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

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Abstract

Since 2014, one million Venezuelans have entered Brazilian territory, 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. In response to this influx, the Brazilian government opened 11 shelters to host Venezuelan refugees across different neighborhoods of Boa Vista (Roraima's capital). Leveraging the quasi-random distribution of these shelters within the city, I explore how this policy affected locals' political support for far-right and anti-migration candidates. The Brazilian detailed election data contains voting outcomes and voters' characteristics at finer units within each polling station. According to the results, Brazilians closer to the shelters exhibited greater support for the far-right presidential and gubernatorial candidates, possibly at the expense of the incumbent governor involved in the shelter initiatives. The estimates were small in magnitude and the shelters' absence wouldn't change the election results. However, the estimates reveal that shelters presented an accountability effect besides shifting locals' political preferences.

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. Moreover, 75% of them are hosted by low and middle-income countries mostly in Africa and Asia.[1] This upward trend is expected to continue in the future given the increase in international and domestic conflicts, the multiplication of fragile states, and global warming pressures escalation - Albu (2023).

Differently from parts of Africa and Asia, South America has limited experience receiving mass migration inflows and was mainly categorized as a sending region. However, the deepening of Venezuela's political and economic crises after 2014 made almost 8 million of its citizens emigrate, the vast majority to neighboring countries (mostly Colombia, Peru, Ecuador, and Chile). The initial response by other South American countries included open borders, the use of existing migration agreements, and high participation of governments (both in terms of policy implementation and financing). However, as Venezuela's refugee numbers evolved, host countries public opinion about migration deteriorated (see Figure 1), the migration inflows became an important part of political debate, and some governments have introduced and are considering new restrictions.[2] This political backlash phenomenon is a global trend also observed in developed countries and usually personified by populist politicians exploiting public concerns for electoral success.[3]

Migrants can influence locals' political choices, potentially shifting preferences towards anti-migration candidates, through economic (labor-market and welfare resources competition, for example) and cultural (such as tradition preservation) mechanisms. Given their vulnerabilities and idiosyncrasies, refugees in particular can enhance those mechanisms. First, they are usually welfare state net beneficiaries (at least for the first years upon arrival) and may compete with local low-skilled workers. Additionally, refugees often qualify for special visa categories and may have significant

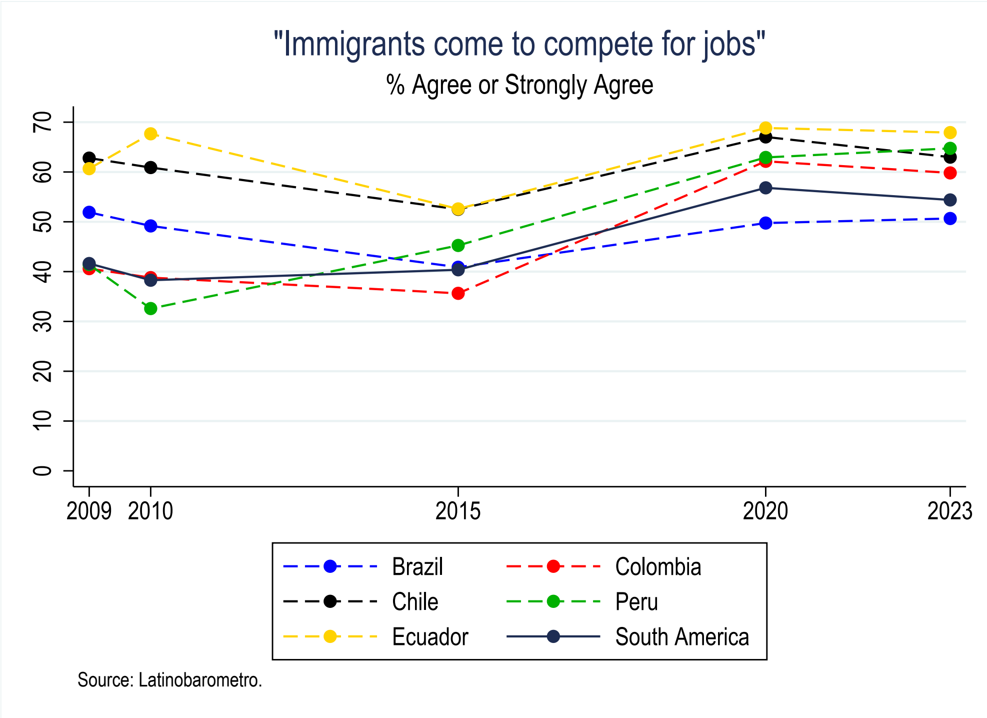
[1]The forcibly displaced population worldwide (refugees, asylum seekers, people in need of international protection, and internally displaced) is around 110 million - see UNHCR Statistics for more.

[2]See "Millions of refugees from Venezuela are straining neighbors' hospitality"

[3]Recent cases in developed countries include Trump's election and the performances of Marie le Pen and the Danish People's Party.

cultural differences from the local population, such as Africans and Middle Easterners in Europe.

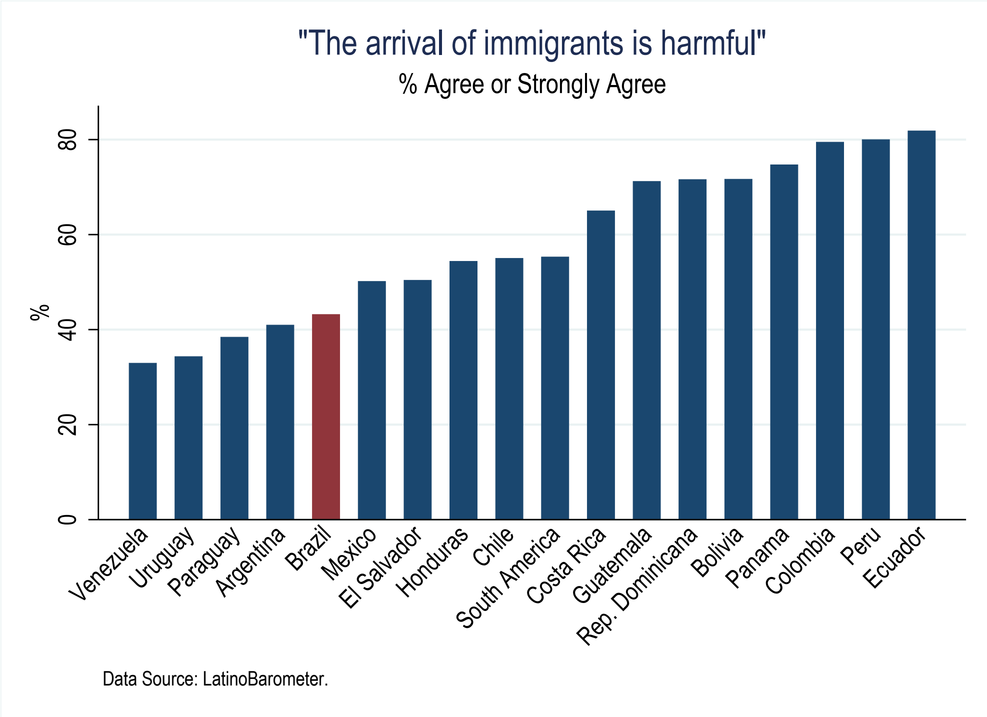
Figure 1: Public Perception about Immigrants in South America (2009 to 2023)



Betts (2021) includes political support ("acceptable to political elites at the global, 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. Additionally, Betts and Collier (2018) points out that the world's main refugee host countries moved from authoritarian regimes in the 60's and 70's to procedural democracies making them now accountable to their citizens. Ultimately, the potential political consequences of migration flows can induce a vicious cycle: first, anti-migration candidates, who are less likely to support migrants' integration policies, are elected. This lack of integration then reinforces locals' negative attitudes towards migrants further sustaining the electoral performance of those politicians.

Since the beginning of the Venezuelan refugee crisis, the Brazilian government kept borders open and granted extensive rights to the displaced population. Different than other South American countries, the Venezuelan flow in Brazil is concentrated in the

Figure 2: Public Perception about Immigrants in South America (2023)



smallest (both in terms of population and GDP) state of the county, Roraima, which is also geographically isolated in the north of the Brazilian Amazon region. Roraima's border with Venezuela concentrates more than 80% of the national refugee entrance inflow with more than 800,000 entrances of Venezuelans between 2016 to 2023. This geographic concentration of exposure to migrants and Brazil's population size could explain why, compared to other South American hosting countries, Brazilians still had a more positive view of migrants despite hosting the third-biggest concentration of Venezuelan refugees in 2023 (see Figures 1 and 2).[4] However, as the number of refugees crossing the border increased, the hostility and conflicts involving locals and Venezuelans in Roraima escalated in frequency and intensity.[5] After constant state and local governments' requests for help, the federal government implemented in 2018, together with local authorities and international organizations, an emergency task-force to organize the border, set up urban shelters, and disperse the refugee population to other parts of the country.[6]

This setting enables us to assess how politicians, parties, and voters reacted to

[4]Approximately 1 million Venezuelans have entered Brazil since 2016 and close to half stayed.
[5]The "monster of xenophobia" haunts the gateway of Venezuelans to Brazil
[6]Roraima authorities ask for 'help' to deal with immigration and want 'dispersion' of Venezuelans.

the refugee flow in Roraima compared with other non-affected states and how the 11 urban shelters set up after 2017 in Roraima's capital (Boa Vista) affected Brazilians' voting. I focus on the second question in this draft version (March 2024).

Most of the literature on the causal electoral effects of migration focuses on developed countries (especially Europe) and mostly concludes that higher exposure to migrants increases the voting for right and far-right candidates and parties.[7] 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 the conventional shift-share instrument approach. Otto and Steinhardt (2014), for example, 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.[8] [9]

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.[10] According to Woldemikael (2022), Colombian municipalities in the Venezuelan refugee route presented higher party fragmentation (number of contenders and independent candidates). Finally, Dinas et al. (2019) compare Greek islands closer and further from Turkey that experienced different inflows of Syrian refugees and concluded that

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

[8]Other examples: Edo et al. (2019) (French Cantons); Barone et al. (2016) (Italian municipalities); 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).

[9]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 variation as an instrument given refugee settlement was highly dependent on rental housing availability.

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

refugee exposure increased the far-right party vote share.[11]

This paper belongs to the second group since I explore the exogenous spatial distribution of Venezuelan refugees induced by urban shelters set up before general elections. I explore the state (governor) and national (president) elections from 2006 to 2018.

This paper contributes to the literature by focusing on refugee inflow effects 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.[12]

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 have looked at how camps in Africa affected earnings, employment, and consumption of families in surrounding villages - see Sanghi, Onder, and Vemuru (2016), Alix-Garcia, Walker, et al. (2018), and Alix-Garcia and Saah (2010). Examining the political consequences of shelters is especially relevant for a "sustainable" refugee policy considering that shelters and camps are widely used in humanitarian relief operations to receive displaced populations around the world. Yet the literature on shelters' causal public policy analysis and "political sustainability" strength is very limited. Moreover, Betts (2021) named the provision of urban refuge as one of the central parts of refugee integration considering that the vast majority of them (78%) live in cities. The shelters in Brazil were a unique approach when compared to other South American countries and even in the biggest refugee hosting countries, camps are mostly geographically isolated from urban centers.

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

[11]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).

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

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%.[13] 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 vast majority to other countries in Latin America and the Caribbean.[14]

Between January 2017 and January 2023, 853,666 Venezuelans entered Brazil, most of them trying to get to other South American Countries (over 420,000 stayed).[15] 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 Guarulhos airport (the biggest international airport in Brazil) and chose Brazil (especially the southeast of the country) 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 crossing the land border and seeking other Brazilian cities on their own.

[13] IMF statistics.

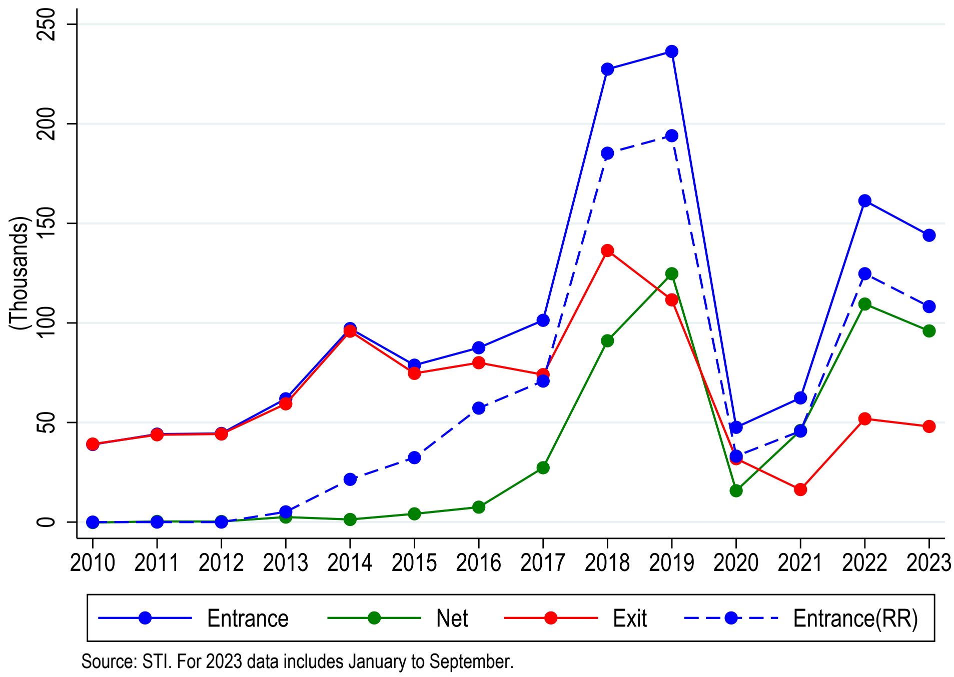
[14] See R4V Platform for statistics by destination country.

[15] Source: Ministry of Justice and Public Security report on Venezuelan Migration for January 2023.

Figure 3: 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 3). 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.

Figure 4: Venezuelan Migration Flows to Brazil and RR



Considering Roraima's national importance as an entry point and its considerable transit migration, the entrance flows best represent the timing of the refugee crisis in the state. The entrance flows at its 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 4).[16]

In Brazil, immigrants, disregarding their legal status, can access public schools and the national health care system (that is free and covers from 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.[17]

To obtain a refugee status (one of the options for regularization) the foreigner must first fill out forms online. The immigrant must then 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 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 January 2023, more than 350,000 Venezuelans possessed residency (either temporary or permanent), 99,520 refugee status requests were being analyzed, and 53,284 Venezuelans were granted refugee status.[18] This might suggest that one should be careful when using the term refugee in this setting, given that most Venezuelans living in the country were not formally recognized as refugees. However, according to

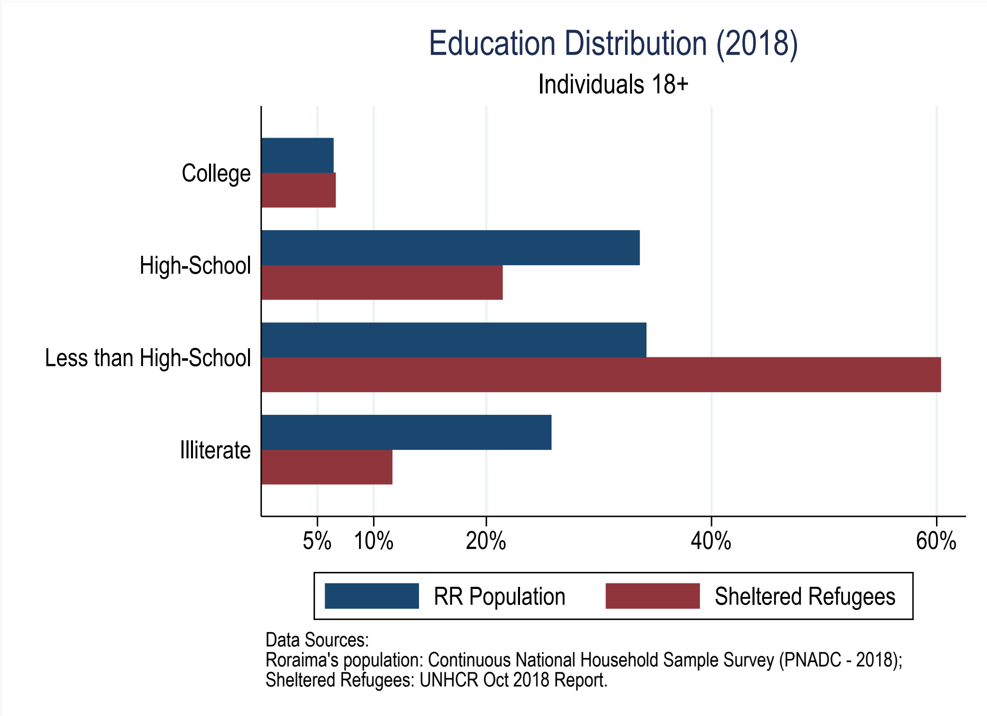
[16] See Figures 19 and 20 in the Appendix for more details about the gender and age composition of the refugee flow.

[17] 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] Source: January 2023 Ministry of Justice and Public Security report on Venezuelan Migration.

Oliveira Tavares and Cabral (2020), residency requests became the main pathway for regularization as a consequence of the Brazilian Government's late application of the refugee regime apparatus recognized by Brazilian migration law and the international agreements signed by the country.[19] Moreover, the increasing Venezuelan flow in Roraima was treated as a refugee crisis by the UNHCR. Therefore, in this paper, I use the word "refugee" for all Venezuelan immigrants, disregarding their documentation and migration status titles.

Figure 5: Sheltered Refugees Vs Roraima's Population - Education



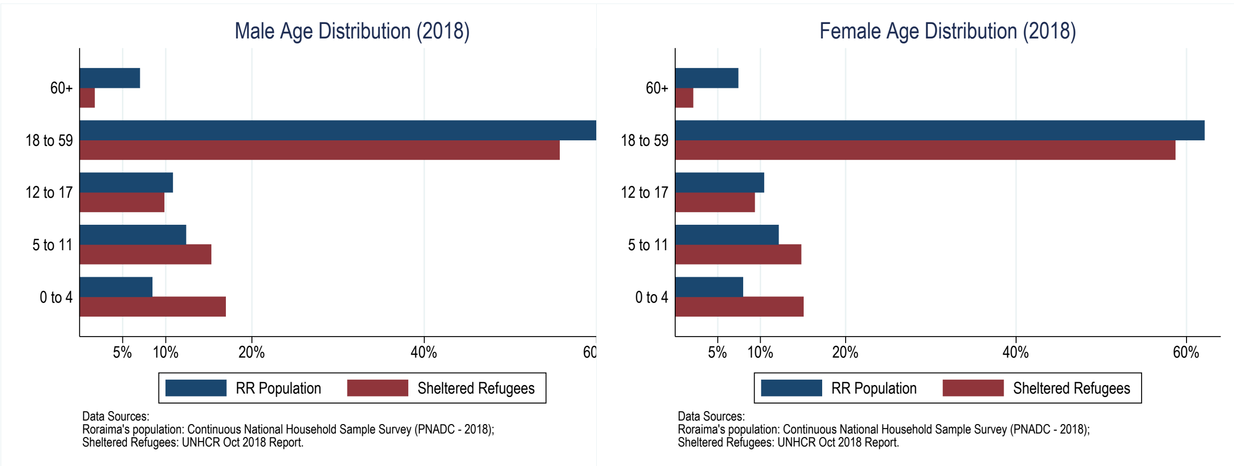
According to a survey conducted by Boa Vista (Roraima's capital) government in June 2018, 25,000 refugees were living in the city (7.5% of its population), and around 10% were homeless.[20] The availability of data about the refugee population in Roraima is limited. The UNHCR, however, published a series of monthly reports containing some demographic and socioeconomic characteristics of the sheltered Venezuelan population. Therefore, I used these reports and the Brazilian household survey (PNAD)

[19] According to Oliveira Tavares and Cabral (2020), it took three years for the 1984 Cartagena Declaration's extended definition of refugees to be applied to Venezuelan requests by CONARE (responsible for analyzing and granting refugee status). For more details and a timeline of the Brazilian migration system decisions regarding Venezuelans' regularization paths, see Raffoul (2018) and Silva and Jubilut (2018).

[20] Source: Newspaper article.

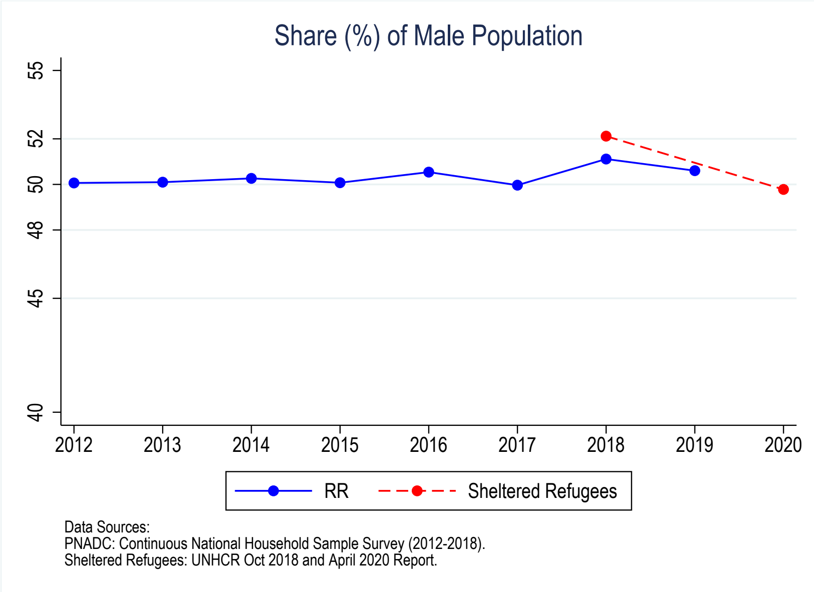
available at the state level to compare Roraima's population and sheltered refugees. The refugees are younger with disproportionately more 11-year-old kids or younger and considerably less 60 years or older individuals (see Figure 6). Moreover, illiteracy is two times less common among Venezuelans on the other hand the proportion of refugees without a high-school degree is larger (see Figure 5). In other words, refugee's education distribution is less polarized than the Brazilian one. Finally, the two populations present a similar gender composition (see Figure 7).[21]

Figure 6: Sheltered Refugees Vs Roraima's Population - Age



[21]PNAD data 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. If anything, this would approximate the statistics measuring the characteristics of the two populations, so the education, gender and age differences presented could be underestimated.

Figure 7: Sheltered Refugees Vs Roraima's Population - Gender



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 by this paper).[22]

During 2018, eleven shelters were spread in Boa Vista; 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 allowed a longer period of residency (the ones with "Refugee Housing Units"), others just for a shorter period (tents and overlays) - see Figure 9. They were managed by the Brazilian army (2 exclusively), NGOs,

[22] Since April 2018, more than 94,000 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.

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.[23] 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.[24] By October 2018 (when the state and national elections happened), 5,000 refugees were living in one of the shelters in Boa Vista.

Figure 8: Shelters' Inside Photos

Tancredo Neves Shelter (Source)

Rondon 1 Shelter (Source)

Figure 9: "Operação Acolhida" logo and shelters' name on outside signs

Jardim Floresta Shelter

Santa Teresa Shelter

Source: Google Maps Street View

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

[24]See Table 4 in the Appendix Section C for 2018 and 2020 shelter-specific statistics.

2.3 Brazilian Elections

Voting Right

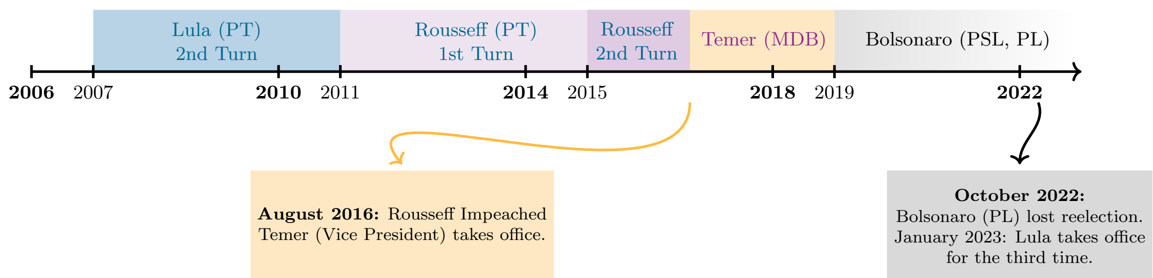
Voting is mandatory for 18 to 65-year-old Brazilians living in the country and optionally for 16 and 17-year-olds. Citizens must go to the electoral registry office bringing an official identification document and proof of residence (utility bills, for example) to get a voter's ID.

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).[25] Therefore, in this setting, Venezuelan refugees are not voting.[26]

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 10: Timeline Brazil's Presidents



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

[26] Unfortunately, information about the number of naturalized citizens among the voters' population is not available.

The 2014 reelected Brazilian President, Dilma Rousseff (Workers' Party - PT), was impeached in 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 "Operação Acolhida". Michel Temer decided not to run again in 2018.[27] 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 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 included as goal to improve refugees' and immigrants' rights and refers to them as a target population for public policies.

"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."

Haddad's Presidential Government Program (2018)

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 11). Moreover, it was the second state that decreased the most its support for the Workers' Party

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

between the 2014 and 2018 second rounds (a decrease of more than 35% - see Figure 12). Therefore, compared with the rest of the country, Boa Vista seems t have disproportionately shifted to the far-right in 2018.

Figure 11: Share of Valid Votes for Jair Bolsonaro - State Capitals

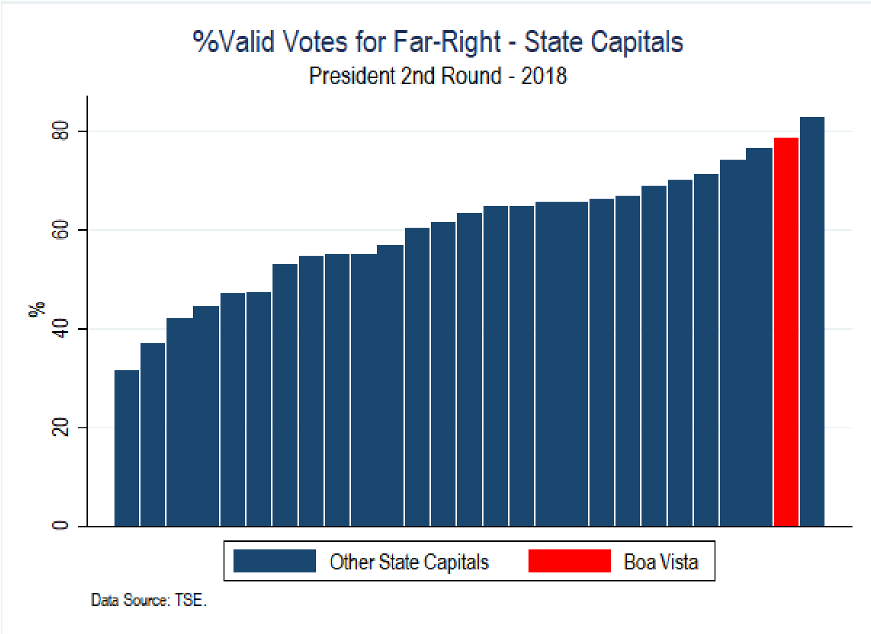
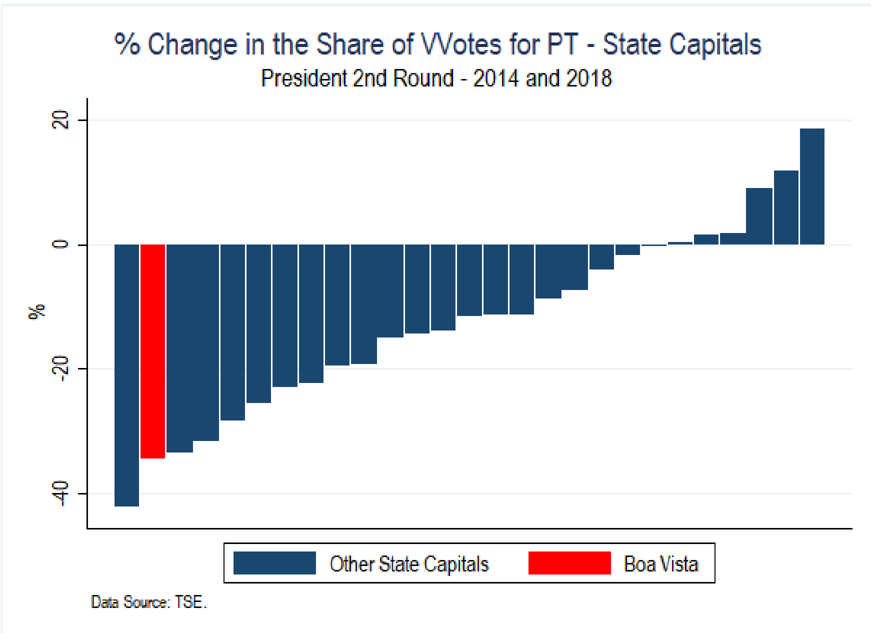


Figure 12: % Change in Workers' Party (PT) performance - State Capitals

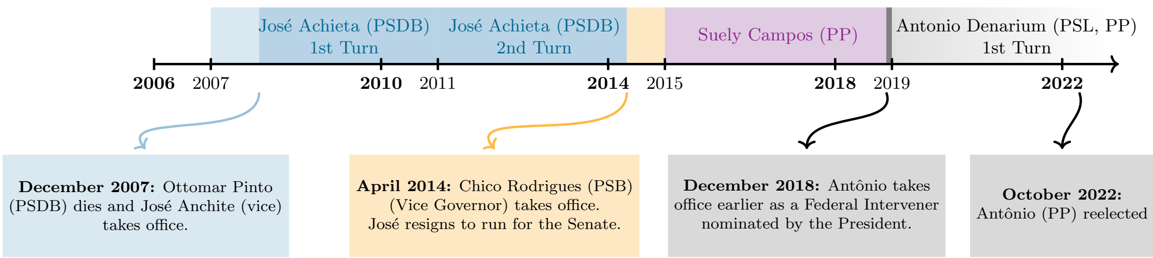


Haddad's Party, PT, launched a candidate in every Presidential election in my data (2006 to 2018). However, for some election years before 2018, PSL (Bolsonaro's

Party) didn't launch a candidate, so I will use the performance of the candidate it supported in those elections. Moreover, to have a complete picture of where votes are migrating to/from, I will also classify the remaining presidential candidates into left, center-left, center, center-right, and right following the party ideology index from Bolognesi, Ribeiro, and Codato (2022). See Table 6 in Section D of the Appendix for more details on how parties and candidates were categorized.

2018 Political Environment (Governor Election)

Figure 13: 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 14: 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"

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 not enough. 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, claiming it was just impossible and that it would violate humanitarian reception principles.[28] 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.[29]

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. Mass escapes and riots were registered in 2018. 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.

"Together with refugees, drug dealers, and criminals are entering; one

[28] Governor of Roraima asks to close Brazil's border with Venezuela.

[29] Government of Roraima signs decree that tightens foreigners access to public services.

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.

Antônio Denarium - 2018 Roraima's Elected Governor

The second most voted candidate in the 2018 first round was Anchieta Júnior (PSDB) who lost the 2018 second round by obtaining 46.66% of the valid 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 in the state.

Therefore, all three main gubernatorial candidates proposed migration restrictions, and the incumbent, even though participated in the shelter policy efforts, can not be considered pro-migration. Therefore, the potential effects of the urban shelters on Suely's performance are more likely to capture an "accountability effect than a shift of political preference.

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's outcomes). Finally, I will classify the remaining candidates into left, center-left, center, center-right, and right following the party ideology index from Bolognesi, Ribeiro, and Codato (2022). See Table 5 in Section D of the Appendix for more details on how parties and candidates were categorized.

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 the panel id as well as 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 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. For robustness, I also explore a polling station panel and construct "fake" voting districts using Voronoi Polygons (see Appendix K for details).

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:

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

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 is the post-treatment period. The treatment assignment level is "higher" than the observations, therefore, standard errors are clustered at the polling station level.

Table 1: Balance Table

	Treated Sections			Control Sections			
	n	mean	sd	n	mean	sd	Diff
Distance (Km) to the closest shelter	297	0.65	0.23	614	2.05	0.99	-1.409***
Average Distance (Km) to all shelters	297	3.52	0.66	614	4.70	1.39	-1.182***
Distance (Km) to Boa-Vista downtown	297	5.04	2.34	614	5.39	2.78	-0.353*
Dummy Balanced Section	297	0.30	0.46	614	0.27	0.45	0.024
Year section first shows up	297	2010.27	5.24	614	2010.88	5.07	-0.610*
Number of Registered Voters	753	328.30	67.96	1469	325.73	72.04	-0.414
Share Men	407	47.81	3.65	855	47.32	4.11	0.489**
Share Illiterate	407	1.44	1.04	855	1.29	1.18	0.149**
Share Less than High-School	407	44.62	13.02	855	41.88	17.29	2.740***
Share with some college	407	22.28	11.77	855	26.50	17.45	-4.226***
Share 16 and 17 Years Old	407	2.31	3.27	855	2.47	3.71	-0.157
Share 18 Year Old	407	2.26	2.32	855	2.53	2.66	-0.269*
Share <25 Years Old	407	20.28	10.75	855	21.79	12.21	-1.516**
Share <40 Years Old	407	46.37	13.70	855	48.08	13.94	-1.715**
Share >65 Years Old	407	6.25	3.96	855	5.87	3.96	0.372
Share of Illiterate Men	407	0.66	0.57	855	0.60	0.59	0.061*
Share of less than High-school degree Men	407	23.85	7.21	855	21.96	9.21	1.883***
Share Young Men	407	15.84	7.08	855	16.66	7.60	-0.821*
Share of Illiterate Women	407	0.78	0.70	855	0.69	0.73	0.088**
Share of less than High-school degree Women	407	20.77	6.59	855	19.92	8.79	0.857*
Share Young Women	407	17.37	6.95	855	18.38	7.35	-1.015**
Share Pregnancy-Age Women	407	30.69	6.31	855	31.89	6.65	-1.196***

Notes: Voters' Characteristics data includes only 2014 and 2018 elections. "Young": 16 to 29 years old; "Pregnancy-Age": 16 to 40

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.[31]

Table 1 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

[30]See Table 8 in Appendix F for descriptive statistics of different covariates.
[31]For a balance table using a balanced section panel data, see Table 9 in Appendix F.

sections are statistically older, less educated, and more male than voters in control sections. The diff-in-diff approach accounts for any outcome level differences induced by those covariate imbalances between control and treated units. However, 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. Therefore, to deal with this potential bias concern, I also run equation (1) specification including covariates.

However, adding covariates biases the TWFE even in a non-staggered design with two time periods - see Sant'Anna and Zhao (2020). Callaway and Sant'Anna (2021) 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.[32] Additionally, I estimate a Matching DiD that first uses pre-treatment covariates to match control units to treated ones before calculating a conventional DiD.[33]

4.3 Identification Assumptions

This section will discuss and test the identification assumptions required for interpreting "β" as the causal effect of the Venezuelan 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

[32] See Table 8 in Appendix F for the complete covariate list.

[33] 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.

voting close enough to their residence, threatening the accuracy of the section results in measuring the surrounding population's political perception. 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.[34] Therefore, after 2013 the correlation between where you vote and where you live likely became even stronger.[35] Finally, I decided to only use voters' characteristics data after 2013. See Appendix J for more details about the voters' info update induced by the fingerprint requirement.

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 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 more welcoming to refugees and shelters). However, "Operação Acolhida" was considered an emergency effort (shelters started to open a month after the first meeting to organize the operation). 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 form and act.

[34] 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."

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

No Spillover Effects

The assumption that control units are not affected by the treatment is hard 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.

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

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 organization's institutional setting likely minimizes this concern. 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 in Boa Vista 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.

To empirically test if treatment affected voters' characteristics (a potential sign of endogenous allocation of voters), I ran equation (1) using those voters' characteristics as outcomes. According to the results (see Table 2), there is no consistent treatment effect over different voters' characteristics. Only the share of voters with a college degree was statistically affected. However, my estimated treatment effects are more than three times bigger than the 0.572 percentage points increment in college-graduated voters in treated units after treatment. Moreover, voters' characteristics will also be added as controls in some specifications as explained in the last section.

Table 2: DiD (Eq. 1) Results - Control Variables as Outcome

	2006-2018		2008-2020	
Outcome	**Treated*Post**	**R2**	**Treated*Post**	**R2**
Share Men	0.092 (0.268)	0.007	-0.101 (0.290)	0.017
Share Illiterate	0.027 (0.058)	0.140	0.037 (0.049)	0.014
Share Less than High-School	-0.126 (0.544)	0.124	-0.206 (0.328)	0.174
Share Some College	0.572*** (0.254)	0.063	0.450*** (0.195)	0.130
Share 16-17 Years Old	-0.371 (0.685)	0.073	0.604 (0.548)	0.228
Share 18 Year Old	-0.289 (0.515)	0.069	0.083 (0.302)	0.214
Share <25 Years Old	-0.864 (1.136)	0.123	-1.471 (0.934)	0.442
Share <40 Years Old	-0.596 (0.861)	0.427	-0.382 (0.615)	0.690
Share >65 Years Old	-0.035 (0.248)	0.475	0.159 (0.267)	0.588
Share Less than High-School Men	-0.140 (0.403)	0.070	-0.243 (0.333)	0.109
Share Working-age Men	0.367 (0.263)	0.017	-0.525 (0.476)	0.026

Notes: standard errors clustered at the polling station level in parenthesis. Columns (2008-2020) show the results using data from the local elections (mayor and city hall member) with the pre-treatment period being 2008, 2012, 2016, and the post-treatment being 2020. Working age: 18 to 60 years old; Young: 16 to 29; Pregnancy-age:16 to 40.

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) 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 3: DiD (Eq. 1) Results - Election Logistics Variables as Outcome

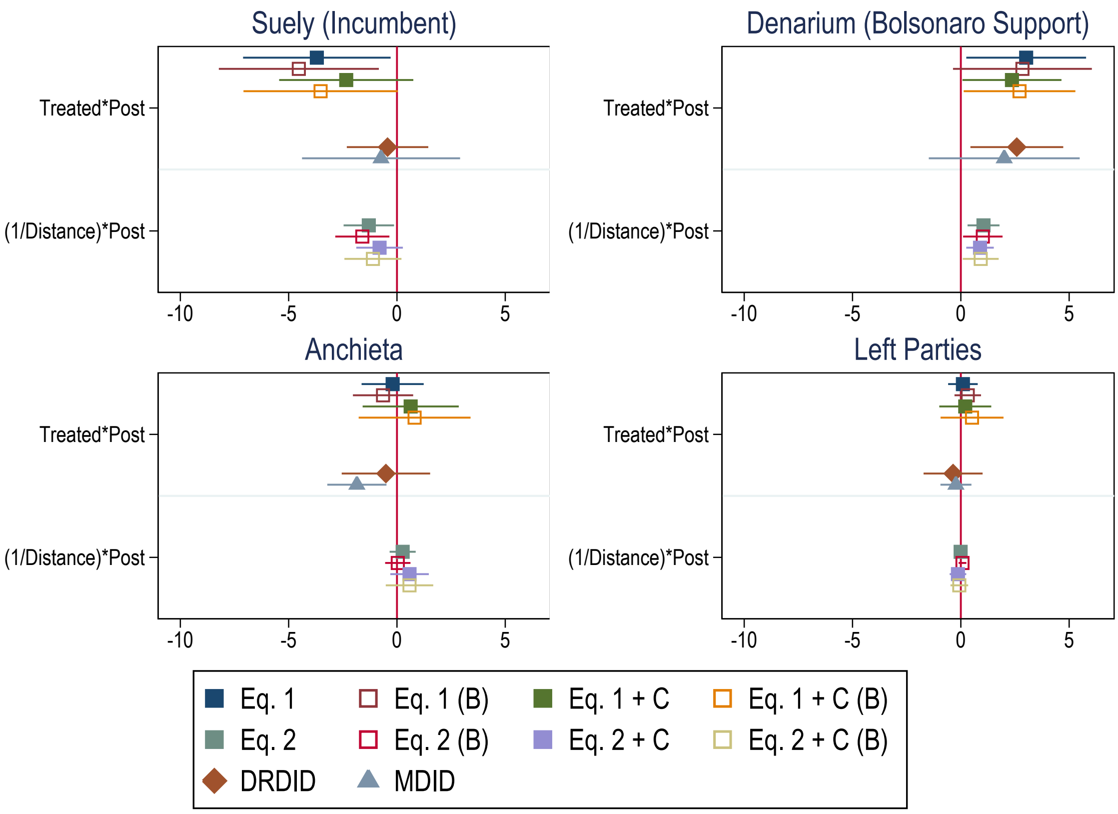
	2006-2018	
Section-level Outcomes:	**Treated*Post**	**R2**
Number of Voters	-1.778 (12.448)	0.218
Polling Station-level Outcomes:		
Lifetime (number of years shows up in the data)	-0.105 (0.293)	0.007
Lifetime (number of years shows up in the data)	-0.105 (0.293)	0.007
Number of Sections	-0.088 (0.209)	0.253
Number of Voters	-87.245 (142.134)	0.157
Average Number of Voters per Section	-15.708 (11.206)	0.160
Number of Voters in the Biggest Section	-10.968 (11.475)	0.201
Number of Voters in the Smallest Section	-25.817 (17.082)	0.097

According to the results presented in Table 3, There was no differential logistics treatment between treated and control units. Therefore, it is unlikely that the election organization affected my estimated results.

5 Results

5.1 Governor Election

Figure 15: Governor Election Results



Notes: Dependent Variable = % of valid votes for each category/candidate. (B) = Balanced Sample; C = Voters' Characteristics Controls.

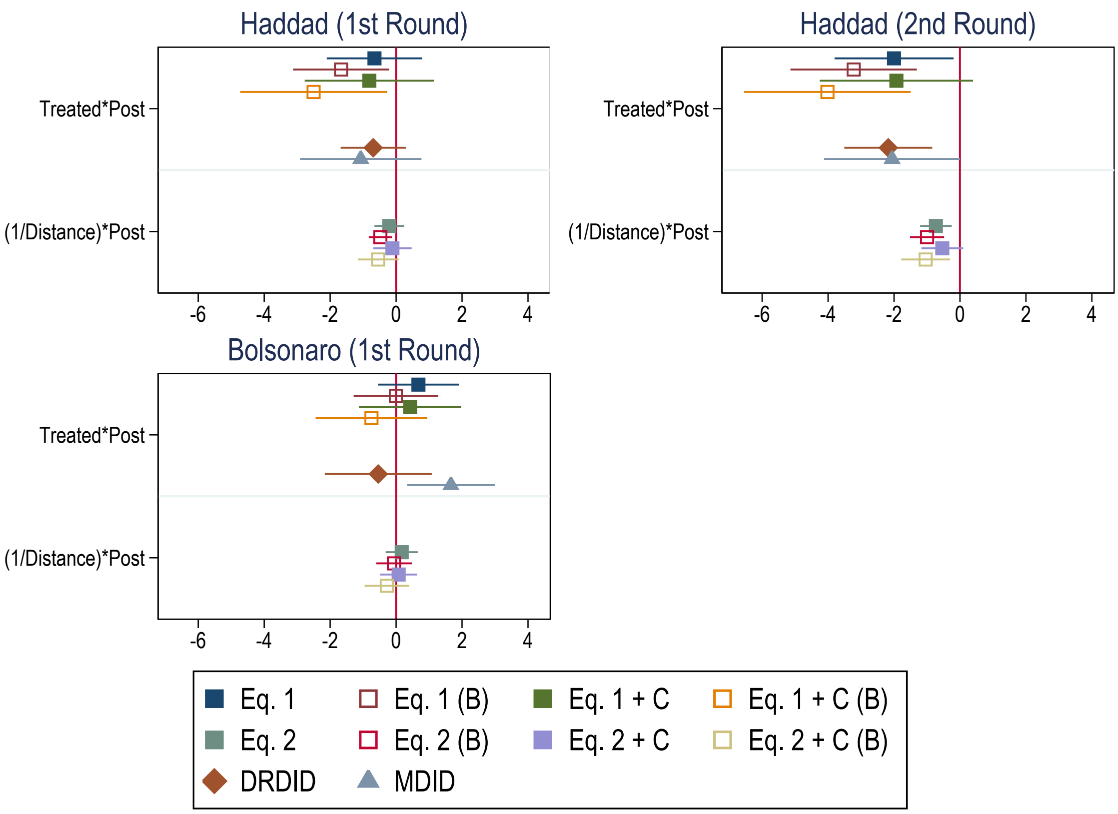
Figure 15 describes the main results of the Governor's election. According to most specifications, the incumbent governor (Suely) lost between 2 to 4 percentage points of the valid votes in sections within treated polling stations. This incumbent "punishment"/accountability result is especially interesting considering that even though Suely participated in the "Operação Acolhida" effort, She engaged in anti-migration proposals in 2018 (tried to close the state's border and restrict refugees' access to public services).

Additionally, the voting loss suffered by Suely migrated to Antônio Denarium supported by Bolsonaro (the far-right presidential candidate). 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.

5.2 Presidential Election

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).[36].

Figure 16: President Election Results



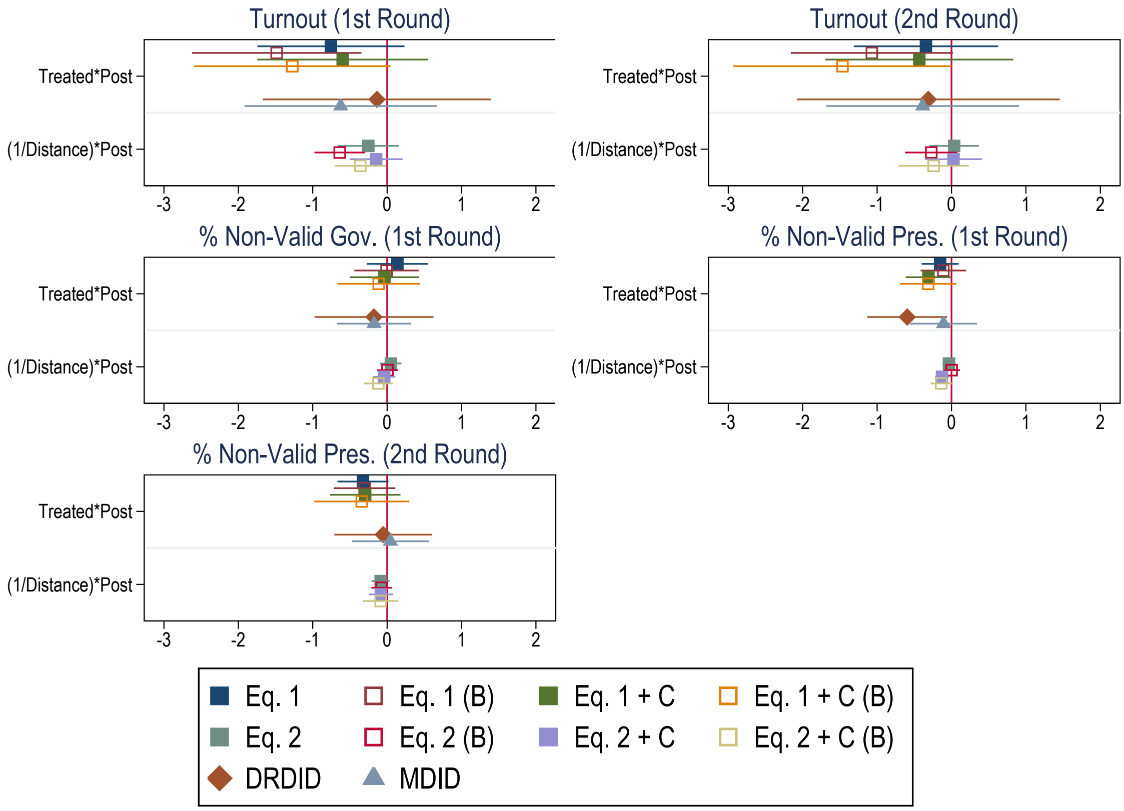
Notes: Dependent Variable = % of valid votes for each category/candidate. (B) = Balanced Sample; C = Voters' Characteristics Controls.

[36]The results for the other candidates were not statistically significant - see Figure 23 in the Appendix G.

5.3 Turnout and Non Valid Votes

According to Figure 17, we don't observe any consistent effect on the share of non-valid votes (voters that showed up but didn't choose any candidate). Results for Turnout rates are noisier and their statistical significance is not consistent across the different specifications.

Figure 17: Turnout and Non Valid Votes Results



Notes: Dependent Variable = % of valid votes for each category/candidate. (B) = Balanced Sample; C = Voters' Characteristics Controls.

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 K for details). The estimates from both panels confirm the section-level results for Governor and Presidential elections (result tables not reported in this draft).

Cross Section and Placebo

Considering the 2013 fingerprint scan procedure, I explore an alternative specification using only the 2014 and 2018 elections:

$$Y_{ij,2018} = \beta \text{ Treated}_j + \gamma Y_{ij,2014} + \epsilon_{ij} \tag{3}$$

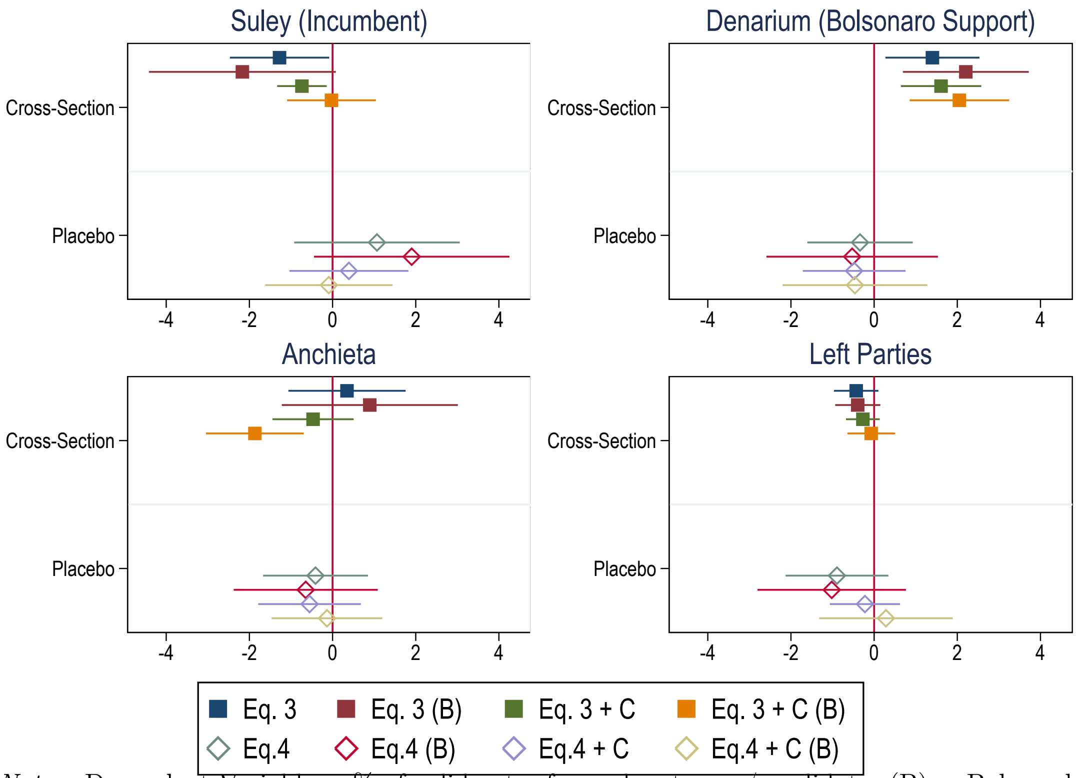
$Y_{ij,2018}$ and $Y_{ij,2014}$ are the outcomes of the section "i" in polling station "j" in 2018 and 2014. Treated_j is a dummy variable indicating whether "j" is treated (less than 1km away from a shelter). Additionally, I estimate placebo tests using the 2014 and 2010 election data (see equation below). In 2014, when there were no refugee shelters, treatment assignment shouldn't explain voting outcomes (i.e. $\beta = 0$).

$$Y_{ij,2014} = \beta \text{ Treated}_j + \gamma Y_{ij,2010} + \epsilon_{ij} \tag{4}$$

Government election results (Figure 18) confirmed the main specification conclusions: shelters negatively affected the incumbent governor and increased far-right supported candidate performance. Moreover, as expected, the placebo effects were not statistically different than zero.

The presidential election results (Figure 24 in Appendix H) confirm the negative effect on Haddad's performance in the second round. Bolsonaro's performance in the first round might have been positively affected by the shelter, however, placebo effects are different than zero in this case. Finally, we don't observe any refugee shelters' effect on turnout and non-valid votes (Figure 25 in Appendix H).

Figure 18: Governor Election Results (Cross-Section and Placebo Results)



Notes: Dependent Variable = % of valid votes for each category/candidate. (B) = Balanced Sample; C = Voters' Characteristics Controls.

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 (see Appendix I) go in the same direction as the ones reported as the main findings. However, as expected, they are noisier (larger standard errors) since 800 observations (36% of the sample) were dropped.

6 Conclusion

The shelters built to receive Venezuelan refugees in Boa Vista (a state capital and the main entrance point for Venezuelans arriving in Brazil) were one of the only refugee shelter/camp units in South America, a continent not used in receiving refugee flows. Providing refuge in camps and shelters is one of the main forms of humanitarian aid for forcibly displaced populations and is extensively used in traditional refugee-hosting regions worldwide.

Locals' attitudes towards migrants can have important implications for immigrants' integration and sustainability of migration policy. Most of the literature studying the effect of immigrants on political outcomes found that migration flows caused an increase in the performance of right and far-right candidates who are usually anti-migration. Refugees are a particularly vulnerable migrant population that can trigger even more political polarization among locals. Therefore, studying how shelters potentially affect electoral outcomes is fundamental to understanding the political sustainability of this widely common refugee aid policy.

According to my results, shelters triggered locals to electorally punish the incumbent governor who participated in the shelter organization efforts led by the federal government. Moreover, the incumbent's voting loss transformed into a higher valid-vote share for a gubernatorial candidate supported by the presidential far-right candidate (Bolsonaro). 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. Therefore, my next step will be to verify how the refugee flow affected the composition of candidates in Roraima and Boa Vista compared with unaffected states and municipalities in the country.

Additionally, there is some evidence that the left Presidential candidate (Haddad) was negatively affected in the second round by losing votes for Bolsonaro (far-right candidate). Combined with the fact that there was no incumbent presidential candidate, my results go in the same direction as the literature, exposure to refugee shelters likely shifted voters to a far-right candidate.

Therefore, shelters presented political accountability and preference consequences. 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 election. The next planned expansions of this paper will incorporate mechanisms analysis (crime and public education services amenities) to disentangle the reasons behind the results.

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.

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.

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

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.

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*.

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

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.

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.

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.

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

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.

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

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.

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 (2016). *Immigration to the US: A Problem for the Republicans or the Democrats?* Tech. rep. National Bureau of Economic Research.

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.

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.

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

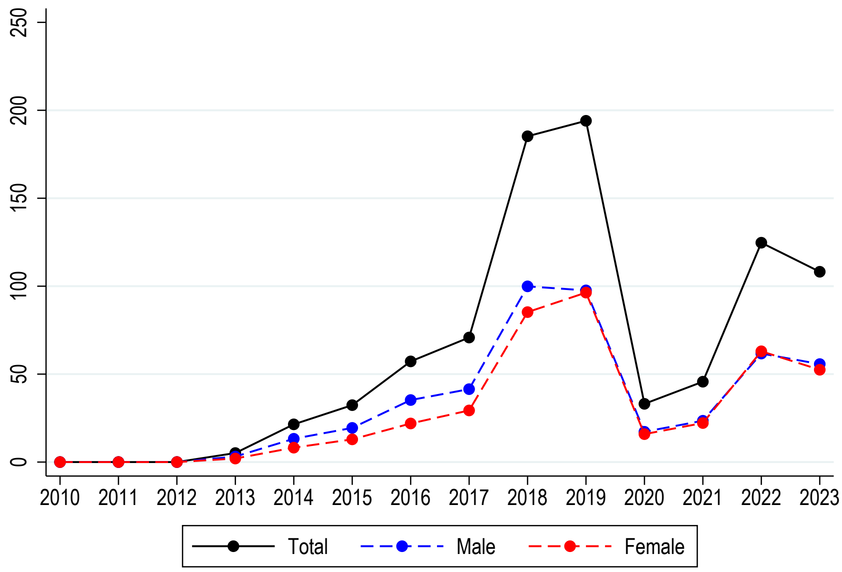
Steinmayr, Andreas (2021). "Contact versus exposure: Refugee presence and voting for the far right". In: *Review of Economics and Statistics* 103(2), pp. 310–327.

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.

Appendix

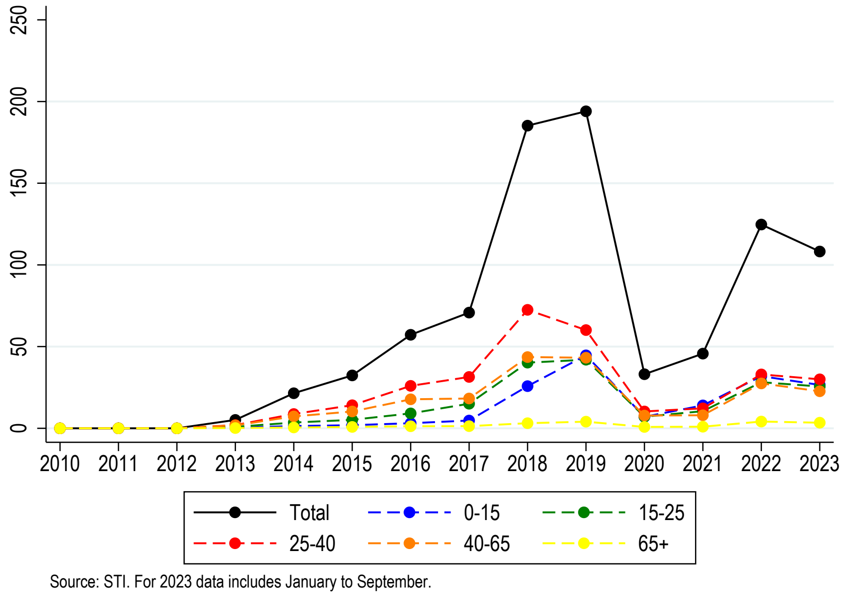
A Venezuelan Refugee Flow

Figure 19: Venezuelan Migration Flows to RR



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

Figure 20: Venezuelan Migration Flows to RR



B Operação Acolhida

Figure 21: Operação Acolhida Anual Budget

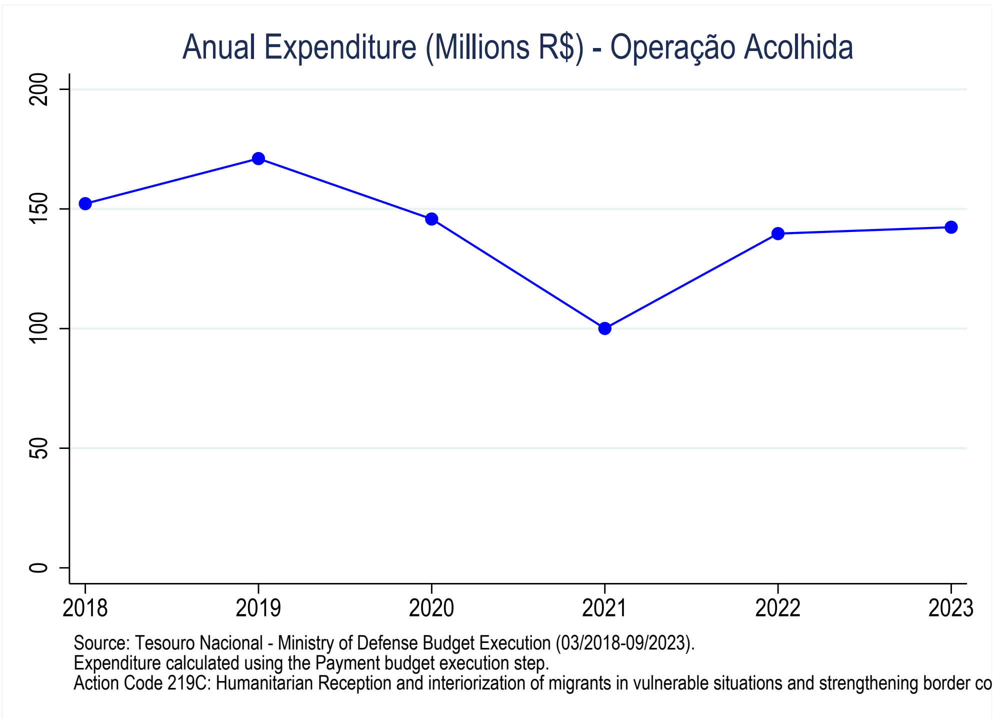
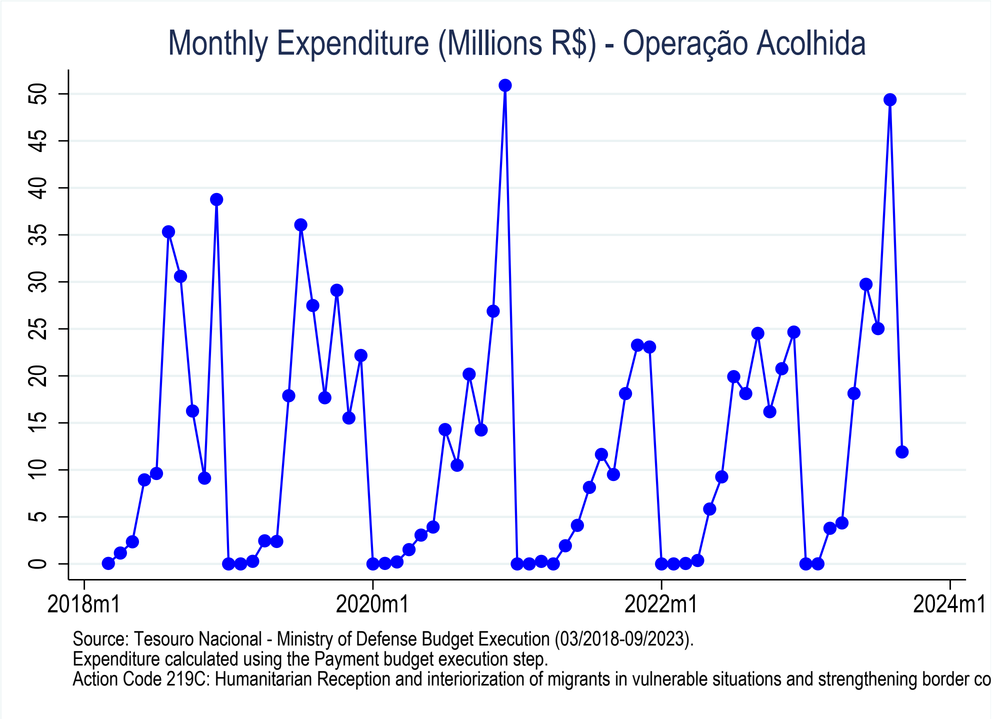


Figure 22: Operação Acolhida Monthly Budget



C Shelters Information

Table 4: 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 - Categories Definition

Table 5: Governor Election - Parties Classification

	2018	**2014**	**2010**	**2006**
Suely (2018 Incumbent Candidate)	PP (8.20)	PP (8.20)	PP (8.20)	PSDB (7.11)
Anchieta Júnior	PSDB (7.11)	PSB (4.05)	PSDB (7.11)	PSDB (7.11)
Denarium (Supported by Bolsonaro)	PSL (8.11)	PSB (4.05)	-	-
Left (Parties from 0 to 4)	PSOL (1.28)	PSOL + PT (1.28) (2.97)	PSOL (1.28) [1.34%]	PSOL + PDT + PCO (1.28) (3.92) (0.61)
Center-left (Parties from 4 to 6)	-			
Center (Parties from 6 to 7)	PTB (6.1)	-	PHS (6.98)	PHS (6.98)
Center-right (Parties from 7 to 8)	-			
Right (Parties 8+)	-			

Notes: The number in parenthesis is the Bolognesi, Ribeiro, and Codato (2022) party ideology classification index (0 is extreme-left and 10 is extreme-right).

Table 6: President Election - Parties Classification

	2018	**2014**	**2010**	**2006**
2018 Incumbent Candidate	-	-	-	-
2018 Center-Right Candidate	PSDB (7.11)	PSDB (7.11)	PSDB (7.11)	PSDB (7.11)
Jair Bolsonaro (Far-Right Candidate)	PSL (8.11)	PSB (4.05)	-	PSL (8.11)
Haddad (Worker's Party Candidate)	PT (2.97)	PT (2.97)	PT (2.97)	PT (2.97)
Left (Parties from 0 to 4)	PDT+PSOL+PSTU (3.92) (1.28) (0.51)	PSOL+PSTU+PCB+PCO (1.28) (0.51) (0.91) (0.61) [%]	PSOL+PSTU+PCB+PCO (1.28) (0.51) (0.91) (0.61) [%]	PSOL+PDT (1.28) (3.92)
Center-left (Parties from 4 to 6)	Rede (4.77)	PSB+PV (4.05) (5.29)	PV (5.29)	-
Center (Parties from 6 to 7)	-	-	-	-
Center-right (Parties from 7 to 8)	PODE+MDB (7.24) (7.01)	PRTB (7.45)	PRTB (7.45)	PRP (7.59)
Right (Parties 8+)	PATRI+NOVO+DC (8.55) (8.13) (8.11)	PSDC+PSC (8.11) (8.33)	PSDC (8.11)	PSDC+PSl (8.11) (8.11)

Notes: The number in parenthesis is the Bolognesi, Ribeiro, and Codato (2022) party ideology classification index (0 is extreme-left and 10 is extreme-right).

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 7 below for the final description of polling stations' geographic coordinates data source.

Table 7: 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 Descriptive Statistics

Table 8: Descriptive Statistics (2006-2018)

	N	mean	sd	min	max
Distance (Km) to the closest shelter	911	1.595	1.056	0.168	6.989
Average Distance (Km) to all shelters	911	4.320	1.320	2.860	9.372
Dummy Distance to the closest shelter $<$ 100m	911	0	0	0	0
Dummy Distance to the closest shelter $<$ 200m	911	0.0110	0.104	0	1
Dummy Distance to the closest shelter $<$ 500m	911	0.0812	0.273	0	1
Treatment Dummy ($<$ 1000m)	911	0.326	0.469	0	1
Distance (Km) to Boa-Vista center/downtown	911	5.278	2.653	0.212	11.84
Dummy Balanced Section	911	0.280	0.449	0	1
Total Number Valid Votes - Governor	2,222	265.9	53.67	65	380
Total Number Valid Votes - National Congress	2,222	268.0	54.84	63	383
Total Number Valid Votes - State Congress	2,222	273.5	55.57	65	394
Total Number Valid Votes - President (1st Round)	2,222	271.3	54.41	64	387
Total Number Valid Votes - President (2nd Round)	2,222	259.2	53.06	56	363
Number of Registered Voters	2,222	326.6	70.68	75	463
Turnout Rate 1st Round	2,222	85.86	4.180	44.67	97.01
Turnout Rate 2nd Round	2,222	82.26	4.940	41.80	95.07
Share Illiterate	1,262	1.335	1.141	0	6.107
Share with some college	1,262	25.14	15.96	2.488	82.78
Share Less than High-School	1,262	42.77	16.08	2.974	80.10
Share 16 and 17 Years Old	1,262	2.421	3.573	0	40.34
Share 18 Year Old	1,262	2.443	2.556	0	20.64
Share $<$25 Years Old	1,262	21.30	11.78	0	69.37
Share less than 30 years old	1,262	34.45	14.11	3.061	77.03
Share $<$40 Years Old	1,262	47.53	13.88	9.417	83.33
Share $>$65 Years Old	1,262	5.993	3.961	0	27.32
Share Men	1,262	47.48	3.970	34.10	73.83
Share of Illiterate Men	1,262	0.617	0.587	0	2.927
Share of less than High-school degree Men	1,262	22.57	8.660	1.487	55.14
Share of some College Men	1,262	10.18	7.520	0	38.61
Share Working-Age Men	1,262	41.38	4.862	23.98	70.09
Share of 18 Year Old Men	1,262	1.167	1.309	0	10.46
Share of $<$25 Years Old Men	1,262	10.18	6.033	0	41.82
Share Young Men	1,262	16.40	7.440	1.531	47.66
Share of $<$40 Years Old Men	1,262	22.48	7.589	3.571	57.01
Share of $>$65 Years old Men	1,262	2.949	1.975	0	14.45
Share of $<$30 Years Old Men without High-School	1,262	8.125	5.361	0	40
Share of Illiterate women	1,262	0.718	0.726	0	3.817
Share of less than High-school degree women	1,262	20.19	8.150	1.487	44.06
Share of some College Women	1,262	14.96	8.760	0.935	47.24
Share Working-Age Women	1,262	46.17	4.552	24.30	58.54
Share of 18 Year Old Women	1,262	1.276	1.402	0	12.57
Share of $<$25 Years Old Women	1,262	11.12	6.119	0	39.72
Share Young Women	1,262	18.05	7.235	1.531	42.01
Share of $<$40 Years Old Women	1,262	11.12	6.119	0	39.72
Share of $>$65 Years old Women	1,262	3.045	2.292	0	15.98
Share Pregnancy-Age Women	1,262	31.50	6.567	8.247	48.74
Share of $<$30 Years Old Women without High-School	1,262	7.596	4.948	0	34.75

Notes: Voters' Characteristics data: only for 2014 and 2018. Working age: 18 to 60 years old; Young: 16 to 29; Pregnancy age: 16 to 40.

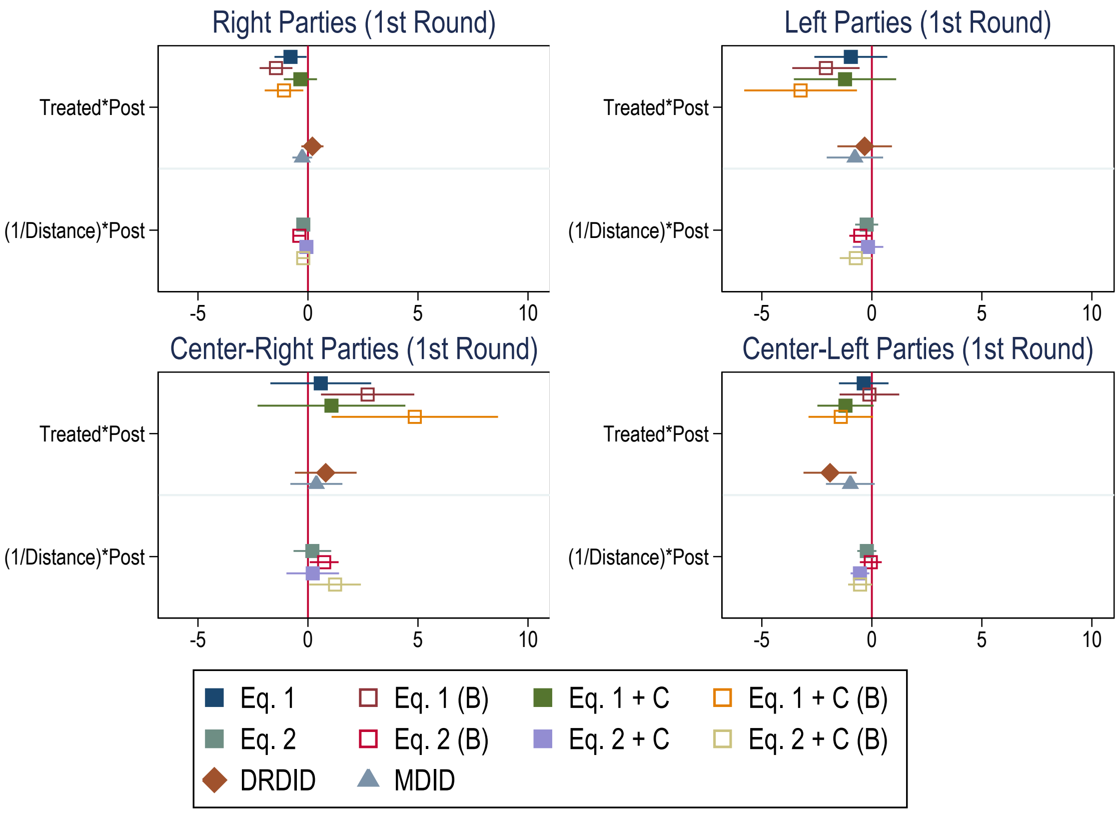
Table 9: Balance Table (2006-2018) Balanced Sample

	Control Sections			Treated Sections			
	n	mean	sd	n	mean	sd	Diff
Distance (Km) to the closest shelter	88	0.58	0.25	167	1.92	1.00	-1.336***
Average Distance (Km) to all shelters	88	3.88	0.54	167	5.11	1.34	-1.230***
Distance (Km) to Boa-Vista center/downtown	88	5.44	2.86	167	4.18	3.21	1.263***
Number of Registered Voters	352	341.53	63.64	668	315.36	72.92	26.871***
Share Men	176	47.55	3.09	334	47.23	3.93	0.321
Share Illiterate	176	1.63	1.01	334	1.08	1.27	0.544***
Share Less than High-School	176	46.33	12.80	334	34.92	16.89	11.408***
Share with some college	176	20.86	12.23	334	33.64	18.90	-12.781***
Share 16 and 17 Years Old	176	2.07	1.71	334	1.77	1.53	0.300**
Share 18 Year Old	176	1.95	1.29	334	1.95	1.53	-0.003
Share <25 Years Old	176	18.52	5.68	334	17.65	7.52	0.869
Share <40 Years Old	176	45.44	11.82	334	44.53	13.95	0.908
Share >65 Years Old	176	6.62	4.08	334	7.13	4.48	-0.506
Share of Illiterate Men	176	0.74	0.57	334	0.51	0.63	0.230***
Share of less than High-school degree Men	176	24.50	7.22	334	18.22	8.82	6.280***
Share Young Men	176	15.10	5.39	334	14.90	6.56	0.207
Share of Illiterate women	176	0.88	0.70	334	0.57	0.74	0.314***
Share of less than High-school degree women	176	21.83	6.36	334	16.71	8.58	5.128***
Share Young Women	176	16.54	5.55	334	16.20	6.59	0.338
Share Pregnancy-Age Women	176	30.41	6.14	334	29.71	7.03	0.705

Notes: Low-Skilled: up to high-school degree; Working-age: 18 to 60 years old; Young: 16 to 29 years old; Pregnancy-age:16 to 40 years old.

G Results (Section-Level Panel)

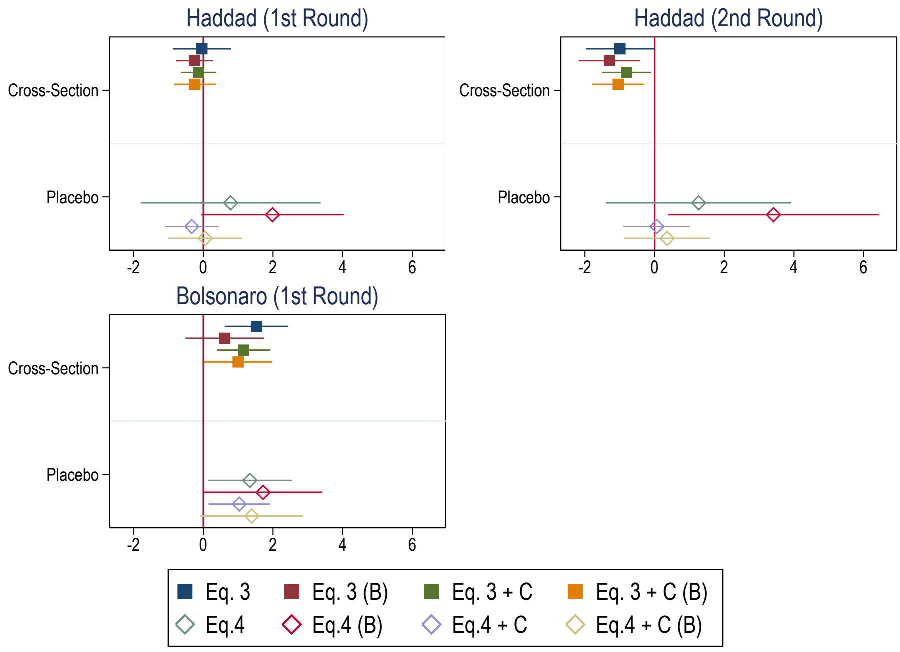
Figure 23: President Election Results (Other Candidates)



Notes: Dependent Variable = % of valid votes for each category/candidate. (B) = Balanced Sample; C = Voters' Characteristics Controls.

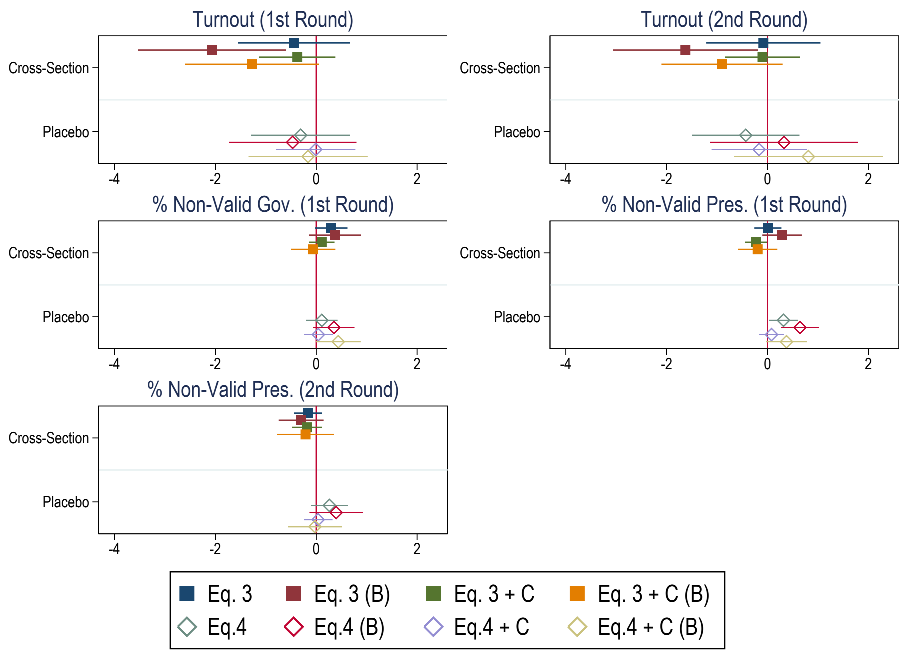
H Cross-Section and Placebo Estimates

Figure 24: President Election Results



Notes: Dependent Variable = % of valid votes for each category/candidate. (B) = Balanced Sample; C = Voters' Characteristics Controls.

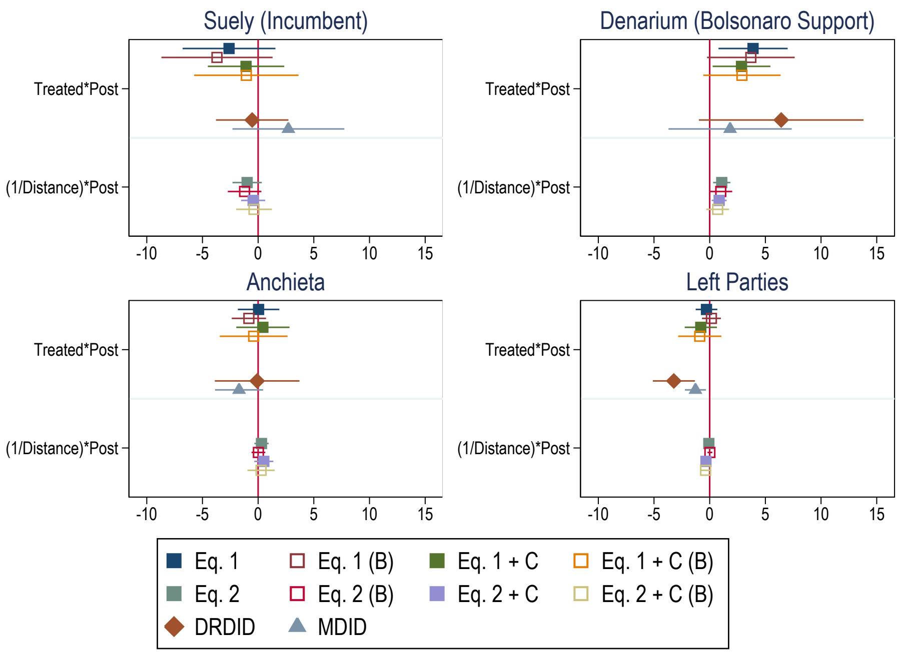
Figure 25: Turnout and Non-Valid Votes Results



Notes: Dependent Variable = % of valid votes for each category/candidate. (B) = Balanced Sample; C = Voters' Characteristics Controls.

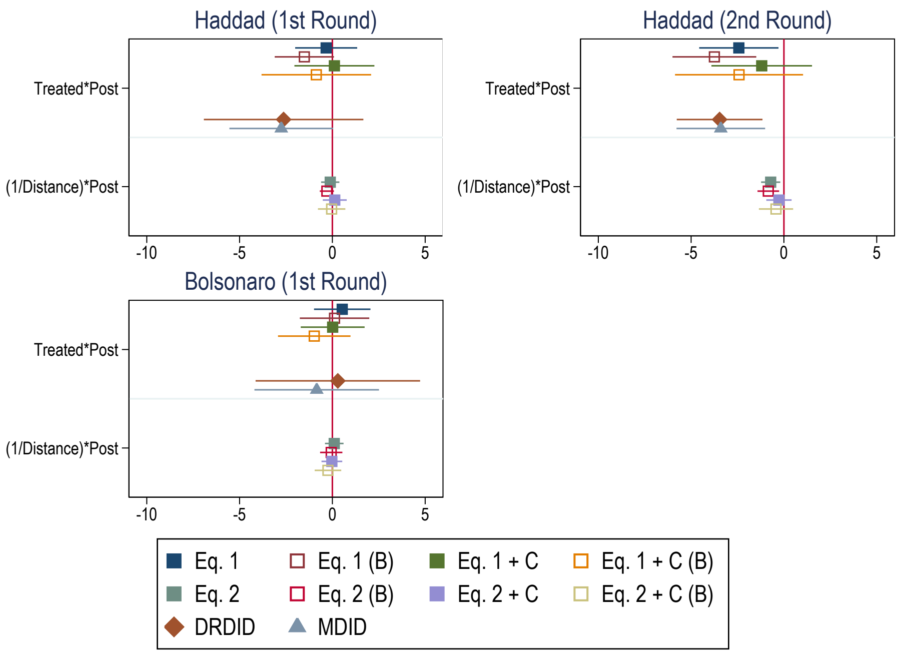
I Alternative Control Group

Figure 26: Governor Election Results



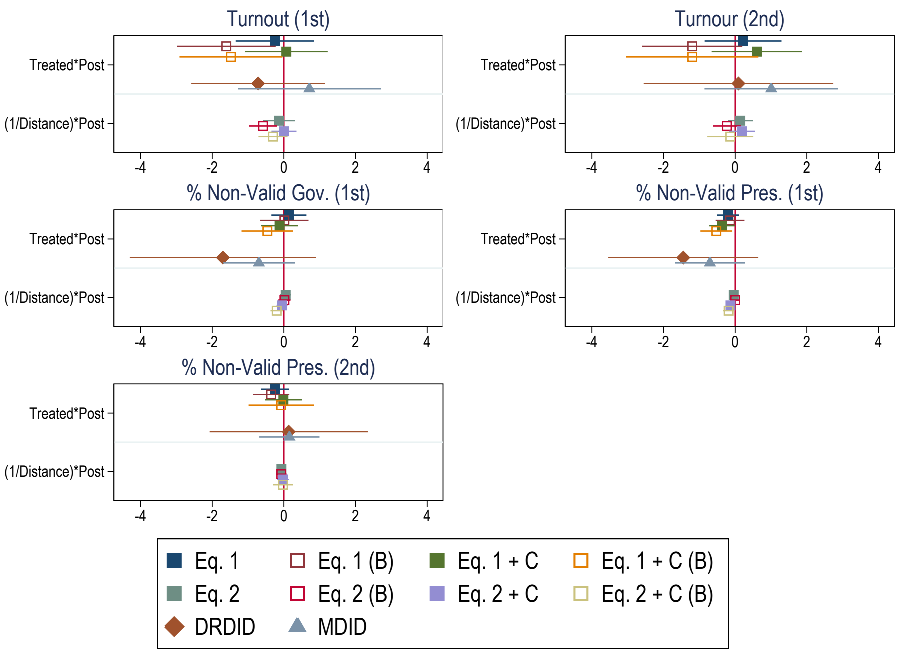
Notes: Dependent Variable = % of valid votes for each category/candidate. (B) = Balanced Sample; C = Voters' Characteristics Controls.

Figure 27: President Election Results



Notes: Dependent Variable = % of valid votes for each category/candidate. (B) = Balanced Sample; C = Voters' Characteristics Controls.

Figure 28: Turnout and Non-Valid Votes Results



Notes: Dependent Variable = % of valid votes for each category/candidate. (B) = Balanced Sample; C = Voters' Characteristics Controls.

J Fingerprint scan and Voters' Demographic Info

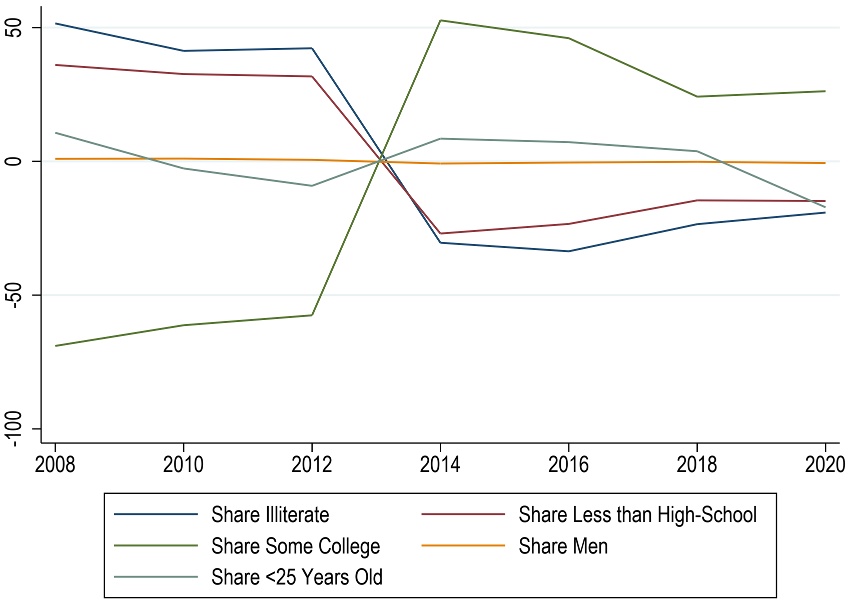
First, I calculated the following yearly index to verify how big the update in voters' demographic variables was after the 2013 fingerprint requirement that made all voters come back to the offices.

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

$\bar{y}_{ij}$ 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 29, 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 29: 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.

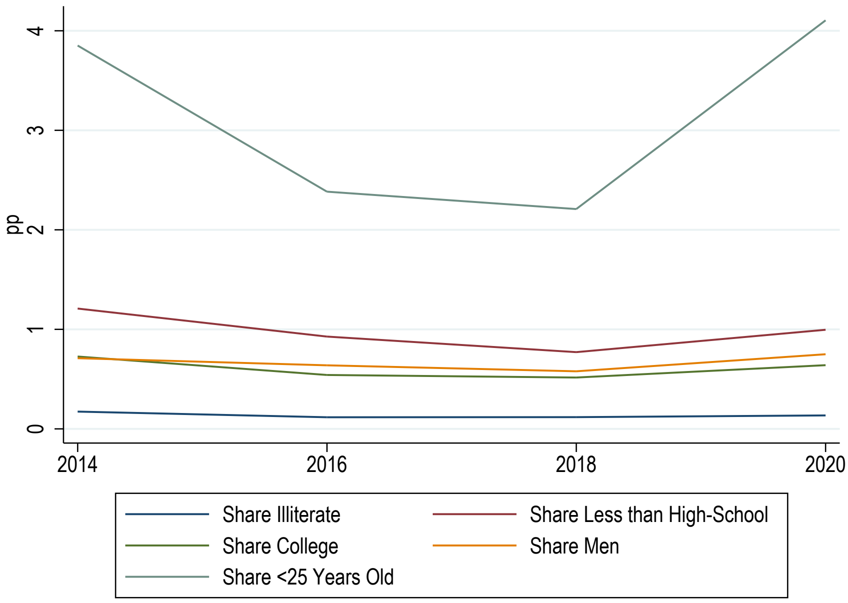
To show that after 2013 the voters' characteristics in each section were stable, i.e. people were not moving between sections over elections and there is an inertia in section assignment (as described by the electoral code), I calculated the following yearly index for $t > 2013$:

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

$\bar{y}_{ij}$ 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 30, 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 30: IA_t for different variables

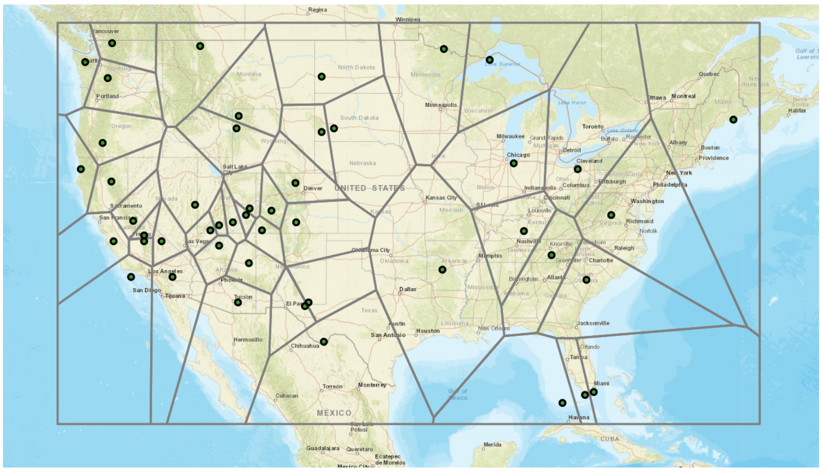


K Voronoi Polygons Panel

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.

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 31 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).

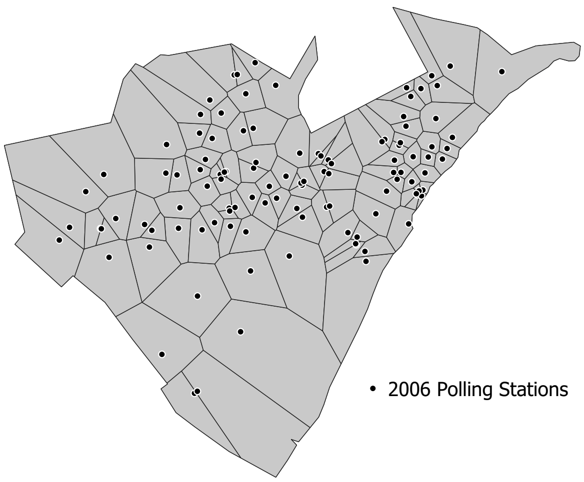
Figure 31: Voronoi Polygons using US National Parks



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 32 shows all the 111 polygons constructed based on the 2006 polling stations.

Figure 32: 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 33 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 33: Overlaping the Voronoi Diagrams of 2006 and 2010 Polling Stations

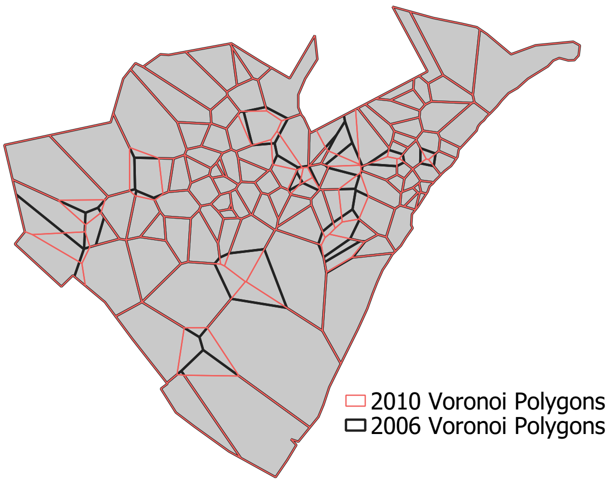
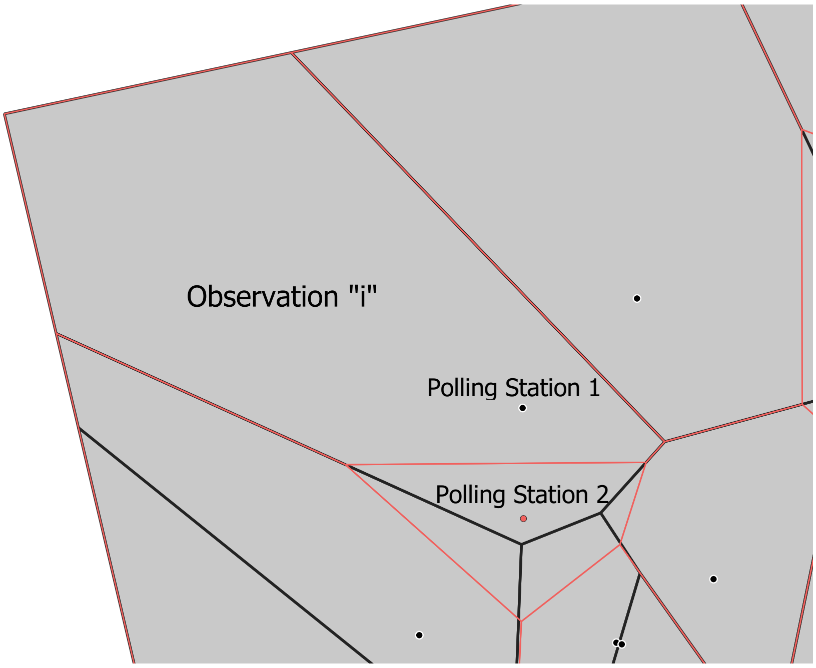


Figure 34 describes an example of how the weighting strategy works. Take observation "i" (the striped polygon). In 2006, its votes were entirely made out of Polling Station "1". Polling Station "2" was opened in 2010, which shrank Polling Station 1 Voronoi borders. Now, 100% of Polling Station "1" Voronoi Polygon and 50% of Polling Station "2" lie within observation "i".

Figure 34: 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.