezuelan Migration for April 2024.
[17]Source: Newspaper article.

with disproportionately more 11-year-old kids or younger and considerably less 60 years or older individuals (see Figure 4). Moreover, illiteracy is two times less common among Venezuelans on the other hand the proportion of refugees without a high-school degree is larger (see Figure 3). In other words, refugee education distribution is less polarized than the Brazilian one. Finally, the two populations present a similar gender composition (see Figure 26).[18]

Figure 4: Sheltered Refugees Vs Roraima's Population - Age



2.2 Operação Acolhida

The "Operação Acolhida" (Reception Operation) was launched by the Brazilian Federal Government 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 in Pacaraima (at the border) and Boa Vista. The Operation consisted of three main foundations: border planning, dispersal policy, and reception/shelters (the one explored

[18]PNAD data are only available at the state level and doesn't allow us to separate foreign and Brazilian individuals, so the statistics for the state could be affected by the refugee population living in Roraima. Therefore, if anything, the differences between the two populations are underestimated.

by this paper).[19]

Figure 5: 2018 Timeline - Shelters and Election

The first meeting to discuss the first efforts and logistics of "Operação Acolhida" happened on February 21st 2018, and the shelters started to be open in march (see Figure 5); they were surrounded by walls and provided food and protection for documented refugees. Teams of volunteers, UN, and government workers offered health services/care, portuguese classes, and activities for children. Some shelters provided the "Refugee Housing Units" model of UN, others used tents and overlays provided by the Brazilian army - see Figure 7. 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 (an exception was made for working situations) and sheltered refugees had an identification card.[20] From the moment they opened shelters were at full capacity (some above it), the smallest one hosted 279 Venezuelans, and the biggest sheltered more than 650 refugees in 2018.[21] By October 2018 (when the election happened), 5,000 refugees were living in one of the shelters in Boa Vista.

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

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

[21]See Table 6 in the Appendix Section C for 2018 and 2020 shelter-specific statistics.

Figure 6: Shelters' Inside Photos

Tancredo Neves Shelter (Source)

Rondon 1 Shelter (Source)

Figure 7: "Operação Acolhida" logo and shelters' name on outside signs

Jardim Floresta Shelter

Santa Teresa Shelter

Source: Google Maps Street View

2.3 Brazilian Elections

Voting Right

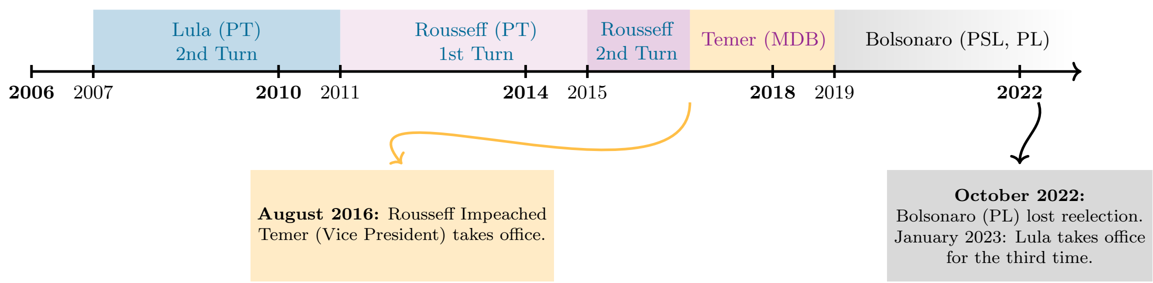
Voting is mandatory for 18 to 65-year-old Brazilians living in the country and optionally for 16 and 17-year-olds. Citizens must go to the electoral registry office bringing an official identification document and proof of residence (utility bills, for example) to get a voter's ID.

Voting is restricted to citizens (born in Brazilian territory or naturalized). The naturalization of individuals without specific family ties with Brazilians takes up to 180 days and involves a minimum number of years living in the country (4 years in most cases) and proof of Portuguese proficiency (for example, a portuguese exam or tertiary degree in a Brazilian education institution).[22] Therefore, in this setting, Venezuelan refugees are not voting.[23]

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 state of Roraima elected their representatives for the following positions: President, State Governor, Federal Deputy (8 vacancies), Senators (2 vacancies), and State Deputies (24 vacancies). Since no candidate for President and Governor reached 50% or more of the valid votes, the second round was held on October 28.

2018 Political Environment (Presidential Election)

Figure 8: Timeline Brazil's Presidents



The 2014 reelected Brazilian President, Dilma Rousseff (Workers' Party - PT), was impeached in august 2016. Her vice president, Michel Temer, from a more centered party (Brazilian Democratic Movement - MDB), took over and made big changes in the government composition. His administration was responsible for launching and leading "Operação Acolhida". Michel Temer decided not to run again in 2018.[24] Therefore, there was no incumbent candidate in the 2018 presidential election. The Workers Party launched Fernando Haddad, who got 29.30% of the votes in the first round and lost the second round (44.90%). The 2018 elected President was Jair Messias Bolsonaro (46% in the first round and 55.10% in the second round). Jair was a federal deputy for the

[22]Source: Ministry of Justice and Public Security.

[23]Unfortunately, information about the number of naturalized citizens among the voters and general population is not available.

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

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.

"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 and Bolsonaro had considerably different views about immigrants. The 2018 Bolsonaro government program doesn't mention immigrants or refugees directly. Contrastingly, Haddad's program explicitly had as goal to promote refugees' and immigrants' rights and refers to them as a target population for public policies.

Haddad's 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."

In 2018, Boa Vista was the second state capital with the highest vote share for Bolsonaro in the second round (almost 80% of valid votes - see Figure 9). Moreover, the support for the Workers' Party between the 2014 and 2018 second rounds decreased by more than 35% - see Figure 10. Therefore, compared with the rest of the country, Boa Vista seems to have disproportionately shifted to the far-right in 2018.

Figure 9: Share of Valid Votes for Jair Bolsonaro - State Capitals

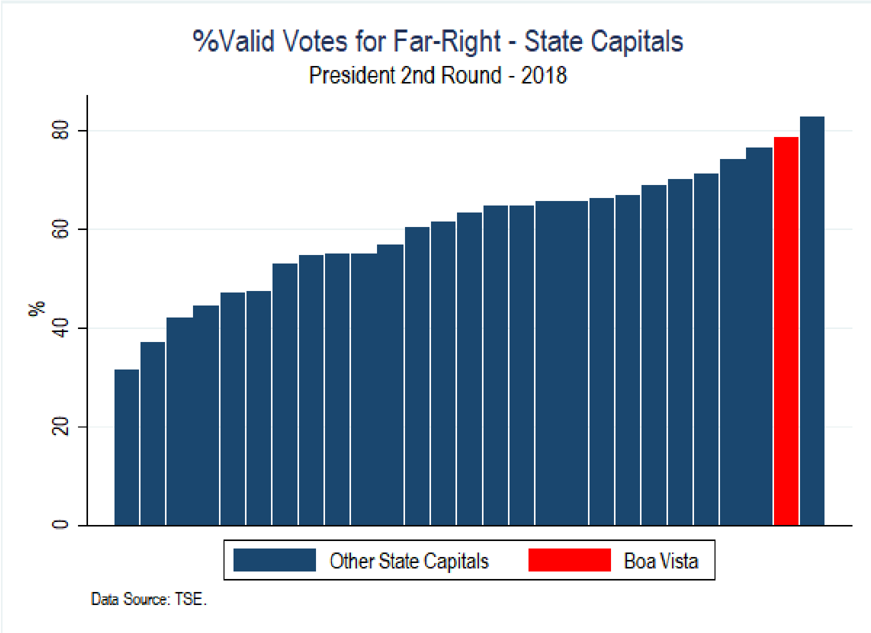
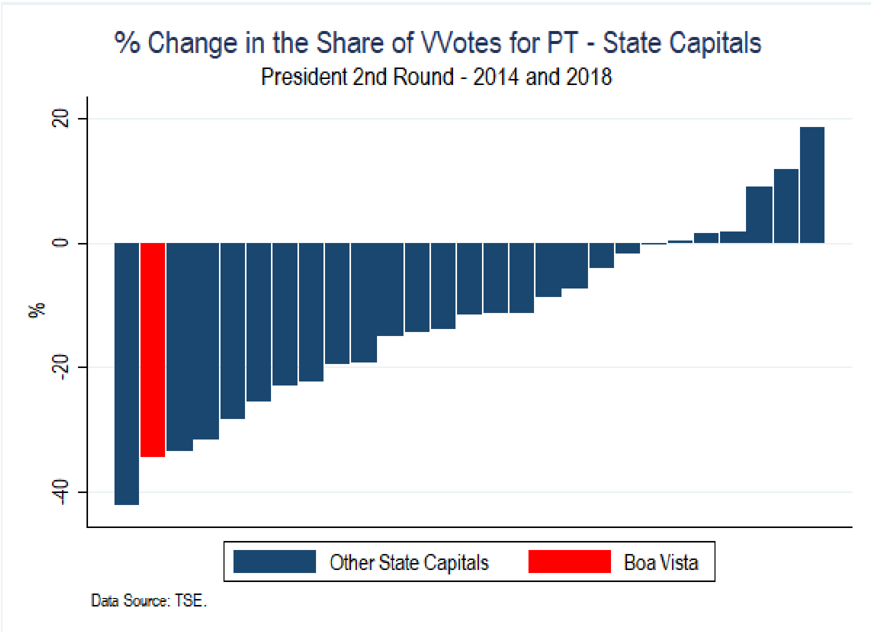


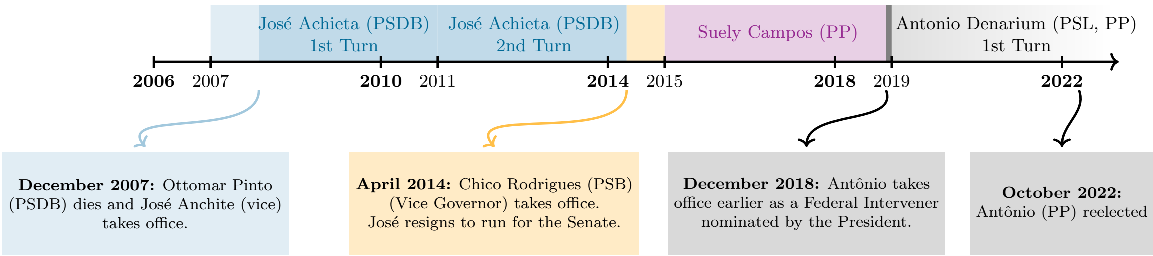
Figure 10: % Change in Workers' Party (PT) performance - State Capitals



Haddad's Party, PT, launched a candidate in every Presidential election in my data (2006 to 2018). However, for some election years before 2018, PSL (Bolsonaro's Party) didn't launch a candidate, so I will use the performance of the candidate it supported in those elections. I also look at the other candidates' party and its support/partnership over the years.

2018 Political Environment (Governor Election)

Figure 11: Timeline RR's Government



From 2014 to 2018 Suely Campos ("Progressistas" - PP) was Roraima's Governor. She won the 2014 second-round election with 54.9% of the valid votes and was running for reelection in 2018 (unsuccessfully with less than 12% of the valid votes).

Figure 12: National Newspaper Headlines Covering Roraima's 2018 Election


ELEIÇÕES 2018 · VENEZUELA

Crise migratória vira principal assunto da eleição em Roraima

Candidatos se unem em discurso contra refugiados, e governadora diz que fronteira aberta afeta popularidade

Na eleição de Roraima, o que importa mesmo é a Venezuela

Candidatos ao governo de Roraima debatem sobre a entrada de imigrantes venezuelanos pelas fronteiras

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

According to "Operação Acolhida" reports and meeting minutes, during 2018 Suely's Government participated directly in the "Operação Acolhida" efforts. The state Government received extra funds for social and health services and, together with the federal government, created different commissions to handle problems related to the refugee flow such as the "State Commission to Eradicate Slave Labor". The state government (in partnership with NGOs and UNHCR) also directly managed two shelters and it was also responsible for several interventions targeting the sheltered population (such as STD testing, distribution of condoms, vaccine campaigns, and nutrition surveillance).

However, 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.[25] Finally, two months before the election, Suely also published an unconstitutional act trying to enhance deportation enforcement and to introduce to Venezuelans a passport presentation requirement to access non-emergency public services.[26]

During 2018, Roraima was also suffering from a financial crisis and a surge in crime. The prison system was especially vulnerable and suffered from overcrowding and a lack of staff and mass escapes and riots were registered in 2018.[27] During the campaign, Suely claimed the former Governor's poor financial management, the unprecedented refugee flow, and the absence of federal government assistance made her deal with "the most challenging environment a Roraima's governor ever faced".

The voting pools in August and September 2018 indicated a poor voting intention for Suely (14% and 9%, respectively). Antônio Denarium (42.47% in the first round) won the second round with 53.34% of the valid votes. His party (PSL) was the same as the far-right presidential candidate Jair Messias Bolsonaro. Additionally, Bolsonaro visited Roraima and participated in political events with Denarium. During the election campaign, Denarium emphasized the importance of increasing the number of Venezuelans sent to other states through the dispersal policy and proposed entrance restrictions at the border.

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 presenting a passport, a criminal record certificate, and a vaccination certificate, which is also very important.*

[25] *"Governor of Roraima asks to close Brazil's border with Venezuela"*

[26] *"Government of Roraima signs decree that tightens foreigners access to public services"*

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

The second most voted candidate in the 2018 first round was Anchieta Júnior (PSDB), he lost the 2018 second round by obtaining 46.66% of the votes. He was a former governor from 2007 to 2014 and, similarly to Suely and Denarium, Anchieta also defended some type of border restriction. In an interview, he proposed the establishment of a quota for the entrance of Venezuelans into the state.[28] Therefore, all three main gubernatorial candidates proposed migration restrictions, even the incumbent who participated in the shelter policy efforts.

Following the same strategy as the Presidential election, I will look at the performance of the three main candidates (Suely, Denarium, and Anchieta). The "Incumbent Candidate" (Suely) vote share for past elections will be calculated from the performance of her party (PP) past candidates or candidates it supported (similarly for Anhieta's and Denarium).

3 Data

3.1 Election

Data for the 2006, 2010, 2014, and 2018 elections 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 2008 election onwards, the characteristics (age, sex, marital status, and education) of the registered voters are also provided at the section level. The marital status information contains a considerable amount of missing, therefore, only data related to voters' education, gender, and age were used.

F. Daniel Hidalgo (Associate Professor of Political Science - MIT), constructed a panel of all Brazilian polling stations, the data contains a panel id and their geographic coordinates. It leverages different administrative datasets to fuzzy string match the address and the polling station name (usually the name of the building it is located). The coordinates come from TSE data and other administrative datasets (such as schools' geographic location from the Education Ministry). Hidalgo's code and some of the input data explored are publicly available. For the details about how

[28] Roraima's Governor Candidates Interview.

this data was used and the procedures taken to confirm each polling station's latitude and longitude, see Section E in the Appendix.

3.2 Shelters and Refugees

UNHCR produced a summary of "Operação Acolhida" efforts containing the shelters' opening and closure dates and a description of other actions and programs of the task force efforts. Additionally, shelter-specific monthly reports published in 2018 contain shelters' location, total capacity, population size, and some refugees' socioeconomic and demographic information. Government meeting minutes available at the Operação Acolhida Website were also used to complement the sheltered population size data for shelters and months not covered by the UNHCR reports.

4 Empirical Strategy

4.1 Defining the Unit of Observation

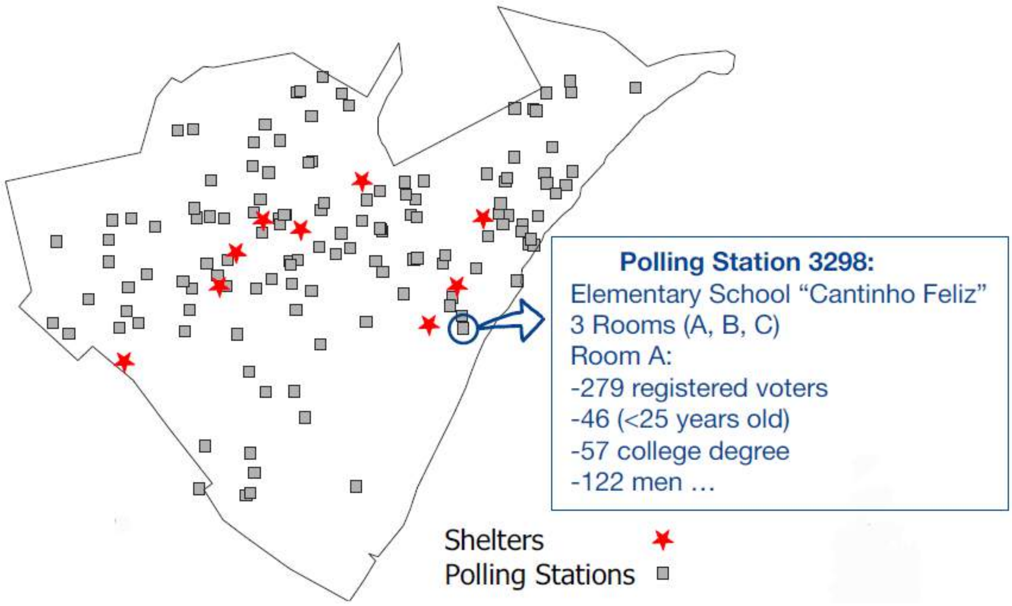
Given the different aggregation options allowed by the detailed voting data, I will first determine the unit of observation explored in the main specification. Hennig (2021), for example, explores the voting districts' geographic definitions in Berlin (each district is served by one pooling station). However, Brazilian election logistics doesn't use voting districts to allocate voters. Instead, voting logistics work with two different allocation levels. First, voters are assigned to a polling station (i.e. a building, usually a public school). Then within that building, they are separated into different sections (i.e. rooms). The following paragraphs from the Brazilian Electoral Code describe 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 electoral section (a room within a polling station) indicated in his voter's ID. If voters move to another municipality, they must go to the office and update the polling station. In case voters move within the same municipality to a neighborhood distant from their polling station, they can (not mandatory) update it to one closer to their new residence.

Therefore, the assignment of voters to polling stations and sections presents two interesting features. First, it creates a positive correlation between where you vote and where you live. Second, there is a certain inertia once you are assigned to a section (people are likely not voting at different places or rooms in each election). Given these desirable electoral code features, I use a section-level panel as the main dataset (see Figure 13 for an example of how the data looks like). For robustness, I also explore a polling station panel and construct "fake" voting districts using Voronoi Polygons (see Appendix I for details).

Figure 13: Boa Vista (Urban Area) Map



4.2 Regression Equations

To estimate the causal impact of the shelters on the electoral outcomes, I will estimate the following Diff-in-Diff equation:

$$Y_{ijt} = \beta \text{ Treated}_j * I(t = 2018) + \gamma_i + \mu_t + Controls + \epsilon_{ijt} \quad (1)$$

Y_{ijt} is the voting outcome of the section "i" in polling station "j" in the electoral year "t". Treated_j is a dummy variable indicating whether polling station "j" is less than 1 kilometer away from the closest Venezuelan refugee shelter. μ_t is the year fixed effects and γ_i is the section fixed effect. The pre-treatment period consists of the 2006, 2010, and 2014 elections, 2018 and 2020 are the post-treatment period. The treatment assignment level is "higher" than the observations, therefore, standard errors are clustered at the polling station level. [29] For controls I use 23 different demographic variables (education, gender and age) of registered voters of section "i" and an interaction of time dummies and the distance of polling station "j" and the city downtown.

Table 1: Descriptive Statistics (2006-2022)

	N	mean	sd	min	max
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 (0.5 km)	238	0.109	0.313	0	1
Treatment Dummy (1 km)	238	0.340	0.475	0	1
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
Share Illiterate	714	1.258	1.387	0	7.407
Share with some college	714	28.66	18.44	0	82.78
Share Less than High-School	714	39.67	17.37	3	91.49
Share 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
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: Different sample sizes come from: voters' education, age, and gender available after 2014 and numbers of voters and turnout rates available for all elections.

[29] A neighborhood level clustered errors were also explored for robustness.

Table 2: Balance Table (2006-2022) Balanced Section Panel

	Treatment			Control			
	n	mean	sd	n	mean	sd	Diff
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***
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 Governor Incumbent	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***

The data includes 911 sections with 330 voters on average, 33% are located in treated polling stations and 28% of the sections are balanced (shows up every year in my data).[30] Sections can be destroyed or created during this period (2006 to 2018) for different reasons, for example, changes in the voters' population size (new stations or rooms are set up to increase capacity) or logistics reasons such as building renovations. I also explore an unbalanced panel of sections for robustness.

Table 2 presents the balance test between treated and control units for different covariates. Treated units are not very different from control ones in terms of their size, "lifetime", and distance to Boa-Vista downtown. However, voters from treated sections are statistically older, less educated, and more male than voters in control sections. The diff-in-diff approach accounts for any level differences of outcomes and control variables between control and treated units. However, I added the controls since it would be a problem for the parallel trends assumption if these covariate differences affect the outcome dynamics after treatment. For example, it is possible to argue that low-educated male voters were the ones who believed/embraced the most the far-right fake news during the 2018 election. Consequently, treated units would have, even in the absence of the shelters, a more steep far-right vote trend.

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)

[30]See Table 1 in Appendix ?? for descriptive statistics of different covariates.

propose a Doubly Robust Diff-Diff for multiple periods with conditional (on some pre-treatment covariates) parallel trends assumption. The DRDiD is a combination of OR (outcome regression) and IPW (propensity score model). Therefore, I also estimate a DRDiD using the 2014 voters's characteristics covariates. Additionally, I estimate a Matching DiD that first uses pre-treatment (2014) covariates to match control units to treated ones before calculating a conventional DiD.[31]

4.3 Identification Assumptions

This section will discuss and test the identification assumptions required for interpreting "β" as the causal effect of the Venezuelan urban refugee shelters on Brazilians' voting outcomes in Boa Vista (Roraima).

Outcomes are accurately capturing residents' political preferences

First, the section voting results should capture the political preferences of locals living around the section's polling station. According to the Brazilian Electoral Code, voters are allocated to places close to their residencies and there is constancy in the assignment. 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, threatening the accuracy of the section results in measuring the surrounding population's political preferences. 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.[32] Therefore, after 2013 the correlation between where you vote and where you live likely became even stronger.[33] Therefore, only voters' characteristics data after 2013 are used. See Appendix H for more details about the voters' info update induced by the fingerprint requirement.

[31]For the Matching DiD, I use the command "diff" in Stata that runs a kernel-based propensity score matching. It will match each treated unit with a weighted average of the controls.

[32]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."

[33]Unfortunately, voter's address/residency data is not publicly available to formally test this. However, we observe significant education info updates (see Appendix H).

Exogenous Location of Shelters

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). First, based on the institutional setting, political preference trends were unlikely to be considered during the shelters' location decisions. 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. Second, an event study version of equation (1) is estimated to empirically test for any pre-treatment statistically significant effect of the shelters.

One could also argue that locals might 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. Therefore, lobby organizations would have had a considerably limited time to organize.

No Spillover Effects

The assumption that control units are not affected by the treatment is unlikely to hold, especially for control units close to treated ones (and, therefore, also close to the shelters). This potential leakage of treatment to controls would violate the SUTVA assumptions of the DiD and would attenuate my estimates. Therefore, I will also estimate a version of equation (1) using the distance to the closest shelter as a continuous treatment (see equation (2) below). 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.

$$Y_{ijt} = \beta \frac{1}{\text{Distance}_j} * I(t = 2018) + \gamma_i + \mu_t + Controls + \nu_{ijt} \quad (2)$$

No locals' endogenous migration or 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 (voters that remained in the treated areas in 2018 could be less anti-migration), leading to a misleading zero or even wrong sign results.

The election logistics minimize this concern given that the TRE-RR (the institution responsible for the elections in Roraima) established that voters had until May 9, 2018, to do it. Considering most shelters (8 out of 11) opened after March 2018, Brazilians had minimal time to change polling stations if they moved (to a different neighborhood or municipality). Therefore, even if Brazilians changed residency in 2018 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 empirically test if treatment affected voters' characteristics (a potential sign of endogenous allocation of voters), I estimate equation (1) using those voters' characteristics as outcomes. According to the results (see Table 3), there is no consistent treatment effect over different voters' characteristics. Moreover, voters' characteristics are added as controls as explained in the last section.

Table 3: DiD Results - Control Variables as Outcome

Outcomes	Eq. (1) Treated*Post	R2	Eq. (2) (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 parenthesis.

No Differential Electoral Logistics

Another possibility would be that election logistics were different in sections closer to shelters. For example, sections closer to shelters could have been inflated (more registered voters or fewer sections) to make voting more difficult. Following the same strategy used to investigate composition effects, I estimated a version of equation (1) using election logistics variables (at the section and some at the polling station levels) as the outcome.

Table 4: DiD Results - Election Logistics Variables as Outcome

Outcomes	Eq. (1) Treated*Post	R2	Eq. (2) (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 parenthesis.

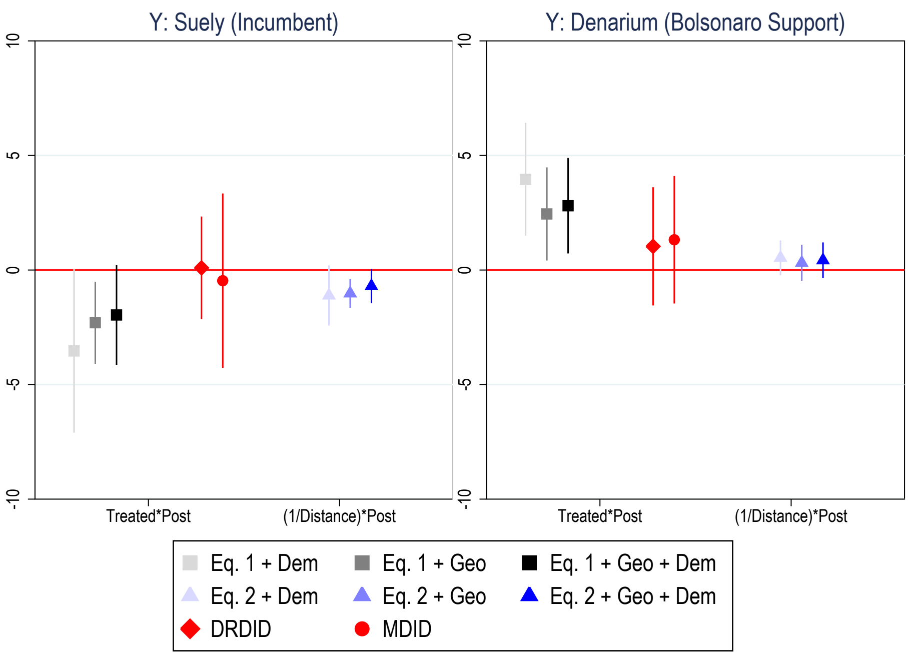
According to the results presented in Table 4, There was no differential logistics capacity between treated and control units. Therefore, it is unlikely that the election organization explain the results.

5 Results

5.1 Governor Election

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

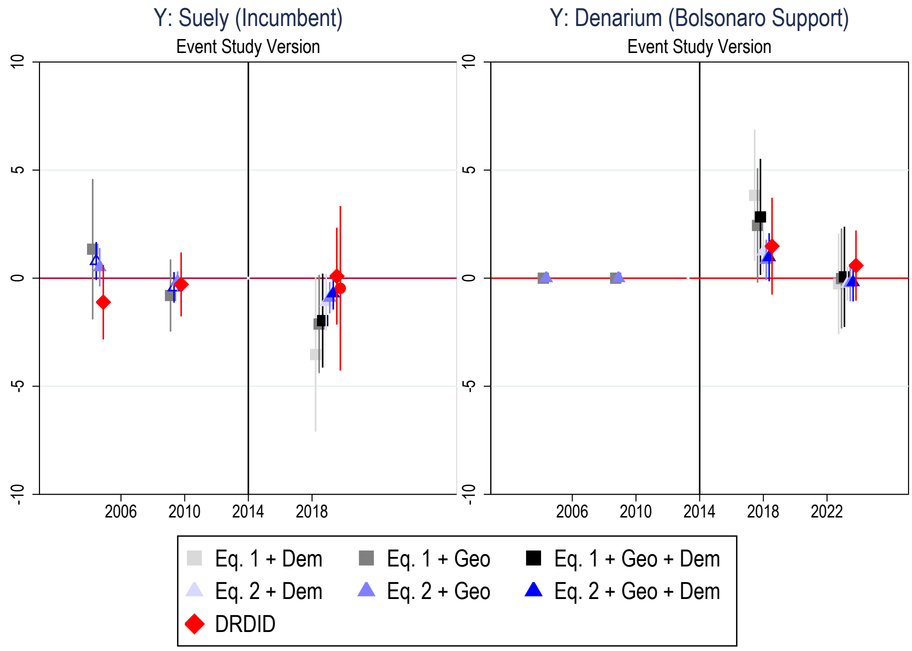
Figure 14: Governor Election Results - Eq.(1) and (2)



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.

Additionally, the voting loss suffered by Suely translated into increase support for Antônio Denarium from the same party as Bolsonaro (the far-right presidential candidate). This is more evident in the event study version (see Table 15), given it only lasts for the 2018 election and is no longer present in the 2022 election. This result goes in the same direction as different papers in the literature that found positive causal effects of exposure to immigrants on vote shares for right and far-right parties.

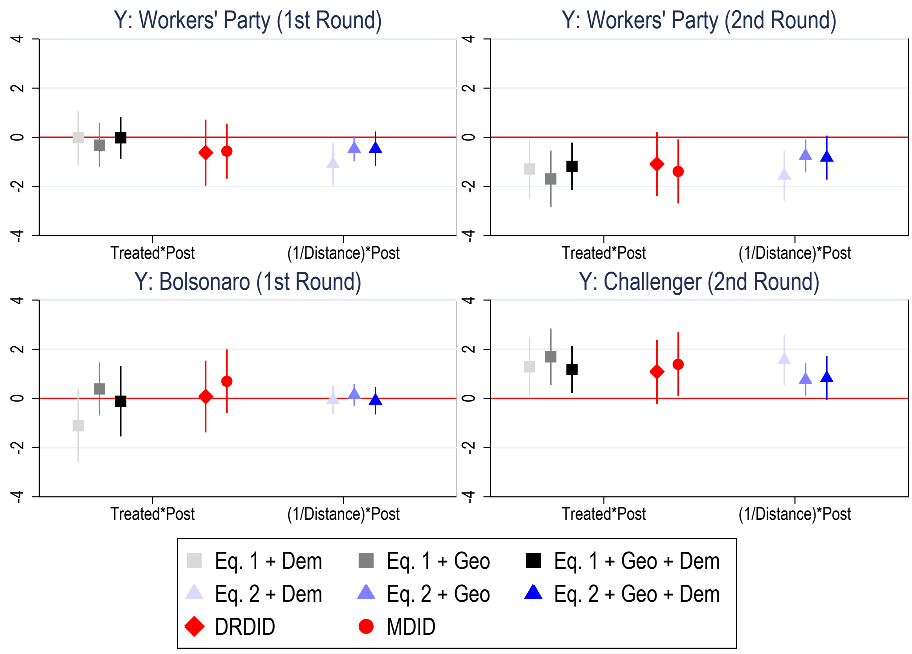
Figure 15: Governor Election Results - Event Study



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.

5.2 Presidential Election

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

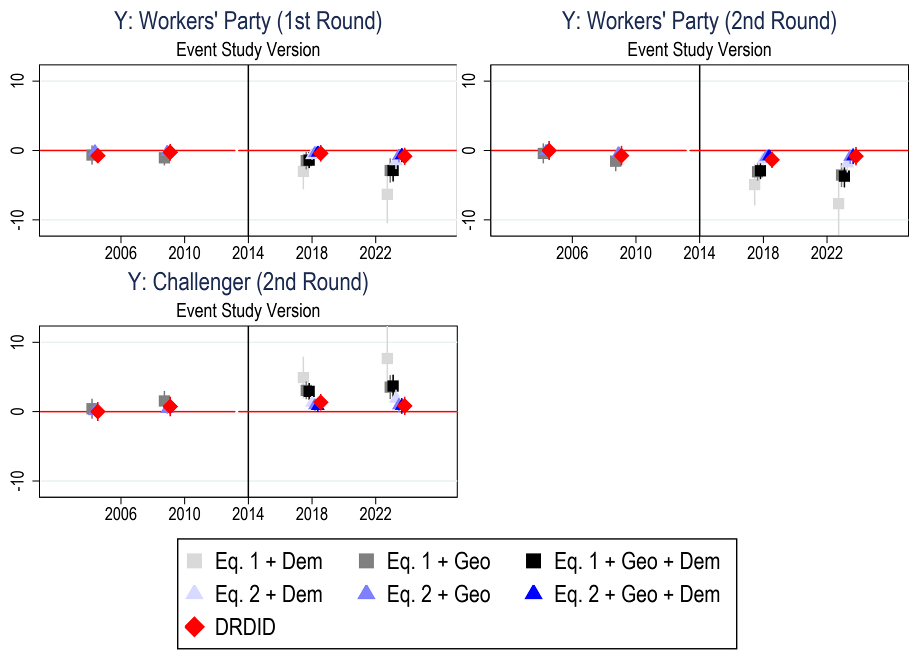


Notes: Dependent Variable = % of valid votes for each category/candidate. Dem = 23 demographic (age, education, and gender) controls; Geo = time dummies interacted with polling station distance to downtown. DRDID = Doubly Robust DiD. MDID = Matching DiD.

According to Figure 23, 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).[34]. Additionally, from Table 17, the results persist for the 2022 election.

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

Figure 17: President Election Results - Event Study

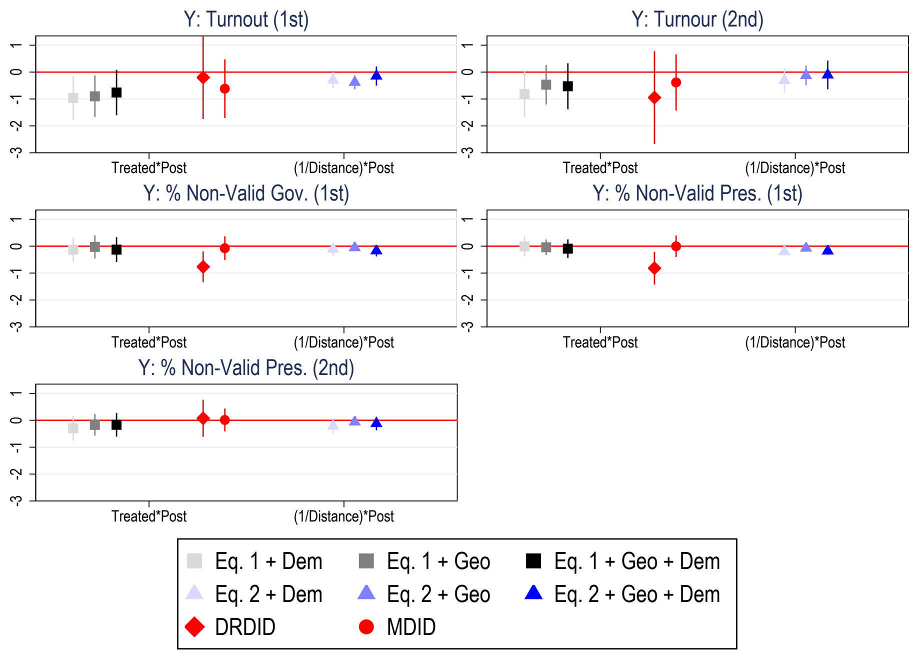


Notes: Dependent Variable = % of valid votes for each category/candidate. Dem = 23 demographic (age, education, and gender) controls; Geo = time dummies interacted with polling station distance to downtown. DRDID = Doubly Robust DiD. MDID = Matching DiD.

5.3 Turnout and Non Valid Votes

Turnout and non-valid votes could explain the results for the governor and president election. In other words, the shelters could have triggered voters who normally don't show up to vote (turnout increase) or voters who usually dont chose a candidate to select one (decrease share of non-valid votes). However, according to Figure 32, we don't observe any consistent 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 18: Turnout and Non Valid Votes Results - 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.

5.4 Robustness Checks

Polling Stations and Voronoi Polygons Panels

As mentioned in Section 4, for robustness I explore different units of observation definitions besides the section level. First, I aggregate all the outcomes and covariates at the polling station level and construct a panel of polling stations. Second I also explore some of the features behind voter allocation to construct a fake voting district using Voronoi Polygons. For this second analysis, the units of observation are, therefore, geographic units (pieces of the urban area of the city), and the polling stations located in those units are gonna be aggregated so outcomes and covariates associated with each polygon should be capturing the polygons residents political preferences and demographic characteristics (see Appendix I for details). The estimates from both panels confirm the section-level results for Governor and Presidential elections (result tables not reported in this draft).

Others

I also run the same benchmark specifications using an alternative control group including only sections in polling stations at the top 30% of the distance to the closest shelter distribution (more than 1.8 km). This group of controls is more likely not to have been treated by the shelters. The results (not reported in this draft) go in the same direction as the ones reported as the main findings. However, as expected, they are noisier (larger standard errors) given the smaller sample size.

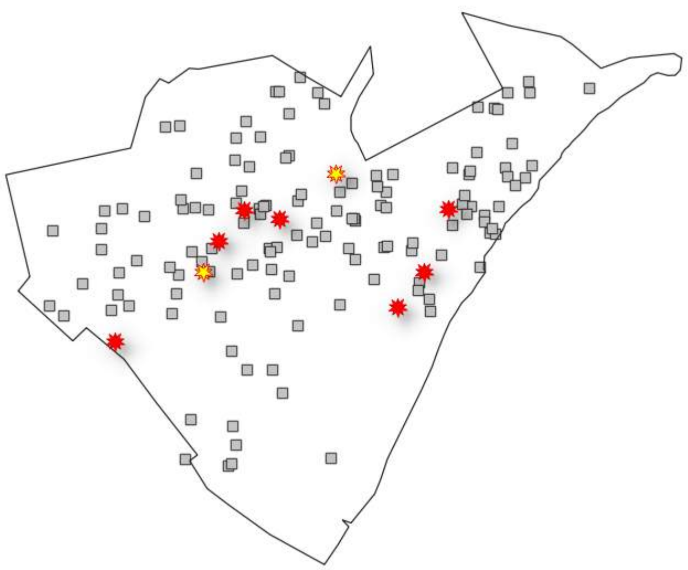
Finally, clustering standard errors at the neighborhood level, weighting the regressions by section's number of registered voters, or exploring an unbalanced panel of sections dont change the results.

6 Mechanisms

The literature has explored different potential mechanisms behind the results. Regarding the potential economic ones, job competition, welfare access, and crime have been studied differently.

6.1 Indigenous Shelters

Figure 19: Indigenous (2) and Non-Indigenous (7) Shelters Map



Among the 11 shelters, 2 are designated exclusively for Venezuelan Indigenous refugees (see Figure 19). These Indigenous populations represent diverse ethnicities with the Warao as the majority.[35] The Warao, or "people of the water," are from the Orinoco River delta in Venezuela. Their society relies on fishing, agriculture, and crafting. The political and economic crisis in Venezuela has forced them to migrate. According to a survey from IOM, the migrants also mention environmental and climate-related reasons (flooding, water contamination, and heavy rains) for leaving their territories in Venezuela. This unprecedented situation adds complexity while addressing the vulnerabilities given the specific cultural dynamics of a displaced Indigenous group with no prior history in Brazil. [36] Table 5, describes the main socio-economic differences between the indigenous and non-indigenous shelters using October 2018 UNHCR shelter reports.

Table 5: Differences between hosted refugee population (October 2018):

	Indigenous Shelters	**Non-Indigenous Shelters**
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%
Hosted Population	1,236	2,636
Capacity	109%	87%

I estimate the following specifications to verify heterogeneous shelters' effect based on whether or not it hosts Indigenous Venezuelan refugee population:

$$Y_{ijt} = \beta_1 \ \textit{Treat-Ind.}_j * \textit{Post}_t + \beta_2 \ \textit{Treat-Non-Ind.}_j * \textit{Post}_t + \gamma_i + \mu_t + \textit{Controls} + \nu_{ijt}$$

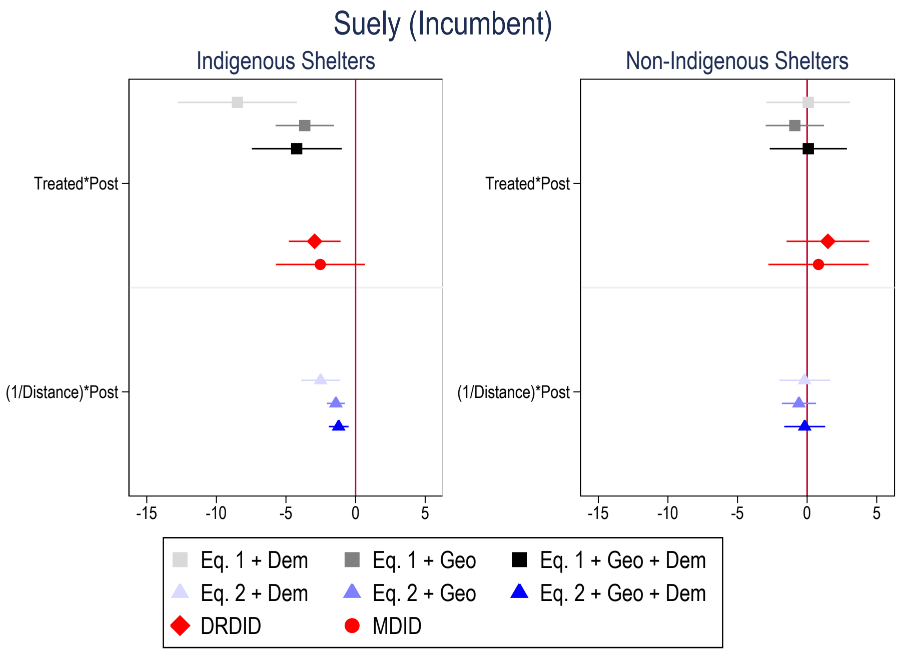
[35]Other groups include the Taurepang, Pemón, Arekuna, and many more, with over 13 Indigenous ethnicities have been registered across Brazil - see the Warao Refugees in Brazil Report by UNHCR

[36]For more see IOM Report.

$$Y_{ijt} = \beta_1 \frac{1}{Dist.\ \ Ind._j} * Post_t + \beta_2 \frac{1}{Dist.\ \ Non\text{-}Ind._j} * Post_t + \gamma_i + \mu_t + Controls + \nu_{ijt}$$

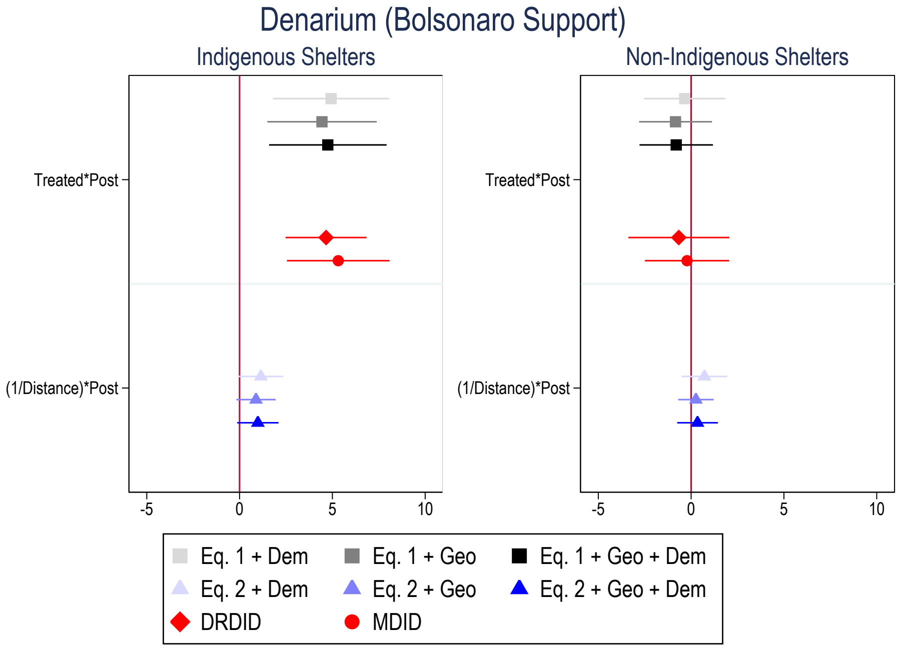
Treated-Ind$_j$ is a dummy variable indicating whether polling station "j" is less than 1 kilometer away from the closest indigenous Venezuelan refugee shelter. *Treated-Non-Ind*$_j$ is a dummy variable indicating whether polling station "j" is less than 1 kilometer away from the closest non-indigenous Venezuelan refugee shelter. *Dist. Non-Ind.*$_j$ and *Dist. Ind.*$_j$ are, respectively the distance of polling station "j" to the closest non-indigenous and indigenous shelters. Given that there are only 2 Indigenous shelters compared with 9 non-indigenous, for robustness I also run the specification using randomly selected 2 non-indigenous shelters for each observation and obtaining *Treated-Non-Ind*$_j$ and *Dist. Non-Ind.*$_j$ based on this random selection.

Figure 20: Governor Election



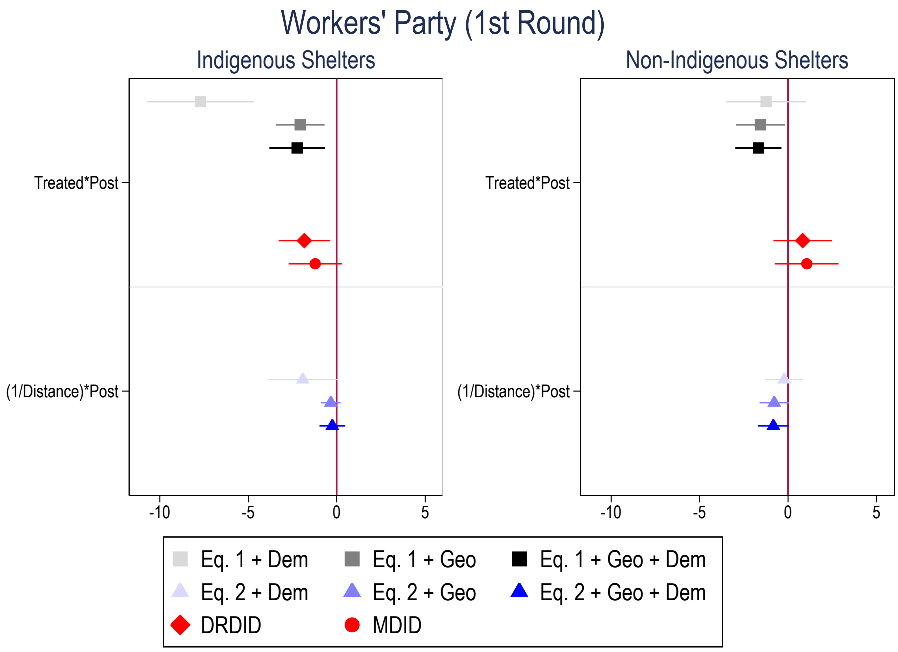
Notes: Dependent Variable = % of valid votes for each category/candidate. Dem = 23 demographic (age, education, and gender) controls; Geo = time dummies interacted with polling station distance to downtown. DRDID = Doubly Robust DiD. MDID = Matching DiD.

Figure 21: Governor Election



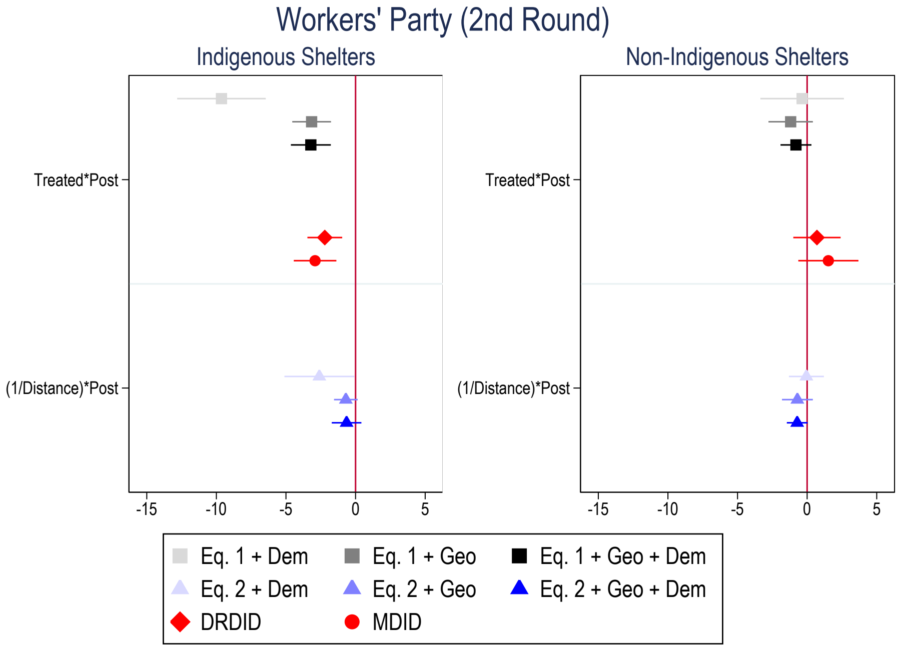
Notes: Dependent Variable = % of valid votes for each category/candidate. Dem = 23 demographic (age, education, and gender) controls; Geo = time dummies interacted with polling station distance to downtown. DRDID = Doubly Robust DiD. MDID = Matching DiD.

Figure 22: President Election



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



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.

According to the results from Figures **??**, **??**, **??** and **??**, The indigenous shelters are the ones driving the results for both the governor and presidential elections.

7 Conclusion

The political and economic crisis pushed millions of Venezuelans to leave the country. South America, traditionally a sending region, had to deal with hosting an unprecedented flow of Venezuelans. Providing refuge in camps and shelters is one of the main forms of humanitarian aid for forcibly displaced populations. However, Brazil implemented an "improved" version of the commonly used secluded shelters in Africa and Asia. Shelters were implemented in an urban area and migrants were granted extensive rights (freedom of movement, access to public services, and labor market).

Locals' attitudes towards migrants can have important implications for immigrants' integration and the political sustainability of migration policy. Most of the literature studying the effect of immigrants on political outcomes concludes that migration flows increase the support for right and far-right anti-migration candidates and parties.

According to my results, shelters triggered locals to electorally punish the incumbent governor who participated in the shelter organization efforts by, at the same time, increasing support for the far-right gubernatorial candidate. Interestingly, the incumbent was not a pro-migration candidate, she proposed during the campaign more restrictive migration entrance at the border and tried to limit migrants' access to public services. Given all candidates were to some extent anti-migration, our estimates mainly capture an accountability effect.

Additionally, the workers'party (left) suffered from a decrease in support for the Presidential election in the second round by losing votes for Bolsonaro (far-right candidate and elected 2018 president). Combined with the fact that there was no incumbent presidential candidate, my results go in the same direction as the literature, higher exposure to refugee shelters likely shifted voters to a far-right candidate.

Therefore, shelters presented a political accountability effect combined with a shift towards far-right populist candidates. However, its effects were small in magnitude compared to the candidate's overall performance and it would not have changed the winners and losers of the 2018 and 2022 elections.

Looking at the mechanisms, the results don't come from differential turnout or share of nonvalid votes. Moreover, the effects are mainly driven by shelters hosting Venezuelan Indigenous refugees who, according to IOM, emigrated also due to climate and environmental push factors. This population presents differential cultural traits (main speaking language is not Spanish) and they are less educated and younger (a larger share of children and teenagers and higher illiteracy rates). By exploring data on education and health public services and crime incidents I plan to investigate further the mechanisms behind the results.

Finally, the results are robust to different definitions of treatment and data aggregations (polling stations, and voronoi polygons) and weighting observations by the number of registered voters or clustering errors at the neighborhood level.

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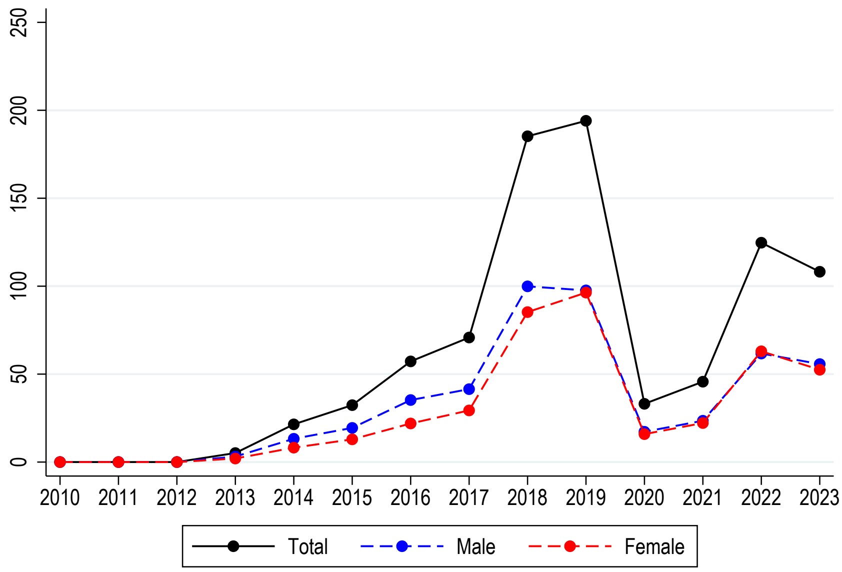
Appendix

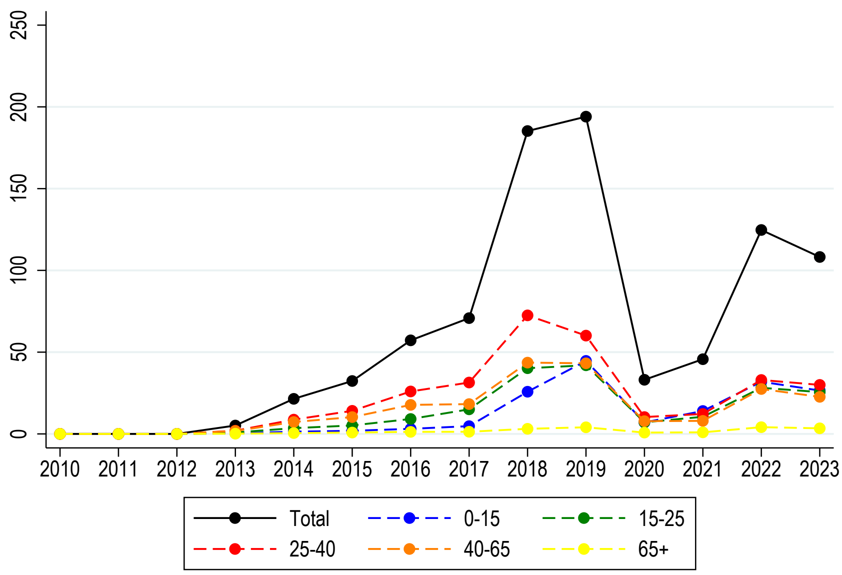
A Venezuelan Refugee Flow

Figure 24: Venezuelan Migration Flows to RR



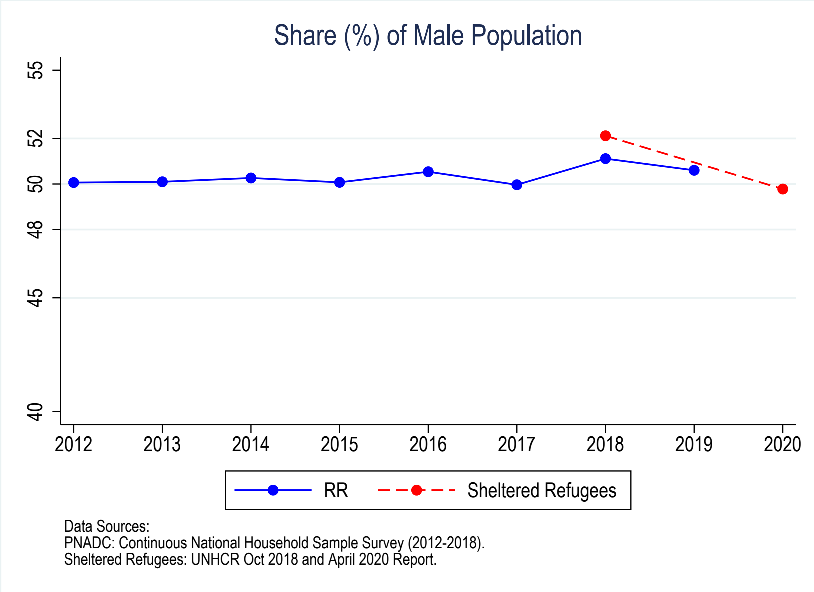
Source: STI. For 2023 data includes January to September.

Figure 25: Venezuelan Migration Flows to RR



Source: STI. For 2023 data includes January to September.

Figure 26: Sheltered Refugees Vs Roraima's Population - Gender



B Operação Acolhida

Figure 27: Operação Acolhida Anual Budget

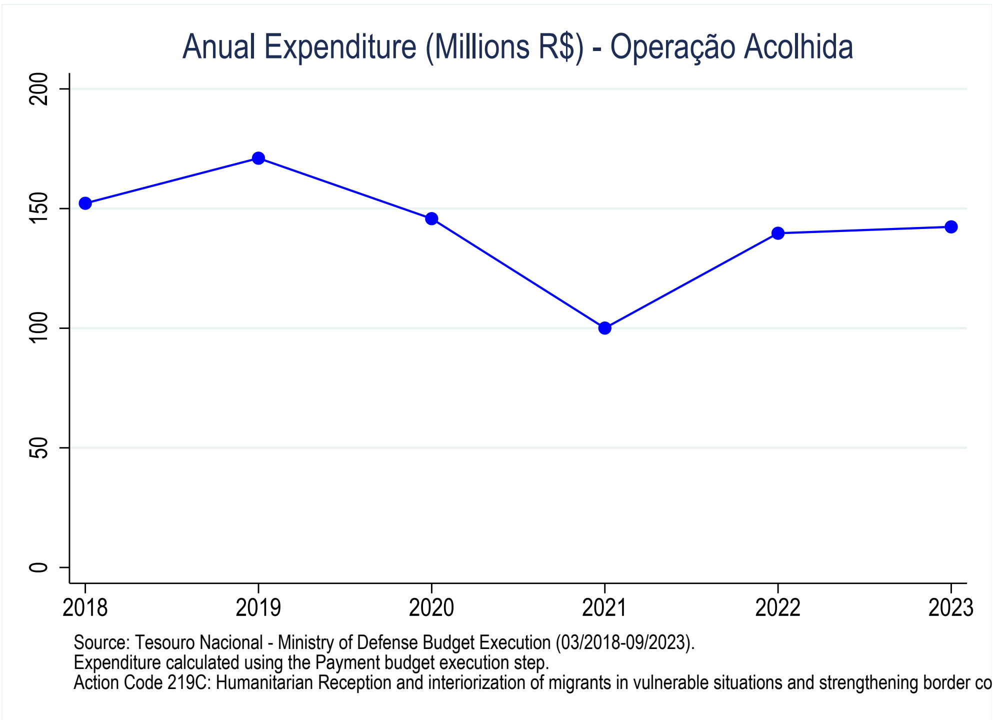
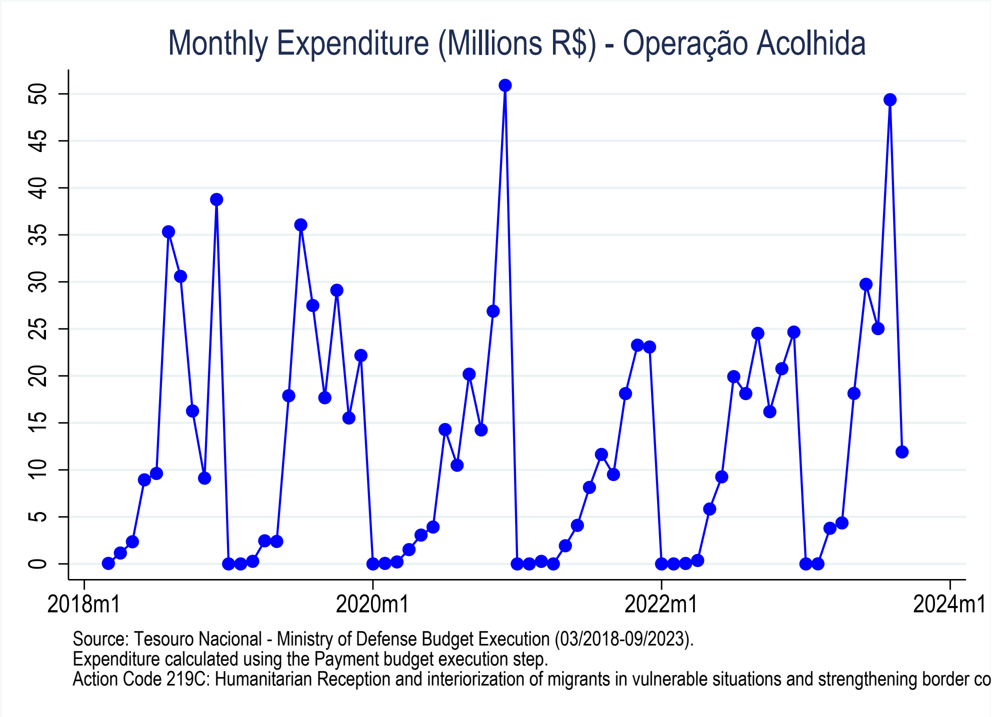


Figure 28: Operação Acolhida Monthly Budget



C Shelters Information

Table 6: 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

D Electoral Outcomes

Table 7: Governor Election - Parties Classification

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

Table 8: President Election - Parties Classification

	2018	**2014**	**2010**	**2006**
2018 Incumbent Candidate	-	-	-	-
2018 Center-Right Candidate	PSDB	PSDB	PSDB	PSDB
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 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. Its 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.

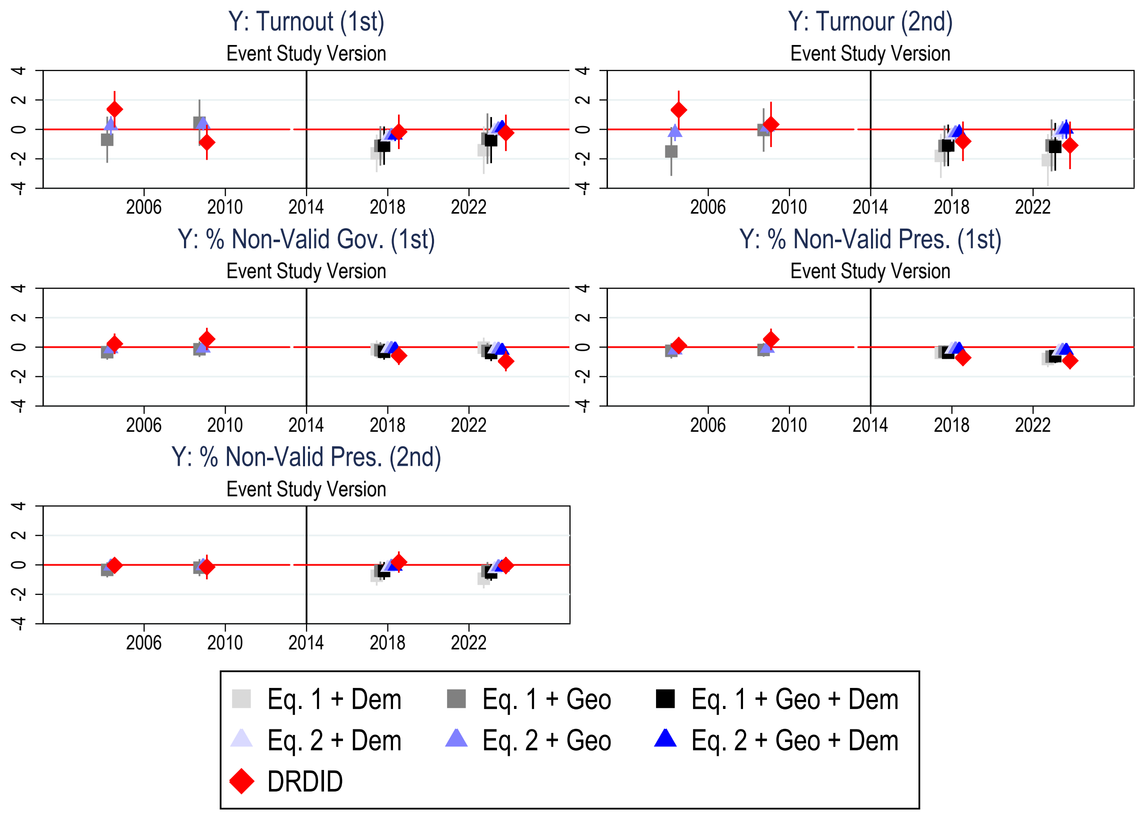
See Table 9 below for the final description of polling stations' geographic coordinates data source.

Table 9: Polling Stations' Geographic Coordinates Data Source

Geo. Coordinate Data Source	% Sample	% Polling Stations
TSE	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

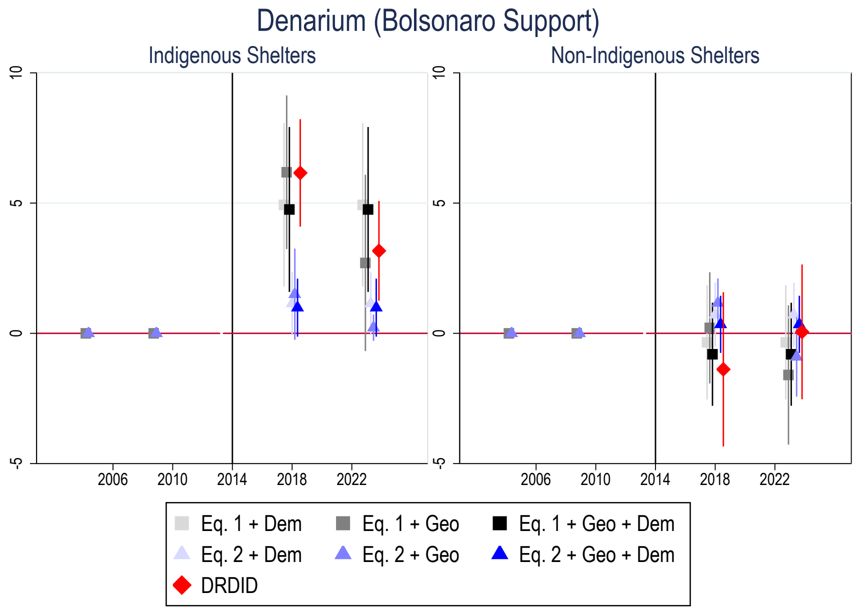
Figure 29: Turnout and Non Valid Votes Results - Event Study



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.

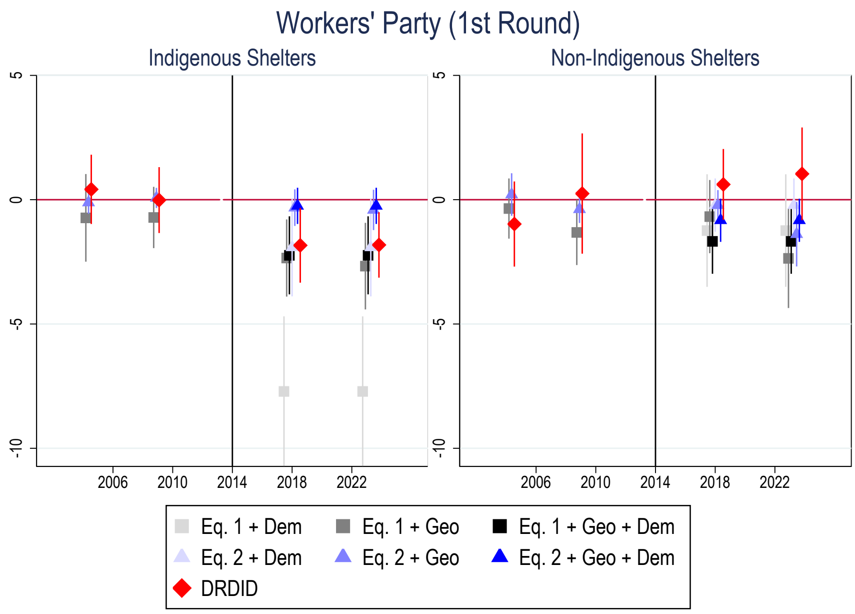
G Mechanisms

Figure 30: Governor Election - Event Study



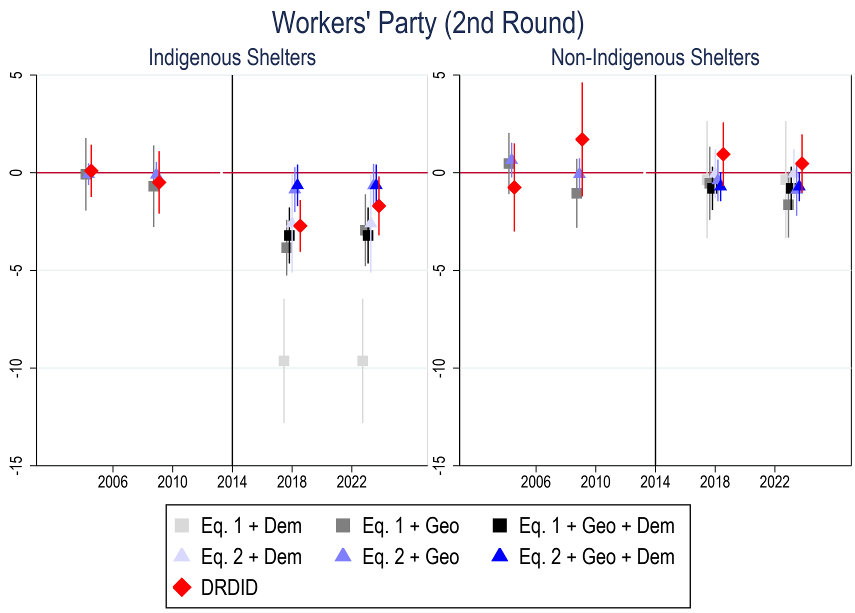
Notes: Dependent Variable = % of valid votes for each category/candidate. Dem = 23 demographic (age, education, and gender) controls; Geo = time dummies interacted with polling station distance to downtown. DRDID = Doubly Robust DiD. MDID = Matching DiD.

Figure 31: President Election - Event Study



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 32: President Election - Event Study



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.

H Fingerprint scan and Voters' Demographic Info

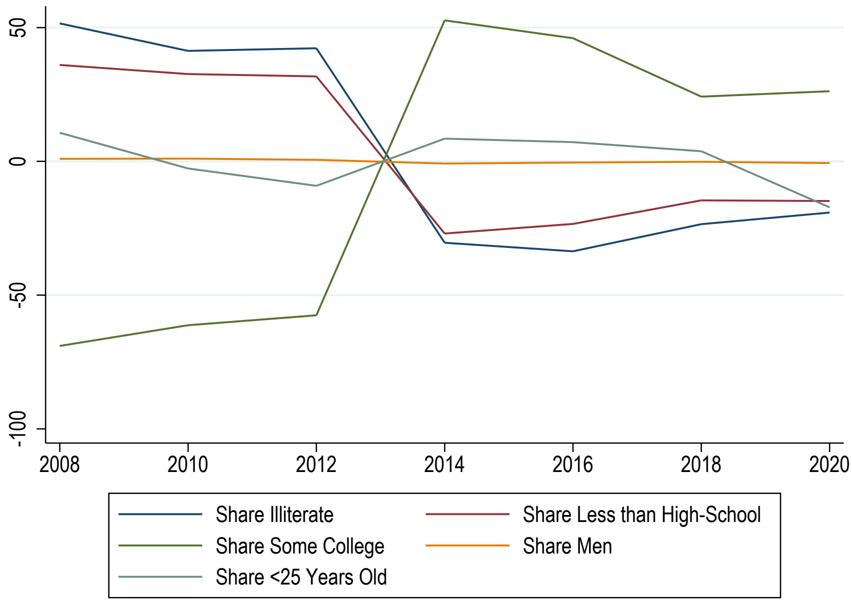
First, I calculated the following yearly index to verify how big the update in voters' demographic variables was after the 2013 fingerprint requirement that made all voters come back to the offices.

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

$\bar{y}_{ij}$ 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.

As we can see from Figure 33, ID_t associated with education variables are consistently above zero before 2013 and negative after. Therefore, education 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 doesn't require any constant updates from the voters, on the other hand, education can change (upgrade) over time. Given voters are regis-

Figure 33: ID_t for different variables



tering 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.

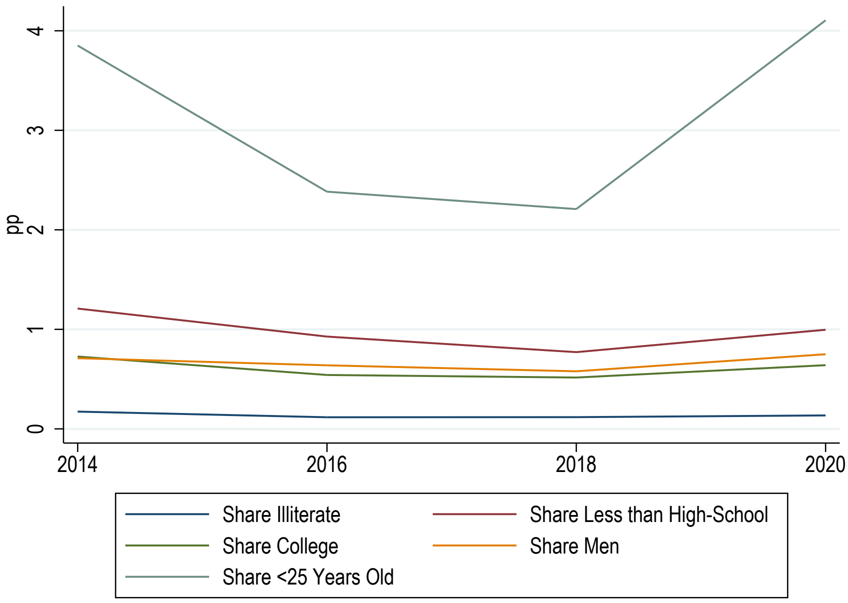
To show that after 2013 the voters' characteristics in each section were stable, i.e. people were not moving between sections over elections and there is an inertia in section assignment (as described by the electoral code), I calculated the following yearly index for $t > 2013$:

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

$\bar{y}_{ij}$ 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.

According to Figure 34, 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.

Figure 34: IA_t for different variables

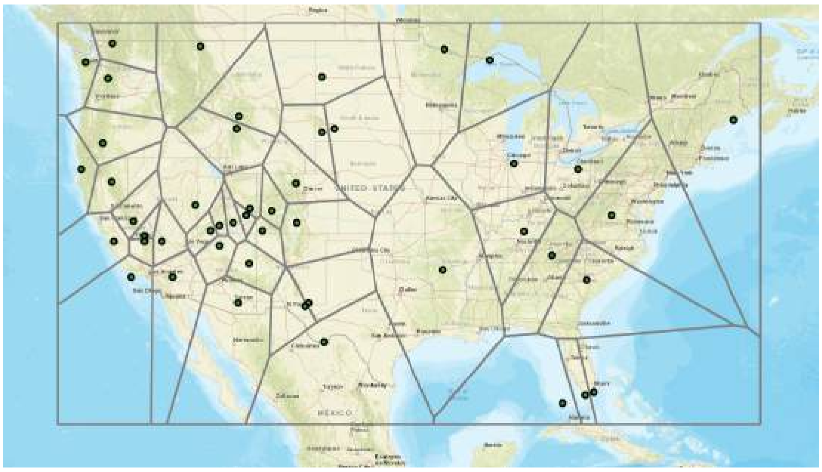


I Voronoi Polygons Panel

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.

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 35 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).

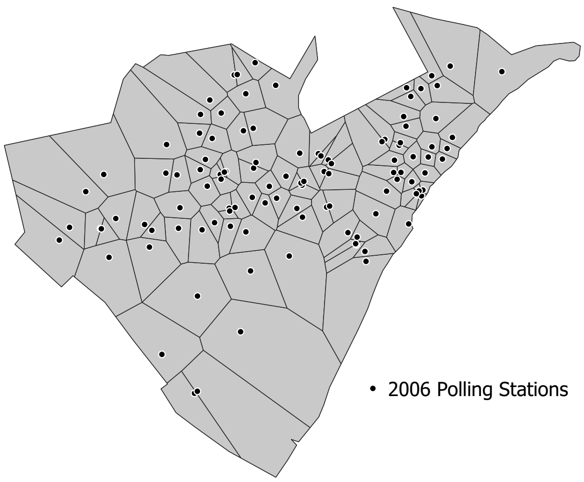
Figure 35: Voronoi Polygons using US National Parks



Note: Image Source.

I used the 2006 and 2008 (the first years of the two panels explored by this paper) 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 36 shows all the 111 polygons constructed based on the 2006 polling stations.

Figure 36: Voronoi Polygons using 2006 Polling Stations (Urban Area of Boa Vista)



By construction, the political outcome of observation "i" in 2006/2008 will be measured using the single 2006/2008 polling station data that generated that polygon "i". However, after 2006/2008, 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 2006/2008. To get the weights, I will first overlap the Voronoi patterns of 2006/2008 and year "t" for $t >$ 2006/2008 (see Figure 37 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 37: Overlaping the Voronoi Diagrams of 2006 and 2010 Polling Stations

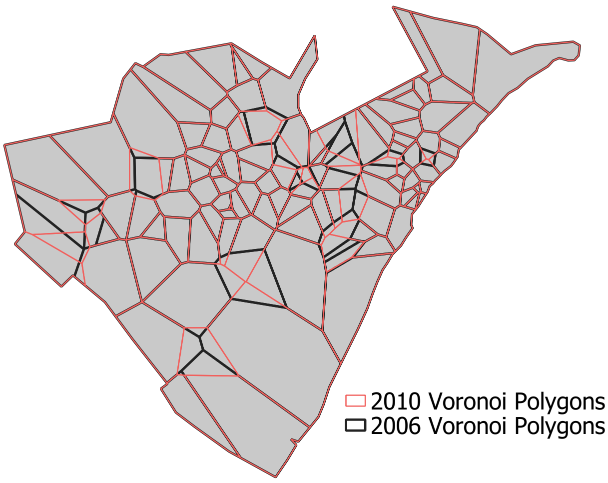
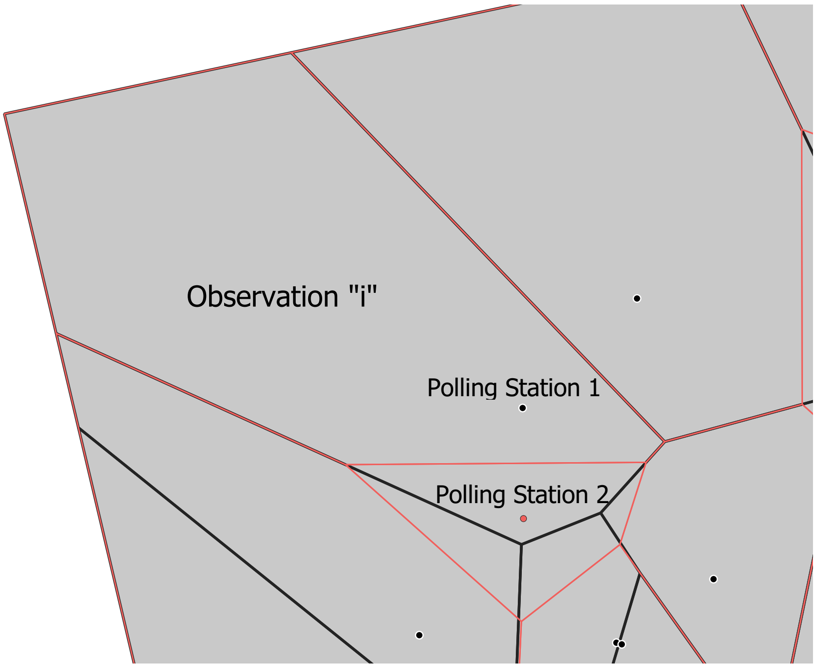


Figure 38 describes an example of how the weighting strategy works. Take observation "i" (the striped polygon). In 2006, its votes were entirely made out of Polling Station "1". Polling Station "2" was opened in 2010, which shrank Polling Station 1 Voronoi borders. Now, 100% of Polling Station "1" Voronoi Polygon and 50% of Polling Station "2" lie within observation "i".

Figure 38: 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.