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The Relation Between Covid-19 Vaccination and Voting Trends in Lithuania: A Spatial Analysis

Saulė Gabrielė Petraitytė

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Department of
Physical Geography and Ecosystem Science
Centre for Geographical Information Systems
Lund University
Sölvegatan 12
S-223 62 Lund
Sweden



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Saulė Gabrielė Petraitytė

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Supervision:

Ulrik Martensson

Department of Physical Geography and Ecosystems Sciences

Jonathan Seaquist

Department of Physical Geography and Ecosystems Sciences

Abstract

In the face of global challenges such as regional conflicts, climate change and economic recession, the emergence of the Covid-19 pandemic added a unique dimension to the complex landscape that governments had to navigate. Unlike other challenges, the pandemic's solution was theoretically straightforward – the only way to stop it was mass vaccination. However, the issue of vaccine hesitancy by a portion of the population created a division in society, shaping two distinct groups with differing attitudes toward health and civic responsibility. This research investigates the intersection of civic engagement in terms of early vaccination and participation in election. It uses data of Lithuania's population vaccination patterns, citizens' voting location and voting results of Lithuania's 2023 Municipal election.

The research firstly looks at the connection between the early vaccinated voters, the level of education and activity in the election. The correlation analysis indicates that individuals with higher education levels are more likely to be early vaccinated with high significance and slightly more active in the election than non-vaccinated voters.

The research follows to explore the spatial distribution of the early vaccinated society. Global Moran's I and Median Local Moran's I are implemented to examine the influence of geographical location on the likelihood of people being vaccinated and voting in the elections. It confirmed that both early vaccinated and non-vaccinated voters are spatially autocorrelated. Investigation of clustering geography revealed that early vaccinated voters exhibit a strong urban concentration, while those who voted without vaccination show clustering in circles around cities, contrary to anticipated rural dispersion.

Lastly, research aims to predict political preference by location and the fact of vaccination. Using the K-Nearest Neighbours (KNN) method, two major winning parties, Social Democrats (LSDP) and Conservatives (TS-LKD) were analysed with early vaccinated, late vaccinated, not vaccinated voters and higher education level as independent variables. These models exhibited distinct spatial patterns, with TS-LKD support concentrated in urban areas and LSDP in central rural regions with high accuracy level. However, the relatively low Cohen's Kappa values for LSDP indicate the need for model refinement and consideration of additional covariates. Such models can be used as a foundation to train deeper prediction model with more independent covariates and with voting results from earlier elections.

In summary, this research offers spatial insights beyond cartographic representation, enhancing our understanding of electoral geography based on vaccination preferences and education level within distinct voting wards. By addressing the gaps in understanding the spatial dynamics of civic engagement during a global pandemic, the research contributes to the broader discourse on electoral geography, public health and societal behaviour. The findings offer policymakers insights into potential interventions, emphasizing the role of education and geography in shaping civic engagement behaviours.

Keywords: Geography, GIS, Big Data, Spatial Analysis, Electoral Geography, Covid-19, Vaccination, Lithuania

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List of Abbreviations

COVID-19: Coronavirus Disease 2019
CSV: Comma-separated values, file format for text data
GP: Green Pass
GEODA: Geographic Data Analysis software tool, open source
GIS: Geographical Information System
HPV: Human Papillomavirus
KNN: K-Nearest Neighbours algorithm
LSDP: The Social Democratic Party of Lithuania (*Lietuvos socialdemokratų partija*)
MAUP: Modifiable Areal Unit Problem
MRNA: Messenger ribonucleic acid
PCR: Polymerase Chain Reaction
SARS-CoV-2: Severe acute respiratory syndrome coronavirus 2
TS-LKD: The Homeland Union – Lithuanian Christian Democrats (*Tėvynės sąjunga-Lietuvos krikščionys demokratai*)
QGIS: Quantum Geographic Information System, open source

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1 Introduction

In recent years, numerous governments have navigated a landscape marked by pervasive turbulence. Amidst a backdrop of simmering challenges like regional war conflicts, climate change effects and economic recession, one of them brought a health system crisis: the global Covid-19 pandemic. Different from other challenges, this crisis had some theoretically simple solutions; either an absolute global lock-down to stop the spread of the virus, or, a more realistic one – a mass vaccination. However, a vaccine is not something that can be done overnight, so it became the main duty of politicians in charge to prepare society and infrastructure for vaccination once it becomes available. An effective containment of the virus demanded not only the existence of vaccination per se, but a vaccinated global population. Therefore it was not enough to provide a vaccine for people that were willing to get vaccinated, but it was also important to consider population that is sceptical of Covid-19 vaccines. Since Covid-19 vaccination was emphasised as the main tool in fighting Covid-19 by the Lithuanian government (Government of the Republic of Lithuania, 2023), it catalysed the split in society for both politicians and citizens. Society divided into two groups; one that involved early vaccinated population as soon as vaccine become accessible, and the other group, that resisted Covid-19 vaccination.

Being a vaccinated citizen and taking care of one's society generated a parallel about being a responsible citizen in terms of the health situation as well as being active in the election. Some studies found a direct link between presence of specific vaccines and voting turnout (Suryadevara, 2019) or even political preferences (Rönn, 2023). However, there have been fewer studies that looks at how vaccination is related to election results in terms of geography (Mansley, 2015), with no research in this topic over Lithuania at all. Most of the geography studies that have been done in this area looked at voting patterns across large regions or on factors such as voting turnout, but not the factors that might influence them other than demographic.

Electoral geography research often considers national elections. The following research aims to ask questions about less examined, but equally important, municipal elections. Can local election patterns be linked to vaccination rates? Many researchers who study urban politics have argued that the divisions that influence elections at the local level are different from those that shape elections at other levels of government. However, more recent research has questioned this perspective by showing that political party affiliation and ideology also play a role in municipal elections and the development of local policies (Lucas & McGregor, 2020). Despite that, the study of Mansley (Mansley, 2015), which looked at geographic variability in relationships between the turnout at a local election and socio-demographic variables in London's 625 wards, stated that “spatial statistical methods are useful to identify what is happening where, but they cannot tell us why a particular process operates differently in different locations”.

1.2 Research aim and questions

This research firstly aims to answer the relation between voter's level of education and early vaccination. Then, it seeks to understand how vaccination and voting relationships varies in space across Lithuania and, finally, to test if voting results can be predicted based on voter's vaccination factor and location. These questions are analysed through correlation analysis, statistical testing of Global and Local Moran's I at the electoral ward level and the KNN models.

The three main research questions are:

1. Are voluntarily vaccinated voters more active in the municipal election and do they tend to have a higher level of education?
2. Are voluntarily vaccinated voters spatially clustered in urban areas while unvaccinated voters scattered in rural areas?
3. How can voting results be predicted based on geography and vaccination status?

2 Background and key topics

2.1 Covid-19 vaccination

In recent years, the global community has been profoundly affected by the Covid-19 pandemic. Initially identified in the city of Wuhan, Hubei province, China, in late 2019, the virus rapidly spread across borders, igniting a pandemic at a global scale. SARS-CoV-2, short for Severe Acute Respiratory Syndrome CoronaVirus 2 (Aliyeva, 2022), presented a unique challenge due to its high transmissibility and wide spectrum of clinical manifestations, ranging from asymptomatic cases to severe respiratory distress and mortality. The pandemic's profound consequences extended well beyond public health affecting economies, daily life, and societal norms in every corner of the world. Governments, healthcare systems and research communities worldwide have been engaged in an intense and ongoing battle against the virus, working to understand its biology, develop effective diagnostics, treatments, and most importantly – vaccines in order to mitigate its spread.

With the emergence of the novel coronavirus SARS-CoV-2, researchers and pharmaceutical companies raced against time to create safe and effective vaccines to curb the virus's spread. Multiple vaccine candidates, employing various technologies such as mRNA, viral vector, and protein subunit approaches, underwent rigorous testing and clinical trials (Lora, et al., 2023) and proved to be efficient in preventing Covid-19 (Halim, et al., 2021). The rapid global distribution and vaccination campaigns have been instrumental in moving societies closer to achieving herd immunity and bringing the hope of a return to normalcy amidst the challenges posed by the pandemic.

However, the global lockdown and mass vaccination brought the rise of Covid-19 scepticism and denial of Covid-19 vaccination. The polarisation of society towards vaccination appeared to correlate with political beliefs (Rönn, 2023). Factors such as mistrust in government, political split, and misinformation campaigns have contributed to higher rates of vaccine hesitancy in some communities. As these factors evolved, understanding the complex relationship between vaccination preferences and election results appeared to be crucial for crafting effective public health strategies and targeting certain areas.

There is a dearth of research between vaccination rates and electoral turnout, however, such ideas were questioned already before Covid-19 pandemic. Suryadevara (Suryadevara, 2019) proposed a study which aimed “to describe relationships between HPV vaccination rates and state voting patterns during the 2016 US presidential election”. The findings are worth mentioning: HPV vaccination rates are associated with state-level voting patterns, meaning that HPV vaccination can be an influencing factor on voting turnout. However, Tdap (meningococcal) vaccination rates did not show the same pattern and cannot be associated with voting patterns. This clearly suggests that different types of vaccines are not equally perceived in the society and therefore cannot be treated as equal indication for voting turnout.

A study by Rönn (2023) investigated the correlation between Covid-19, flu vaccination and voting patterns during the pandemic. The study used data from Covid-19 vaccination coverage (2021-2022) and flu vaccination surveys (2010-2022). The research showed that there is a clear

pattern between “state-level Covid-19 vaccination coverage and voting share for the Democratic candidate in the USA presidential elections” that took place in 2020. This relationship between flu and Covid-19 vaccination appeared to be the strongest in the young people's age group.

The lack of studies looking at the correlation between Covid-19 vaccination rates and political preferences brings an opportunity to investigate this field not only to analyse the relationship between voting patterns and vaccination, but also to analyse this relationship in space using geographical information systems (GIS).

2.2 Electoral Geography

Electoral geography is a subfield of political geography, focusing on the interaction of space, place, and electoral processes. (Pattie, 2009). This sub-discipline within political geography and political science focuses on understanding how geographic factors, such as the distribution of voters, the delineation of electoral districts, and the spatial patterns of political engagement, influence elections and political outcomes. Electoral Geography encompasses a range of topics, including gerrymandering, the impact of urbanization on voting behaviour, the role of spatial contexts in shaping political attitudes, and the geographical representation of diverse communities within electoral systems (Johnston, 2015).

Usually the data used for electoral analysis in space is aggregated (e.g. population census). Such data allows us to see the contextual factors specific to a particular location, allowing us to discern which of these factors are significant in explaining variations in activity (Warf & Leib, 2011). However, as spatial econometrics and electoral geography research have progressed, it has become clear that sociodemographic variables alone are not enough to explain spatial differences in electoral behaviour. According to Burneikaitė (2018), to properly interpret the impact of contextual factors on electoral activity, it is essential to consider space itself as a significant explanatory variable. The influence of space can be expressed through spatial heterogeneity, indicating different effects of the same variable in different locations.

The use of aggregated data requires to consider the Modifiable Areal Unit Problem (MAUP). MAUP is a statistical issue in spatial analysis that arises when data are aggregated into different areal units, leading to potential variations in results based on the choice of spatial scale or boundary delineation (Wong, 2009). The MAUP can impact the accuracy and reliability of spatial analyses, making it essential to carefully consider and address the implications of areal unit choices in any study. The following research uses sum of individuals with different features per ward and considers single shapefile, i.e. boundaries from only one election, thus decreasing the potential effect of MAUP.

2.3 The electoral system of Lithuania

The Lithuanian election context is analysed in depth by Tučas (2016). His book provides information on the development of multiple election systems in Lithuania, describing differences in municipal, Presidential, Parliamentary and European Parliament elections. He points to one very important aspect about the Lithuanian political ecosystem: there is no clear division

between right and left political parties (such as polarisation between democrats and republicans in the USA). However, there is a division communicated through key politicians between ex-communist and pro-European parties.

According to Vidzbelis (Tučas & Vidzbelis, 2018), we cannot compare countries with long-established democracies to post-communist young democracies. Voter preferences and participation are relatively stable in mature democracies, while in young democracies, like Lithuania, they can be unpredictable for every election. Such unpredictable behaviour of voters is mainly influenced by periods of undemocratic rule, when voters lose their identity, and the electoral process becomes a mere formality, suppressing fundamental voter duties. The rapid transformation of the political system did not significantly affect the voter, as political socialization is a lengthy process in the development of democracy.

This research was performed on municipal election data. Lithuanian municipal elections take place every four years and play a vital role in shaping the local governance landscape. During municipal elections, Lithuanian citizens can cast their votes for mayors, municipal councils, and local government representatives using proportional representation. Municipal elections generally have a more localised influence and greater diversity in terms of political party representation compared to national elections. According to Tučas (2016), the diversity of parties elected in local government elections (and independent candidates and committees since 2011) is always much greater than in parliamentary elections. In rural municipalities, social democratic and agrarian-leaning parties are more popular, as well as parties whose leaders have come from or actively participated in the life of those municipalities. In some regions, regional parties have a significant influence. This made this research intentionally not suitable for political party interpretation at national elections, where the competition and impact are much higher.

3 Research scope

3.1 Research area

The research area is within Lithuania. It is a country located in north-eastern Europe (Figure 1) and it is the southernmost of the three Baltic states. It covers an area of approximately 65.300 square kilometres and has a population of around 2.8 million people.



Figure 1. Lithuania's location in Europe: geographical centre of the European continent.

The majority of Lithuania's population is concentrated (Figure 2) in three main cities: Vilnius (with 541.000 inhabitants as of 2023), Kaunas (390.000 inhabitants) and Klaipeda (154.000 inhabitants) on the seaside, with Vilnius being the capital and the only city in Lithuania with a growing population (Lithuania's State Data Agency).

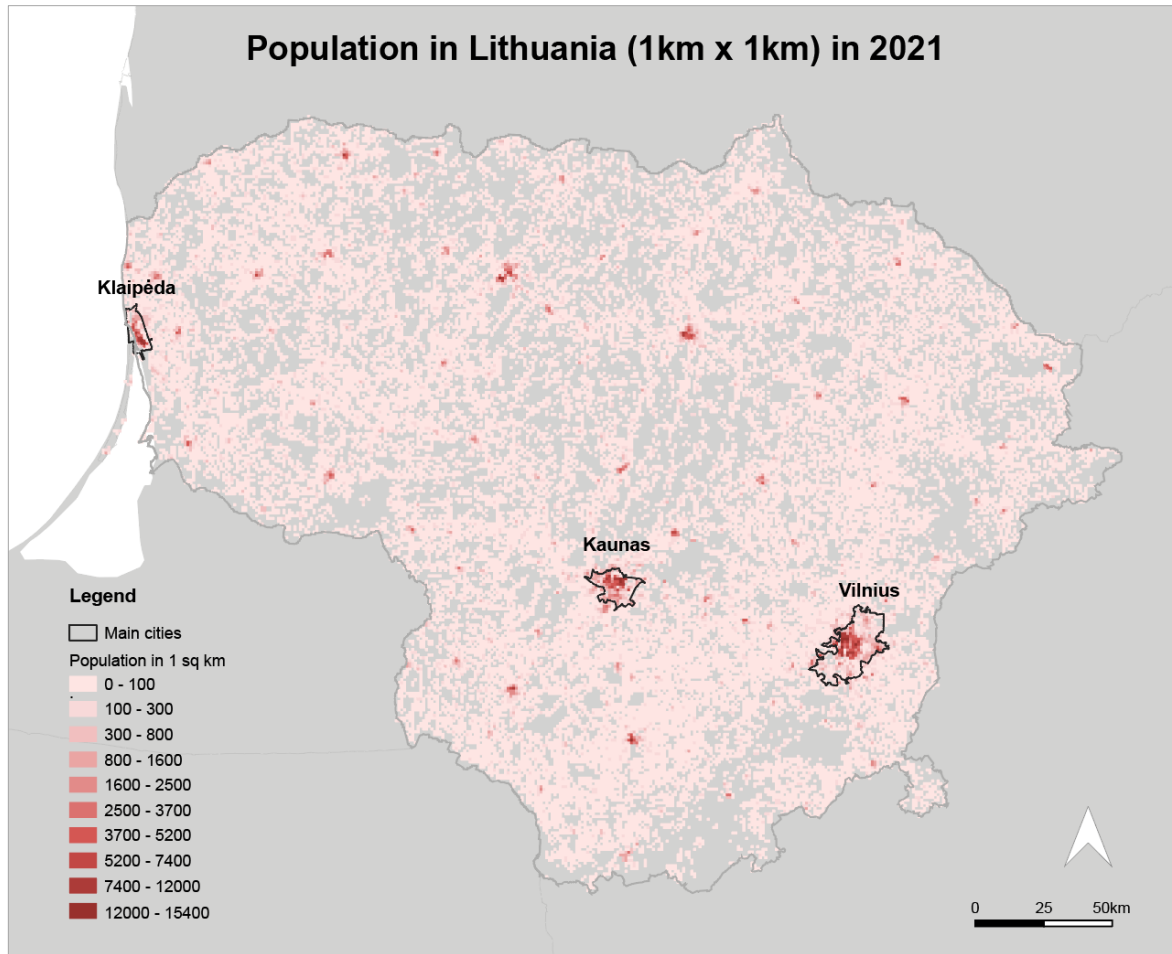


Figure 2. The distribution of Lithuanian population concentrated in three major cities: Vilnius, Kaunas and Klaipėda (source: State Data Agency, grid 1km x 1km).

In terms of elections, the research uses results and boundaries from Lithuania's Municipal election in 2023 (Lithuania's Central Electoral Commission, 2022). This election took place on March 5th (the 1st tour) and March 19th (the 2nd tour). For the better data representation this research considers the 1st tour data, since the 2nd tour involved only those wards and municipalities that did not manage to elect their representatives during the 1st tour.

In Lithuanian Municipal elections electoral territories exhibit functional diversity, distinguishing municipalities and voting wards. Municipalities represent area, for which the candidates are competing. These municipalities are crafted from voting wards. Voting wards, serving as the smallest electoral units, are pivotal for organizing and conducting elections. They facilitate direct voter participation, ballot distribution, voting supervision, and vote counting. Typically voting wards occupy a small area (except in sparsely populated regions) to be easily accessible to voters. In cities, they may consist of several streets, while in rural areas, they may encompass larger settlements with surrounding villages. In Lithuania, the number of voters in voting wards varies from 5000 (in cities) to 200 or fewer (in rarely inhabited areas). Two requirements are applied to optimize the territorial level of voting wards: ensuring easy access for voters and avoiding excessively small or large wards, as this complicates the formation of voting words commissions or burdens their work excessively.

For the 2023 Municipal election there were 1927 voting wards (Lithuania's Central Electoral Commission, 2023) and the following research is spatially based on their boundaries (Figure 3), meaning that all the data further on is aggregated from individual point to the voting ward level.

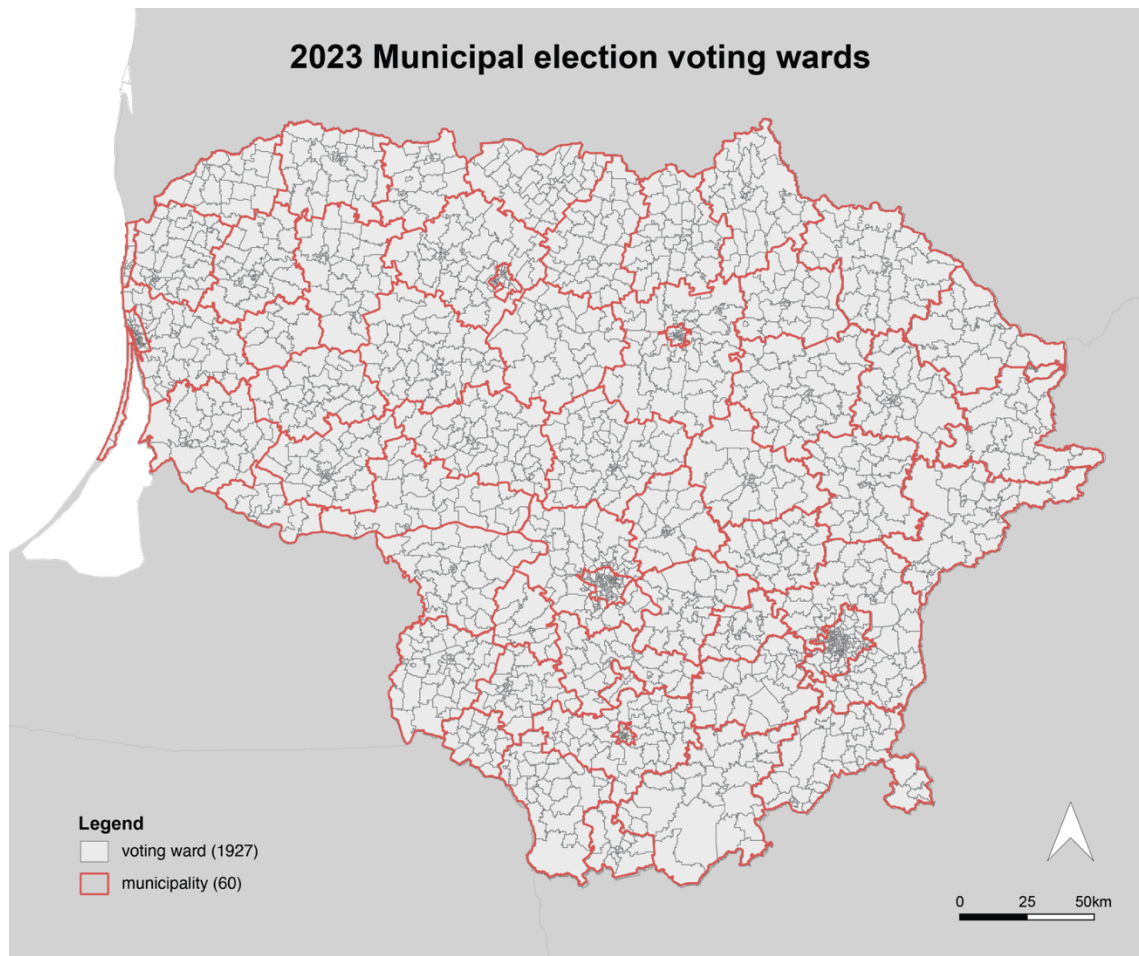


Figure 3. 2023 Municipal election voting wards distribution in Lithuania (source: Lithuania's Central Electoral Commission).

3.2 Research period

In terms of Covid-19 vaccination data, it is important to define the research period from which it is possible to assume that the citizen is early vaccinated, potentially considering it is done on a voluntary basis. The mass vaccination started in mid-2021 followed by the introduction of the Green Pass (Ministry of the Economy and Innovation of the Republic of Lithuania, 2022). The Green Pass (GP) served as a digital certificate and was obtained by either having a Covid-19 vaccination, recent Covid-19 infection or a paid negative PCR test in the last 72 hours.

The absence of a GP made it difficult to visit public services, restaurants, and events without proof of vaccination starting from 2021 September 13. This obstacle motivated part of the population to get vaccinated even though they didn't do it in the first place. Thus this date in the

research serves as a way of distinction if citizen is early vaccinated or late. Finally, there is a part of the population remaining that was never vaccinated. To better understand and define key dates relevant for the participation in vaccination, the Covid-19 events timeline in Lithuania was created as the starting point of the research (see 8.1 Covid-19 events and media review table in the Appendix).

4 Method

The project's workflow can be divided into three phases (Figure 4). The initial step involves data collection. In this part the Covid-19 related events timeline is created, the dataset with the population's Covid-19 and education information is collected and 2023 Municipal election results dataset is downloaded. Collected datasets are then pre-processed. As part of the pre-processing, data are cleaned, transformed and merged into one single spatial dataset for the further analysis. The analysis stage is dedicated to investigating the relationship between early vaccination, level of education and activity in election, as well as ward based spatial clustering through Spearman correlation matrix, Global and Local Moran's I methods and the KNN algorithm.

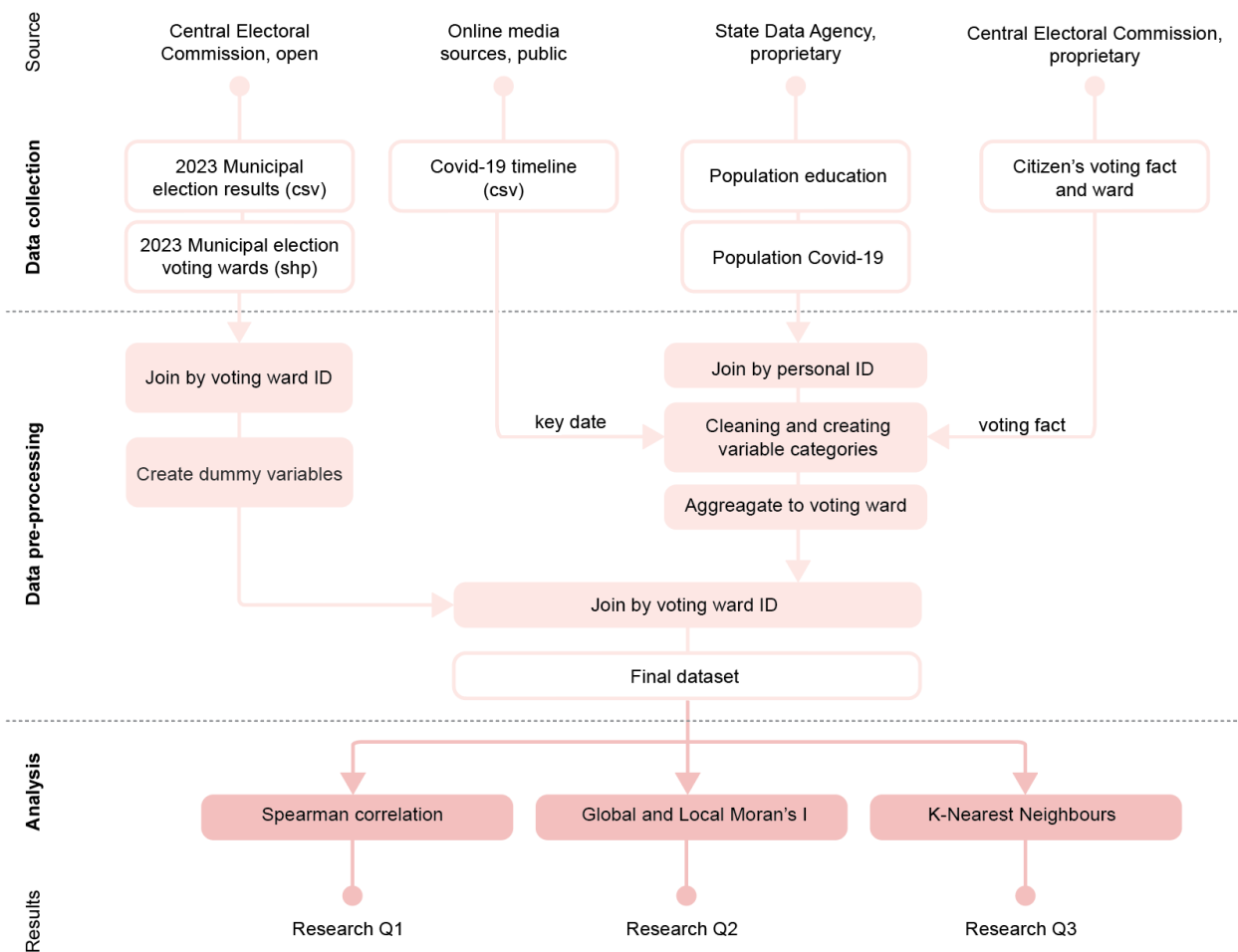


Figure 4. Project's workflow and main steps.

4.1 Data collection

Data used in the project can be divided into three categories, namely the research of Covid-19 related events and creation of its timeline, information about population at the individual level and results of the Municipal election, that took place on 2023 March 5th. Full list of datasets can be found in Table 1.

In general, data used in the project comes in two types of sources: open and proprietary. Open data, used for this research, is accessible publicly from Lithuania's State Data Agency (Lithuania's State Data Agency, 2023), Lithuania's Central Electoral Commission (Lithuania's Central Electoral Commission, 2023) or collected from publicly accessible online sources for timeline analysis. Proprietary, sensitive data is prepared by Lithuania's State Data Agency, meaning that the data at the individual level cannot be downloaded and must be analysed only within the Agency's infrastructure. The data about individual's Covid-19, education and the factor of voting in the election (if person did or did not vote in the election, i.e. if one took the voting ballot or not) is at the very individual, but fully encoded level. After cleaning and extracting only necessary fields and variables by the scientists of the Agency, this data is aggregated to voting wards and published as open data for anyone to use.

This research uses voting wards from only one election, and the dataset includes features that are upscaled from individual level of each citizen to voting ward level where each citizen belongs. This way there are no different scales in the research that could lead to data distortion caused by dealing with multiple spatial datasets, e.g. when population data comes from openly published grids.

Table 1. Datasets used for the research

Dataset	Description of variables	Source	Type
Covid-19 events timeline	Covid-19 in Lithuania "timeline", i.e. important dates and announcements by the government and political parties about Covid-19 vaccination, start and end of use of digital certificates, Covid-19 infection peaks, etc. Collected by date – action – type categories.	Publicly accessible from online media sources, full list of sources can be found in the appendix (Table 5).	csv
Voting wards	Voting wards polygons and names for the Municipal election in 2023 (open)	Lithuania's Central Electoral Commission	shp
Voting results	Voting results for each voting ward for the Municipal election in 2023 with the winning party name at the 1st voting round (open)	Lithuania's Central Electoral Commission	csv

Population education	Data includes individual identification number and the level of education	Proprietary encoded under State Data Agency	n/d
Population Covid-19	Data includes individual identification number, date of each vaccination and date of each confirmed Covid-19 infection case	Proprietary encoded under State Data Agency	n/d
Citizen's voting presence	Data includes individual identification number, the fact if the voting ballot was taken or not by the individual in the Municipal election on 2023 March 5th and the voting ward that person is assigned to	Proprietary encoded under State Data Agency from Lithuania's Central Electoral Commission	n/d

4.1.1 Covid-19 events timeline

The Covid-19 timeline is a dataset consisting of multiple events regarding Covid-19 from 2020 to 2023. This timeline is used to test the relationship between vaccination and public events that might have influenced the vaccination (e.g. if the person got vaccinated when it became hard to operate without digital certificate, assuming that the person didn't get vaccinated voluntarily in the first place but was forced to do so by circumstances).

The investigation of Covid-19 related events, government actions and political announcements were collected through a media review. The timeline starts from the 31st of January 2020, when the media reports about "an outbreak of unknown origin pneumonia in China" (World Health Organization). The last input in this database is from the 1st of August 2022 with the call to get vaccinated with the 4th booster vaccine for those in risk group (Lithuanian National Broadcaster). Each event was assigned a category based on its content: Covid-19, lock down, Green Pass, politics, election, testing, medicine, vaccination. The whole table with dates, categories and media headlines can be found in the appendix (Table 5. List of Covid-19 events in media).

This database allowed to identify a crucial date within the analysed period, the 13th of September 2021. On this date the digital Green Pass (GP) certificate was introduced as the only way to participate in public events and to access majority of public services. GP could either be obtained by getting vaccinated, having recovered from a confirmed case of Covid-19 infection, or by getting a PCR test that would confirm one not being infected with Covid-19 in the last 72 hours. This date sparked a division in society (and respectively in the Parliament) between people that were willing to get vaccinated earlier and people who saw this is a way to force people to get vaccinated against their will. In this research it allowed to divide vaccinated population into early vaccinated and late vaccinated citizens.

4.1.2 Covid-19 and education dataset

The data about individuals used for this research includes information about every Lithuanian citizen's Covid-19 vaccination and infection status, education level and presence in the election. All the data in this chapter is collected by Lithuania's State Data Agency. Election data is collected by Lithuania's Central Electoral Commission, but then transferred to the State Data Agency for further processing.

The data about the characteristics of population is at the very individual level, meaning that there are 2.8 million encrypted rows. This data consists of information with all records about when citizen had Covid-19 infection (for all infections, if more than one) and when one had Covid-19 vaccination (for all vaccinations, if more than one).

In terms of appearance of election, such data was collected by marking in the information system if an individual collected his/hers voting ballot, meaning that there is a record if one has arrived in the voting ward (or voted in advance) or not. The outcome of this dataset is the fact of voted or not voted as well as the voting ward, where one's vote is assigned to.

Records about education comes in 6 categories (Table 2), with one of them assigned to each citizen:

Table 2. Types of education variables

Variable name	Description
Education 1	Higher education, i.e. university degree (<i>aukštasis</i>)
Education 2	Post-secondary tertiary (including secondary specialised), e.g. professional college (<i>aukštesnysis</i>)
Education 3	Secondary, i.e. high school / gymnasium, 12 (out of 12) grades (<i>vidurinis</i>)
Education 4	Basic, 8 (out of 12) grades (<i>pagrindinis</i>)
Education 5	Primary, 4 (out of 12) grades (<i>pradinis</i>)
Education 10	No primary education (<i>nebaigė pradinio</i>)

4.1.3 Municipal election 2023 dataset

The last category of data used for this research includes the spatial boundaries of administrative voting wards and the Municipal election's results in each of it. The boundaries come as polygon shapes in a shapefile. Election results are from the first election round, which is chosen due to wider selection of political parties than in the second election round, so the data and electorate choices are more amenable for the further analysis. Also, the turnout is higher during the first election. Election results come as a table in the csv format with voting turnout percentage and winning party name.

The data are publicly available at Lithuania's Central Electoral Commission website (Lithuania's Central Electoral Commission, 2023).

4.2 Data pre-processing

Data pre-processing includes creating the dataset about population (working with encrypted proprietary data) and preparing a spatial file (from open sources) where it is joined with voting results.

4.2.1 The population dataset

The goal of the population dataset is to prepare a dataset representing people that were eligible to vote and were either vaccinated or infected with Covid-19 before and after 2021 September the 13th (when GP became mandatory to use public services). The data about society comes at the very detailed (individual) level, meaning that it could be analysed only within the infrastructure of Lithuania's State Data Agency under encryption and later the dataset is published as open data through the National Lithuania's open data portal.

1. **Cleaning.** The first step involved cleaning the dataset by removing people that were born in 2006 and later (so the remaining people were 16 years and older when the mass vaccination started in 2021 and 18 years or older during the election in 2023), as well as removing people that died before 2023 March 5th (the date of the election). This reduced number of records from 2.8 million to 2.3 million rows. The analysis of the vaccination timeline (Figure 18 in the Appendix) allowed us to conclude that the 4th vaccination is irrelevant due to its relatively small volume compared to 1st, 2nd and 3rd vaccinations. Also records about 4th (less than 30 records) and 5th (only 4 records) infection were removed (Figure 19 in the Appendix).
2. **Creating new variables.** After cleaning it was important to create new variables, that indicate if the person got infected or vaccinated before 2021 September 13th or after as well as if one had a GP (meaning either was infected or vaccinated before that date). New columns were also created for every educational level as well as for the participation in the election (e.g., attendance on 1st tour and individual's voting ward, that was imported from Central Electoral Commission).
3. **Aggregating.** The final step was to aggregate all previously prepared data into voting wards, so the final table would include all the relevant information with the numbers of individuals that match described characteristics per each voting ward.

4.2.2 Spatial pre-processing

This data pre-processing step is about creating a spatial file of voting wards and election results from the open sources. The election results dataset was downloaded from the Central Electoral Commission open data portal and key aspects were chosen from the first election, specifically ward name, ward id, voting turnout and winning party name. Then those variables were joined (using *Join attributes by ID*) with the shapefile of voting wards (through ward as a key) to create a spatial foundation dataset in QGIS.

In order to proceed to KNN analysis, the name of the selected winning political party must be converted to a dummy variable, since it describes a category, not a specific numeric value.

Dummy variables are typically binary, taking on values of 0 and 1 to represent two categories or groups (1 for selected political party presence, 0 for all other parties). They serve to include categorical variables in the model while making them compatible with the mathematical framework of regression (Robert Nisbet, 2009). Therefore, there are two more variables created; one for LSDP political party, and the other one for TS-LKD.

After the population dataset was published openly, it was joined (through the ward as a key, using *Join attributes by ID*) to the spatial file. The spatial dataset was created (n=1927) for the following analysis with records about every voting ward in a shapefile format.

The following table (Table 3) indicates the metadata about the final dataset which is used for the research. The final list with all variables can be found in the Appendix (Section 8.2 List of all variables used for the analysis).

Number of Rows	1927
Coordinate Reference System (CRS)	EPSG:3346
Bounding Box	[306496.1705 5973291.0499 680103.2771 6257813.452]
Length	1927
dtype	geometry
Spatial Extent	373607.1065999996 x 284522.40209999867

Table 3. Metadata of the final dataset

4.3 Data analysis

Data analysis consists of three major parts that refer to each of the research questions. To test the first research question about early vaccinated people in relation to their activity in elections and their education level, a Spearman correlation analysis was carried out between the status of vaccination, education level and participation in election (section 4.3.1). To answer the second question, if there is specific pattern in space of the early vaccinated and non-vaccinated voters the global and local Moran's I were applied (section 4.3.2). Finally, to study the third research question, if there is a dependence and if it is possible to predict election results by specific criteria the KNN model was created (section 4.3.3).

4.3.1 Relation between the period of vaccination, activity in election and education level

The first research question aims to investigate the relationship between the status of vaccination (early, late or not vaccinated), education level and participation in election. To do so, the Spearman rank correlation matrix is carried out in Python inside the Google Collab environment (a cloud-based platform that provides free access to Jupyter notebooks. The full code can be found in the appendix (Section 8.8 Spearman Rank code).

For the purpose of this research, the Spearman rank correlation was chosen over other correlation methods due to the nature of the data, which involves non-normally distributed variables (see the Appendix for detailed distribution analysis in Section

8.7 Variables distribution analysis). Its non-parametric approach is robust against outliers, making it suitable for datasets with potential skewness or the presence of extreme values.

Additionally, Spearman rank can capture monotonic relationships, regardless of linearity, which seemed more appropriate for the specific characteristics of the variables included in this research.

The Spearman rank correlation is denoted by ρ and calculated by the following Equation 1.

Equation 1:

$$\rho = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)}$$

Here, d_i represents the difference between the ranks of corresponding pairs of observations and n is the number of paired observations. The formula involves computing the squared differences between the ranks of paired observations, summing these values, and then applying the formula to obtain the final correlation coefficient. This non-parametric method assesses the strength and direction of monotonic relationships between variables, with a range from -1 (perfectly inversely correlated) to 1 (perfectly correlated).

Also, the research includes the assessment of significance, the p-value. It is the probability of observing the obtained correlation between two variables under the assumption that there is no true correlation in the population. The significance level, commonly set at 0.05, serves as a threshold for determining the statistical significance of the correlation. A low p-value ($p < 0.05$) indicates that the observed correlation is unlikely to be a result of random chance alone. A high p-value ($p > 0.05$) suggests that the observed correlation could reasonably occur due to random variability.

4.3.2 Spatial clustering of voters by vaccination preferences

In order to answer the second research question about if and where early vaccinated and not vaccinated voters are spatially autocorrelated, Moran's I is calculated in GeoDa software.

The two different variations of Moran's I serve two different purposes: Global Moran's I assesses the overall spatial pattern of a variable across the entire research area. In this research it is used to understand if variables such as early vaccinated or not vaccinated voters are spatially autocorrelated in the whole research area (Lithuania). If variables are spatially autocorrelated, Local Moran's I can identify specific locations with levels of local clustering that differ from the overall pattern, including urban areas versus rural ones. Global Moran's I provides a broad perspective on the dataset's spatial relationships, while Local Moran's I allows us to pinpoint local hotspots within the research area. Identification of such locations can lead the analysis of a more specific investigation in related areas as well as allow policy makers to target vaccination and voting performance.

Global Moran's I

Moran's I is a measure that examines how each data point relates to its nearby neighbours within a dataset and calculates the average of these relationships. When there's a complete positive

spatial autocorrelation, Moran's I is equal to 1, signifying a strong positive spatial autocorrelation. A Moran's I of 0 indicates spatial randomness, where no spatial relationships exist. In cases of complete negative spatial autocorrelation Moran's I becomes equal to -1.

According to GeoDa workbook (University of Chicago, 2023), it is a cross-product statistic between a variable and its spatial lag, with the variable expressed in deviations from its mean. GeoDa software uses the following Equation 2 for Moran's I statistic:

Equation 2:

$$I = \frac{N}{W} \frac{\sum_{i=1}^N \sum_{j=1}^N w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^N (x_i - \bar{x})^2}$$

Here N is number of wards, W is a of spatial weights (a measure of the spatial relationships between units), x_i and x_j are values of the variable of interest in spatial unit I and J ; \bar{x} is the mean of the variable of interest across all spatial units, and w_{ij} is the Spatial weight between units I and j .

To calculate Moran's I, it is needed to create a spatial weight matrix that defines the weight of interactions between neighbours. For this analysis the first order queen contiguity method. The first-order queen contiguity method measures spatial autocorrelation by considering neighbouring regions that share a common boundary, including those that share corners. It computes the spatial lag for each region by averaging the attribute values of its neighbouring regions, then assesses the correlation between these spatial lags and the original attribute values across all regions to determine spatial clustering or dispersion patterns. It differs from other methods, e.g. from rook contiguity, which only considers regions that share an edge, neglecting corner adjacency. All variables were considered except infection factors for both voters and non-voters, since getting infected is not the factor that one can choose voluntarily.

Local Moran's I

The Local Moran's I output provides a breakdown of the overall Global Moran's I value, helping to identify how each location influences the global spatial autocorrelation (Rogerson, 2001). With Local Moran's I each observation has a statistic and can be mapped to reveal spatial patterns on the map.

To identify spatial clusters or outliers in each single variable in this research the Median Local Moran's I (MLI) is used. It uses the median of the Local Moran's I values, which is less sensitive to extreme values than usual Local Moran's I. The GeoDa software uses the following Equation 3 to compute Local Moran's I:

Equation 3:

$$I_i = \frac{(x_i - \bar{x})}{S^2} \sum_{j=1}^n w_{ij} (x_j - \bar{x})$$

In this I_i is the local Moran's I for observation I , x_i is the value of the variable of interest for observation I , \bar{x} is the mean of the variable over all observations, S^2 is the variance of the variable, n is the total number of observations, and w_{ij} is the spatial weight between observations I and j .

Then MLI is calculated by taking the median of the local Moran's I values across all observations according to the following Equation 4, where the median is calculated for the set $\{I_1, I_2, \dots, I_n\}$ that includes the local Moran's I values for all observations (n).

Equation 4:

$$MLI = Median (\{I_1, I_2, \dots, I_n\})$$

In GeoDa, the significance of Local Moran's I is assessed through the calculation of p-values associated with each local Moran's I cluster value. P-values indicate the likelihood of observing the local spatial autocorrelation patterns under the assumption of spatial randomness. $P < 0$ in this research indicates that the local spatial autocorrelation pattern for a specific location is statistically significant, while $p > 0$ indicates the opposite, low significance for the local spatial autocorrelation pattern.

Based on Local Moran's I value and its significance, Local Moran's I clusters can be divided into high positive values (High-High) and high negative values (Low-Low), e.g. if a location has a high positive Local Moran's I and the p-value is low, it suggests that the location and its neighbouring locations have high values and are part of a statistically significant cluster. A high positive Local Moran's I with a high p-value suggests a high positive outlier, where a location has a high value surrounded by locations with low values (or vice versa). A high negative Local Moran's I with a high p-value indicates a high negative outlier where a location has a low value surrounded by locations with high values.

The significance of Local Moran's I helps to identify whether the observed spatial autocorrelation patterns at each location are likely due to non-random spatial processes. Significant results can be indicative of spatial clusters or outliers, providing valuable insights into the spatial structure of the data.

4.3.3 Political preference dependence on voter's location and the fact of vaccination

In order to answer the third research question about predicting political preferences by voter's location the K-Nearest Neighbours (KNN) algorithm is used. The KNN algorithm is a non-parametric, instance-based machine learning algorithm used for both classification and regression tasks. Also, KNN is well-suited for binary classification tasks, that is relevant in this

research (if party won or not in the specific voting ward). For data estimation, KNN predicts the value of a target variable at a given point based on the values of its k-nearest neighbours. It uses the fundamental assumption that similar instances exist in proximity to each other and has received a great attention in the statistical literature for analysing multivariate data (Kara, 2017). Since it does not make any assumptions about the underlying data distribution and postpones the learning phase until a prediction is needed, it is suitable for the non-parametric data that was used in this research.

To address the research question the KNN model was executed in Python using the `sklearn.neighbors` library (scikit-learn developers) within a Jupyter notebook environment. To start with, it is necessary to identify the target variable (the one that needs to be predicted) and those that are independent variables, also known as features or predictors, that are the variables used to make predictions. Independent variables should have little or no multicollinearity, which can be inspected through the Variance Inflation Factor (VIF) calculation.

After the variables are identified, the algorithm computes the distance between the target data point (X_{new}) and all other data points in the training set (X_{train}). The most commonly used distance metric is the Euclidean distance, which is calculated between two points $(x1, y1)$ and $(x2, y2)$ by the following equation:

Equation 5:

$$Distance = \sqrt{(x2 - x1)^2 + (y2 - y1)^2}$$

Then the algorithm performs nearest neighbour selection, meaning that it identifies the k data points with the smallest distances to the target point. These data points are the "nearest neighbours."

Then the estimated value of the target variable is calculated by the following equation:

Equation 6:

$$\hat{y}_{new} = \frac{1}{k} \sum_{i=1}^k y_i$$

Here \hat{y}_{new} is the estimated value, y_i is the target variable of the i -th neighbour. Once the models are fitted for each voting ward, predictions are made for each location on the map. These predictions represent the estimated probability of the target variable at each spatial unit.

The model also considers hyperparameter k (unlike model parameters, which are learned from the training data, hyperparameters are set prior to the training process). The choice of k is crucial, since a smaller k makes the model more sensitive to noise but more flexible, while a larger k provides a smoother decision boundary. The most optimal k value can be identified through the model's validation process.

Model's validation is a standard workflow to evaluate its performance and parameters. This research applies 5-fold cross validation process, meaning that the training set is split into 5 folds, and the model is trained and evaluated five times using a different fold as the test set. After that, the hyperparameter tuning is used to calculate the most optimal k value. Finally, the evaluation of the Test Set is calculated, which allows to see the accuracy of the performance and compare it to other models.

5 Results and discussion

In the following chapter the results and the discussion of the research are presented. Prior to research questions, section 5.1 draws insights about general voting patterns across Lithuania. Section 5.2 discuss results of the Spearman correlation matrix regarding the first research question. It is followed by the section 5.3 with Global and Local Moran's I on the second research question. Finally, section 5.4 concludes with results and discussion of the KNN algorithm for the third research question.

5.1 General election results pattern

Primary election results analysis allows to identify general voting and vaccination patterns across Lithuania. It is done through GeoDa and QGIS software for both statistical and visual interpretation.

Voting turnout average is 49% per ward (Figure 5) and it is clearly visible that the more active areas are along eastern and southern borders and in the area next to Kaliningrad, while the northern region (*Samagotia*) remains less active in the election. However, in terms of total number of people that voted (which varies from 41 to 2692 per ward), cities and areas around them appear to have more active electorate (Figure 6).

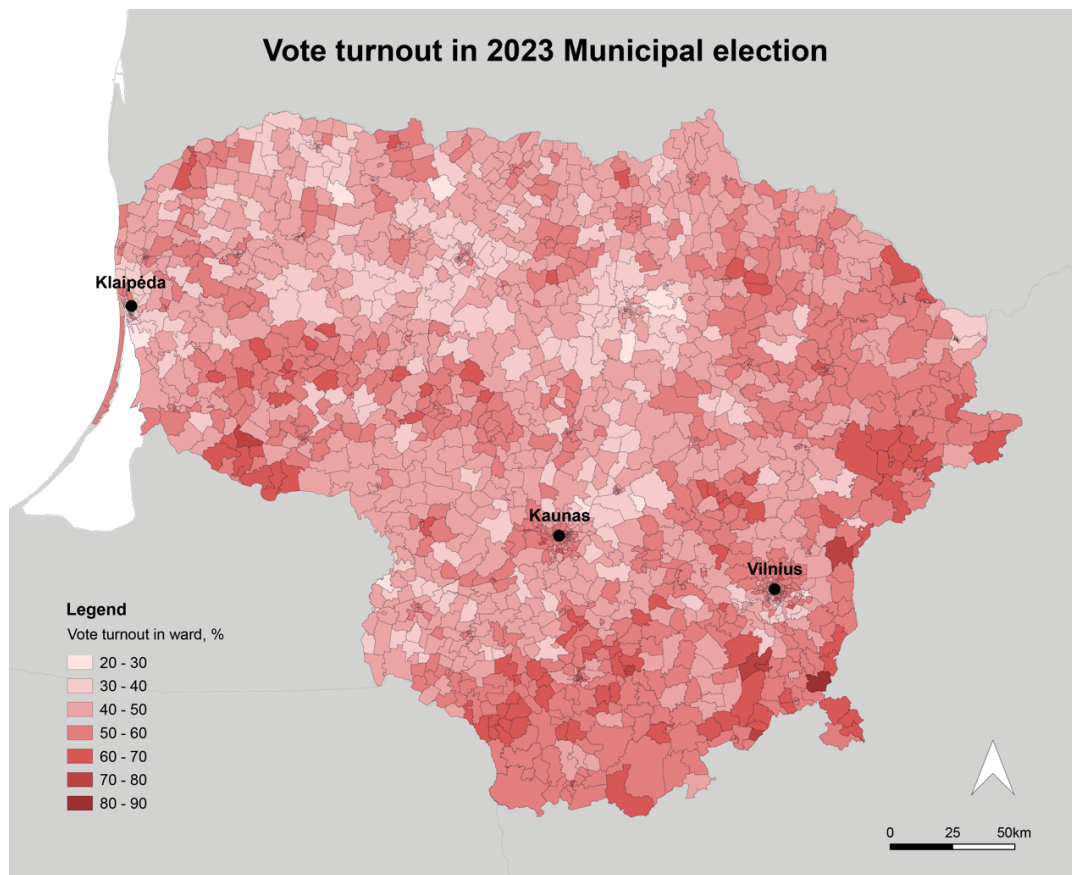


Figure 5. The map of voting turnout during 2023 Municipal election highlights more active areas along eastern and southern borders, with northern region being less active in the election (source: Lithuania's Central Electoral Commission).

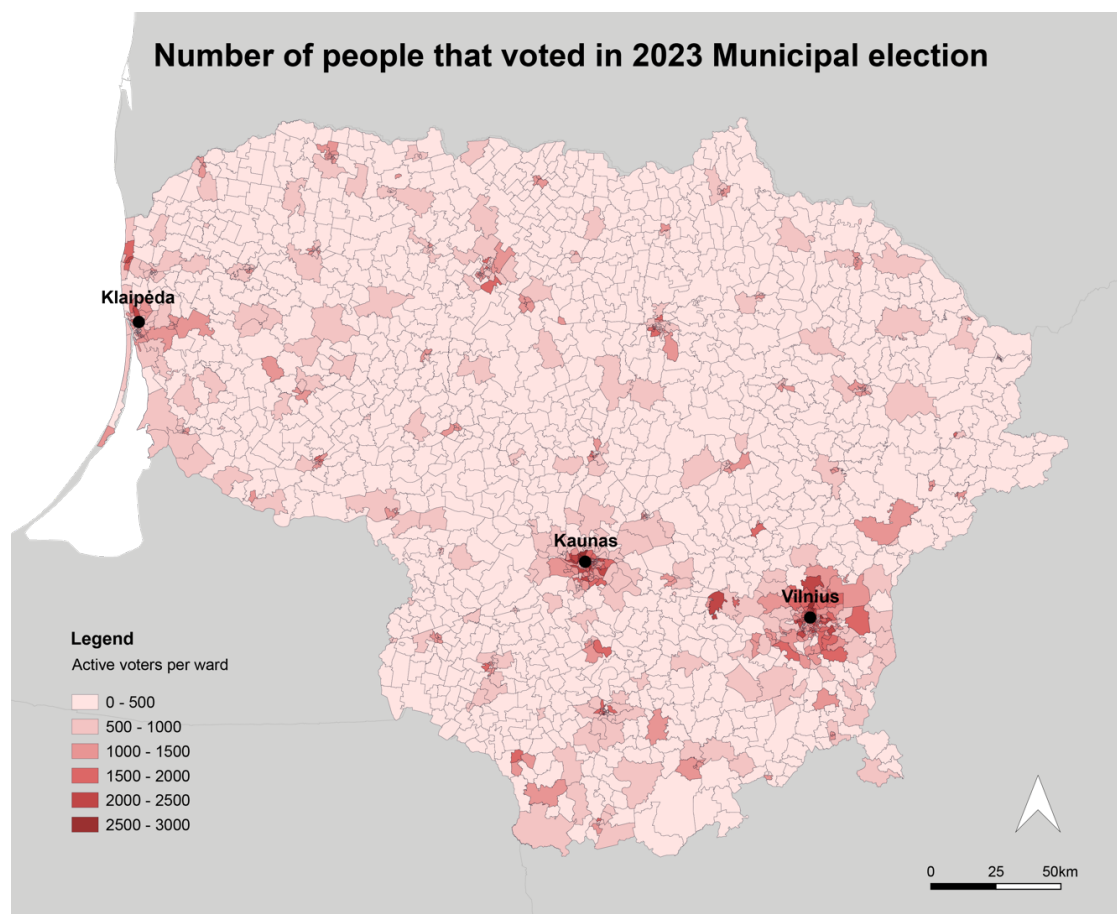


Figure 6. In terms of total number of people that voted in 2023 Municipal election cities and areas around them appear to have more active electorate (source: Lithuania's Central Electoral Commission).

The average number of people with GP is 520 per ward (Figure 7), of which the average number of vaccinated before 2021 September 13th is 447 people (86%) and the average number of infected before 2021 September 13th is 73 people (14%). This leads to the conclusion that most people received GP due to early vaccination, with only a minority that were able to use it due to previous infection without vaccination.

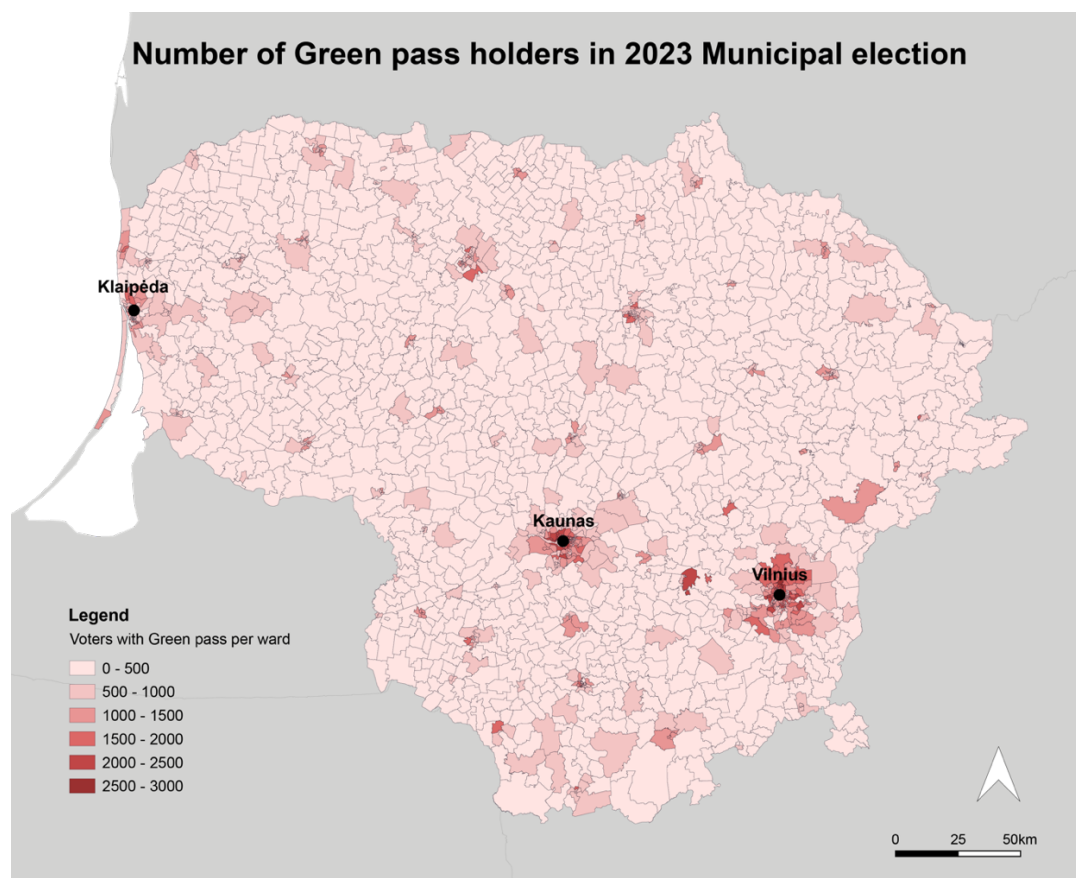


Figure 7. Number of people that voted and had Green Pass in 2023 Municipal election shows concentration in urban areas (source: Lithuania's Central Electoral Commission).

The most winning party (Figure 8) in terms of wards is LSDP, Centre-left social democrats (Lietuvos socialdemokratų partija), the second - TS-LKD, Centre-right liberal conservatives - (Tėvynės sąjunga-Lietuvos krikščionys demokratai), the third is LVŽS, Centre-left. The full list of political party abbreviations can be found in the appendix (Table 7. Lithuania's Political parties' abbreviations (2023 March Municipal election)).

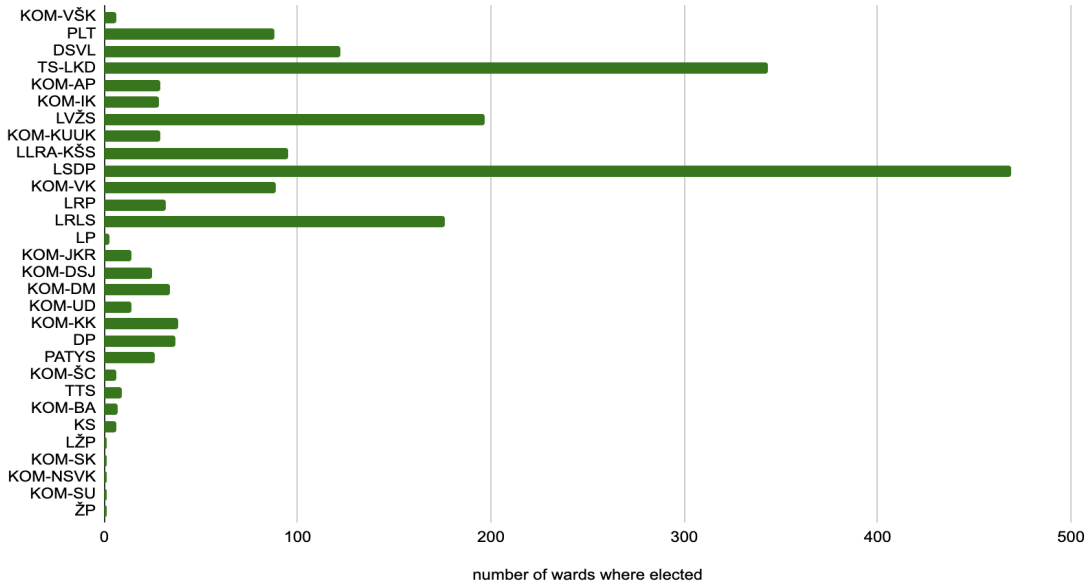


Figure 8. The number of wards where political party is elected with the LSDP being the leader.

5.2 Relation between the period of vaccination, activity in election and education level

In order to answer the first question about how the period of vaccination and voting in the election is related to education the Spearman Rank correlation matrix was created. The Spearman method was chosen due to non-normal distribution of the data. It looks at the relationship between voters that were early vaccinated, late vaccinated, and non-vaccinated versus the factor of each education level, total number of voters and voting turnout per ward (Figure 9). Additionally, P-values matrix (Figure 10) looks at the significance of each relationship. Spearman Rank on extended list of variables can be found in the appendix (see 8.9 Spearman Rank for more variables).

Spearman correlation matrix revealed that the strongest relationship is between early vaccinated voters and *Higher* education level ($\rho=0.97$). Accordingly, not vaccinated voters have a lower relationship with *Higher* education level ($\rho=0.87$) and increases for *Secondary* ($\rho=0.95$) and *Basic* ($\rho=0.91$) education levels. Early vaccinated voters appear to be the majority of all voters in general, therefore it shows the strongest relationship with *Number of voters* ($\rho=0.99$), and higher *Voting turnout* ($\rho=0.17$) compared to not vaccinated voters ($\rho=0.15$). Weaker relationship between the same factors and not vaccinated voters ($\rho=0.93$ and $\rho=0.15$ accordingly) might indicate that this group is less active in election compared to early vaccinated voters, however, the differences are relatively small.

All the relationships are positive, indicating that there are no apparent negative correlations in the subset of variables provided. Also, all relationships between vaccination factor, activity in election and education are significant in all categories except for *No Education* factor, which represents the smallest group of population (0.15%) in the dataset (see 8.6.3 Volume of people that voted within each education category) and therefore is less relevant.

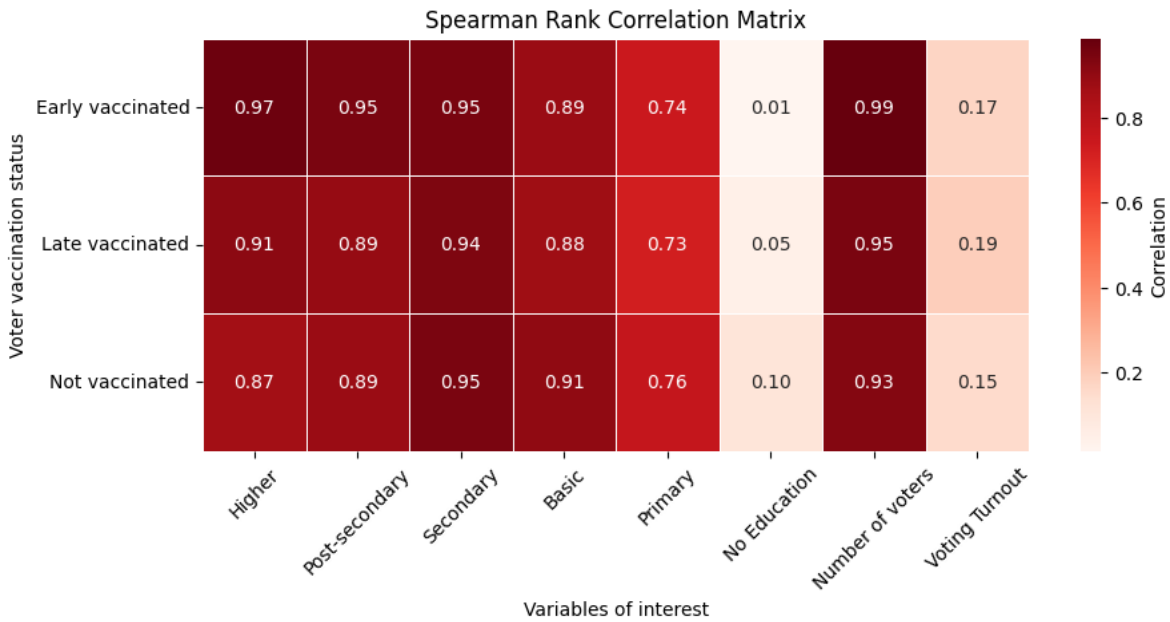


Figure 9. Spearman Rank correlation matrix between variables and different education levels

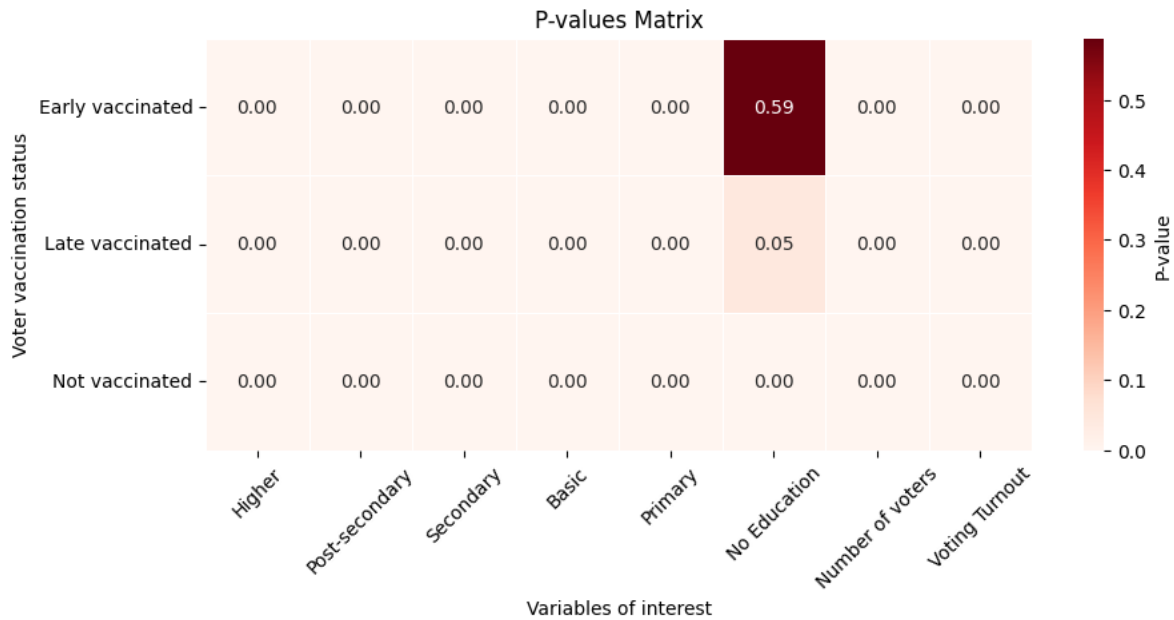


Figure 10. P-values matrix

The Spearman correlation matrix showed significant positive correlation between early vaccinated voters and the highest education level (*Higher*) as well as activity in election (*Number of voters* and *Voting turnout*). However, while difference between vaccination and education seems higher between different status of vaccination (0.97, 0.91 and 0.87), in terms of activity in election the difference appears relatively too small to be considered (0.99, 0.95 and 0.93)

This answers the second research question that early vaccinated voters are more likely to be educated at the higher level compared to non-vaccinated voters with the similar, but much less significant tendency for activity in election. Correlation does not mean causation, therefore the relationship between education and vaccination as well as turnout highlights social patterns but does not mean that by enforcing education the society would be more vaccinated or more active in election.

5.3 Spatial clustering of voters by vaccination preferences

The second research question examines if early vaccinated and non-vaccinated voters are spatially clustered. To investigate it the Global and Local Moran's I were implemented. Global Moran's I offers a comprehensive view of the spatial relationships in the dataset through the Queen 1st order method, whereas Local Moran's I allows us to identify hotspots within the research area for early vaccinated and unvaccinated voters.

5.3.1 Global Moran's I

Global Moran's I (Figure 11; resulting Table 6 can be found in the appendix) is made for all variables used in the research and shows that most of them are spatially autocorrelated ($I > 0.5$ for all variables except for voters with basic education, voters and non-voters with primary education and voters / non-voters with no education). Top 5 spatially autocorrelated variables are the highest education level for both voters and non-voters ($I=0.788$ and $I=0.792$ accordingly), voters with GP ($I=0.695$), early vaccinated voters ($I=0.694$) and early vaccinated non-voters ($I=0.693$).

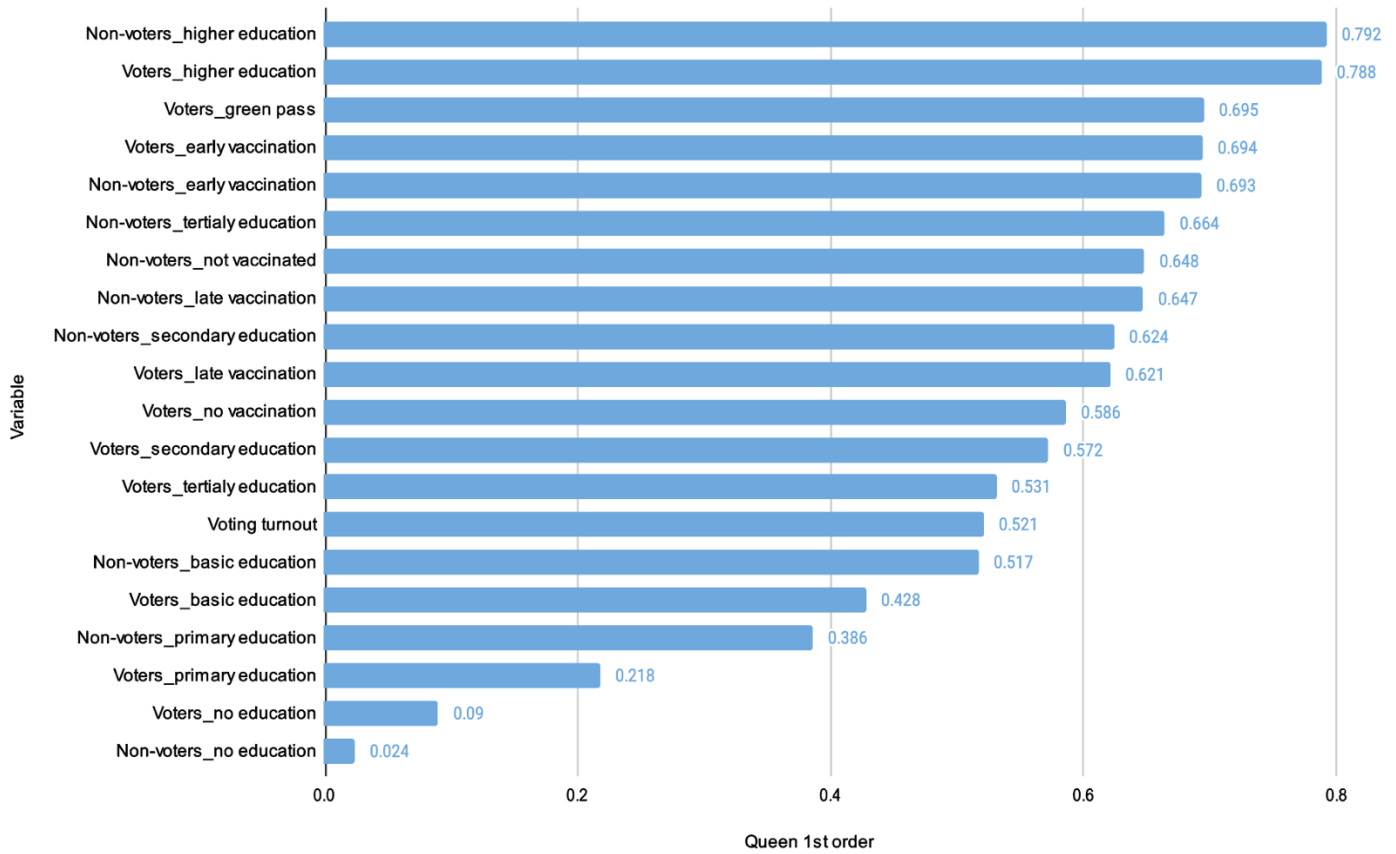


Figure 11. Global Moran's I result for different variables using the Queen 1st order method reveals the highest autocorrelation for higher education variables among both non-voters and voters.

The analysis of Global Moran's I confirmed that mostly spatially autocorrelated factors in this research are higher education and early vaccination for both voters and non-voters. The following analysis of Local Moran's I aims to identify the clustering of early vaccinated voters ($I=0.694$) and non-vaccinated voters ($I=0.568$) in space.

5.3.2 Local Moran's I

While Global Moran's I has confirmed that the spatial autocorrelation exists for early vaccinated voters, Median Local Moran's I (MLI) is used to analyse the type of such clusters in space, digging into the second research question if such voters are clustered in cities. MLI is used for two variables: early vaccinated voters and voters, that were never vaccinated.

MLI for early vaccinated voters (Figure 12) revealed, that this part of society is strongly concentrated in cities (high-high values), while areas with low numbers of early vaccinated voters (low-low values) are clustered more towards the north of Lithuania. However, in the city of Klaipėda, high-high values are observed in the suburbs, but this seems natural since this city has a major part of population that lives in suburban areas. This answers the second research question that early vaccinated voters are spatially clustered in urban areas.

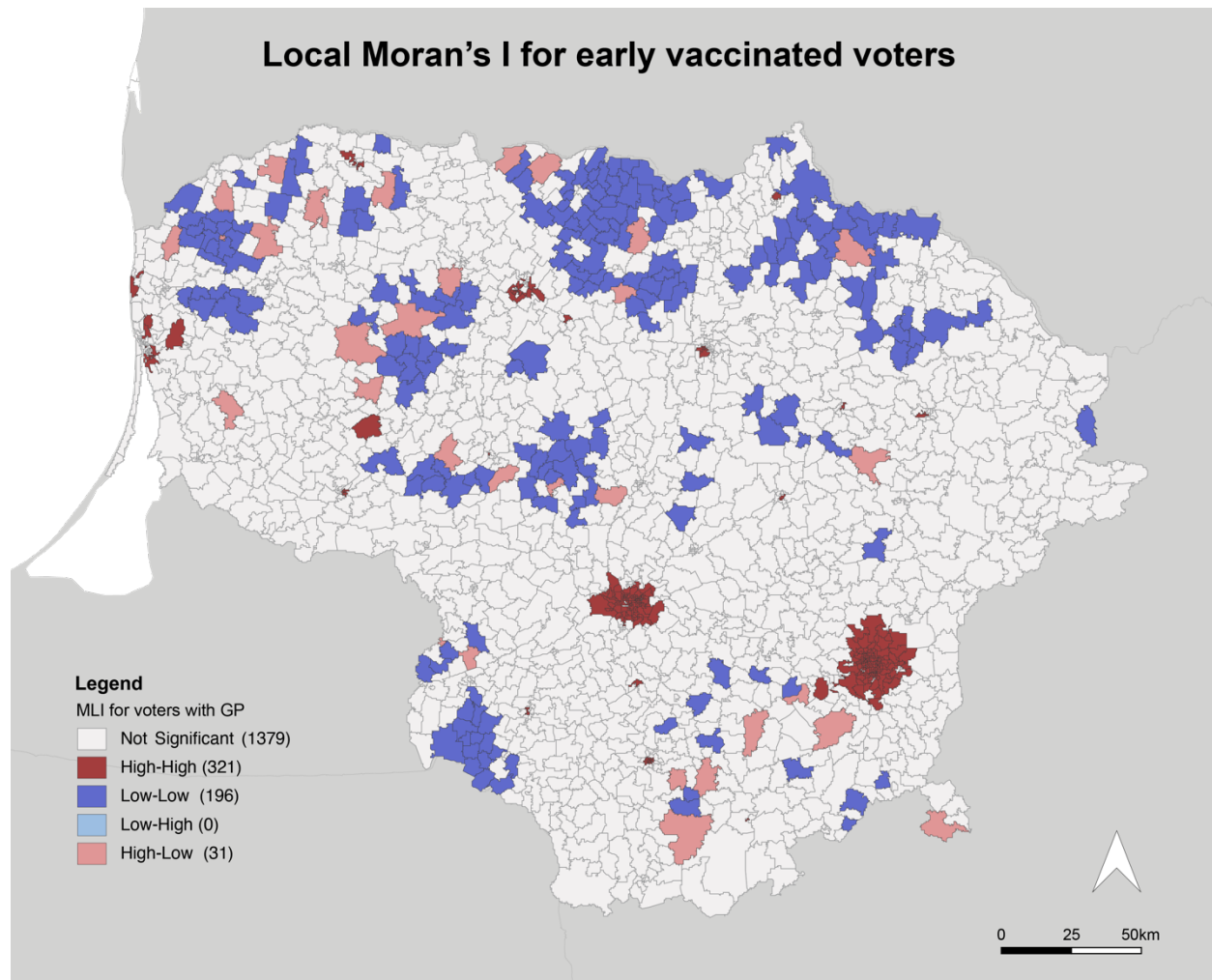


Figure 12. Local Median Moran's I for early vaccinated voters shows clustering in urban areas.

High-high values of society that voted but have never been vaccinated tend to cluster around cities (Figure 13) and to be the opposite of what is happening in cities. It is an interesting finding, since it was expected for unvaccinated voters to be randomly scattered in rural areas between cities, following the pattern of non-vaccination in general. However, areas around cities tend to cluster people that are unvaccinated (which is more common in rural areas) but participate in election (which is more common in urban areas). One can clearly see the “rings” of high-high values around Vilnius, Kaunas, Klaipeda and some smaller cities.

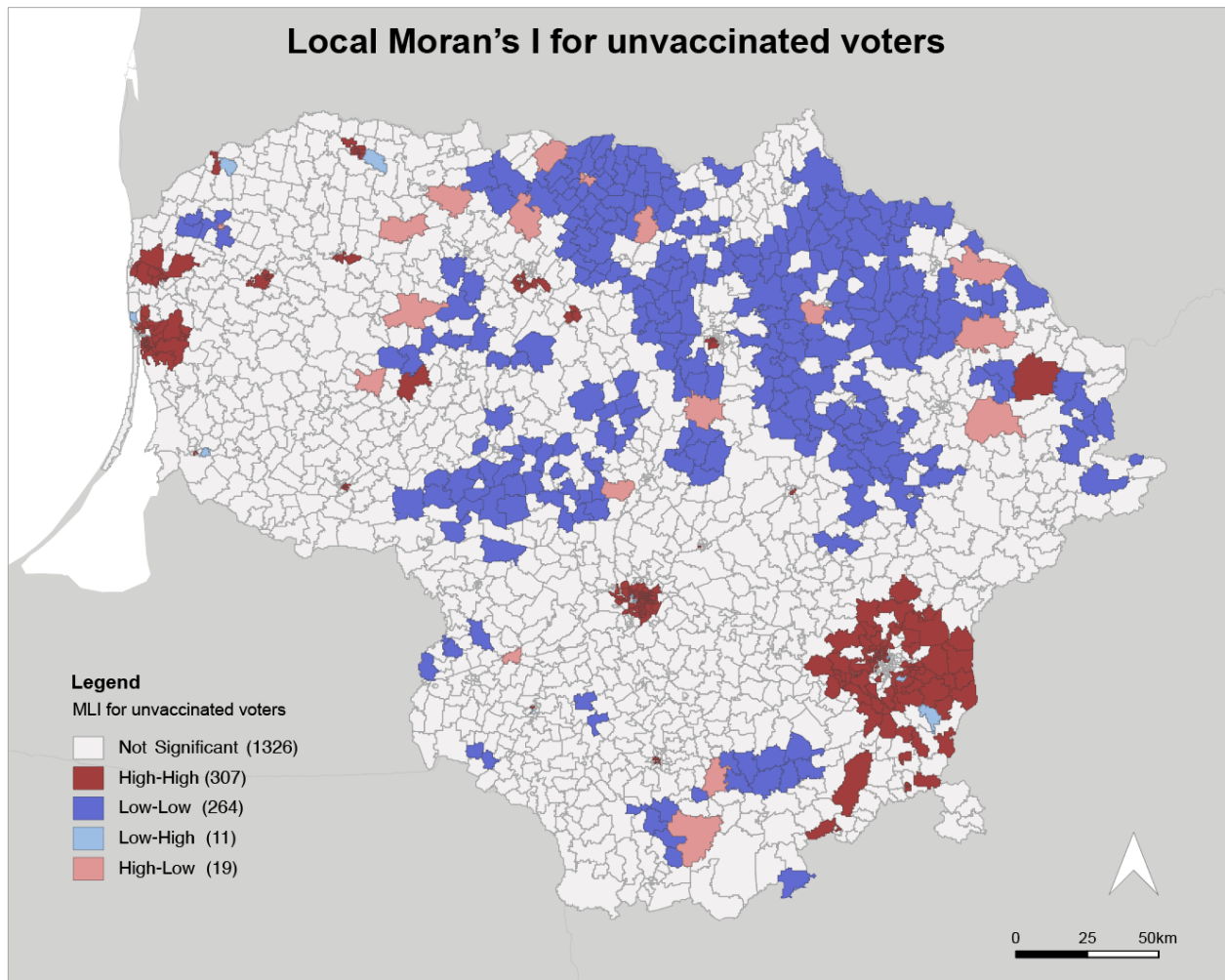


Figure 13. Local Median Moran's I high-high values for voters that do not vaccinate tend to surround cities.

To sum up, the Local Moran's I indicates that the combination of the early vaccination and participation in election tends to cluster in urban areas. Individuals who vote without being vaccinated also exhibit spatial clustering with a notable concentration around cities rather than random dispersion throughout the region.

5.4 Political preference dependence on voter's location and the fact of vaccination

The third research question led to the investigation if an algorithm could be applied to create prediction model for specific political parties based on vaccination factor of voters and non-voters. The analysis performs KNN method for two major winning parties LSDP and TS-LKD as target variables since they gained votes in voting wards across the whole country. The outcome is visualised on map with estimated values for both political parties based on independent variables and is followed by diagnostic tests to validate and compare performed estimation.

For independent variables the model uses early vaccinated, late vaccinated and not vaccinated voters as well as non-voters and the highest education level. After the model is performed for

both political parties (see the full code in the section 8.4.1 KNN model for TS / LSDP), the prediction maps are created. In this case the map represents the predicted level of support for a selected political party in each voting ward on the map based on independent variables. Since it is a binary outcome, the predicted values may be interpreted as probabilities – a predicted value close to 0 suggests a low probability of support for the political party, while a value close to 1 indicates a high probability of support.

In case of LSDP (Figure 14), higher values are distributed across central Lithuania. Such trend is naturally related to the actual election results (Figure 16 in the appendix), which is a visual validation of the model’s performance.

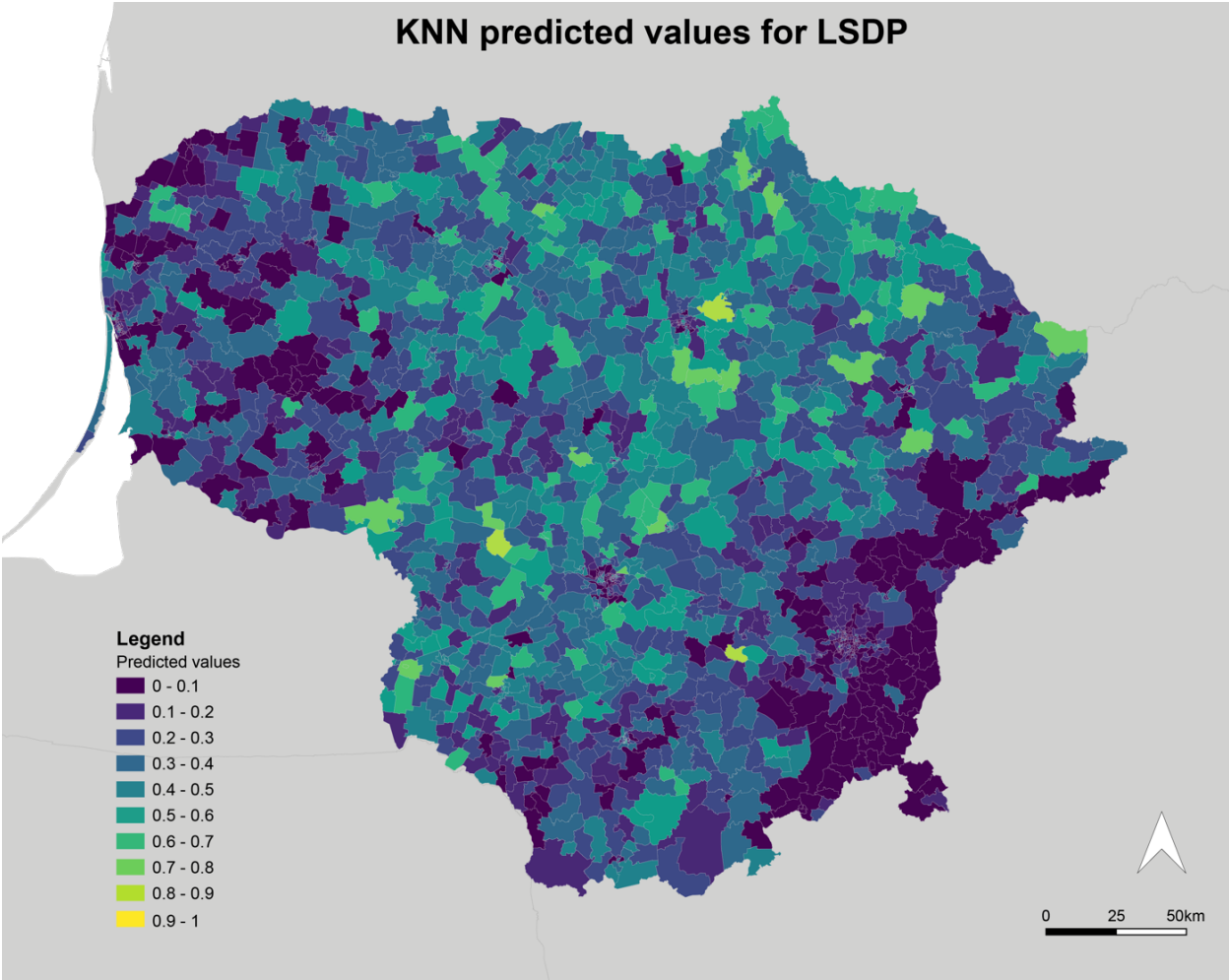


Figure 14. KNN predicted values for LSDP political party shows higher values concentrated in central Lithuania and along Northern border.

The TS-LKD prediction map (Figure 15) shows higher values being strongly concentrated in Vilnius and in some other urban areas. This appear to be quite the opposite from the LSDP prediction map, identifying the difference in voting habits of different regions and direct correlation with the actual election results.

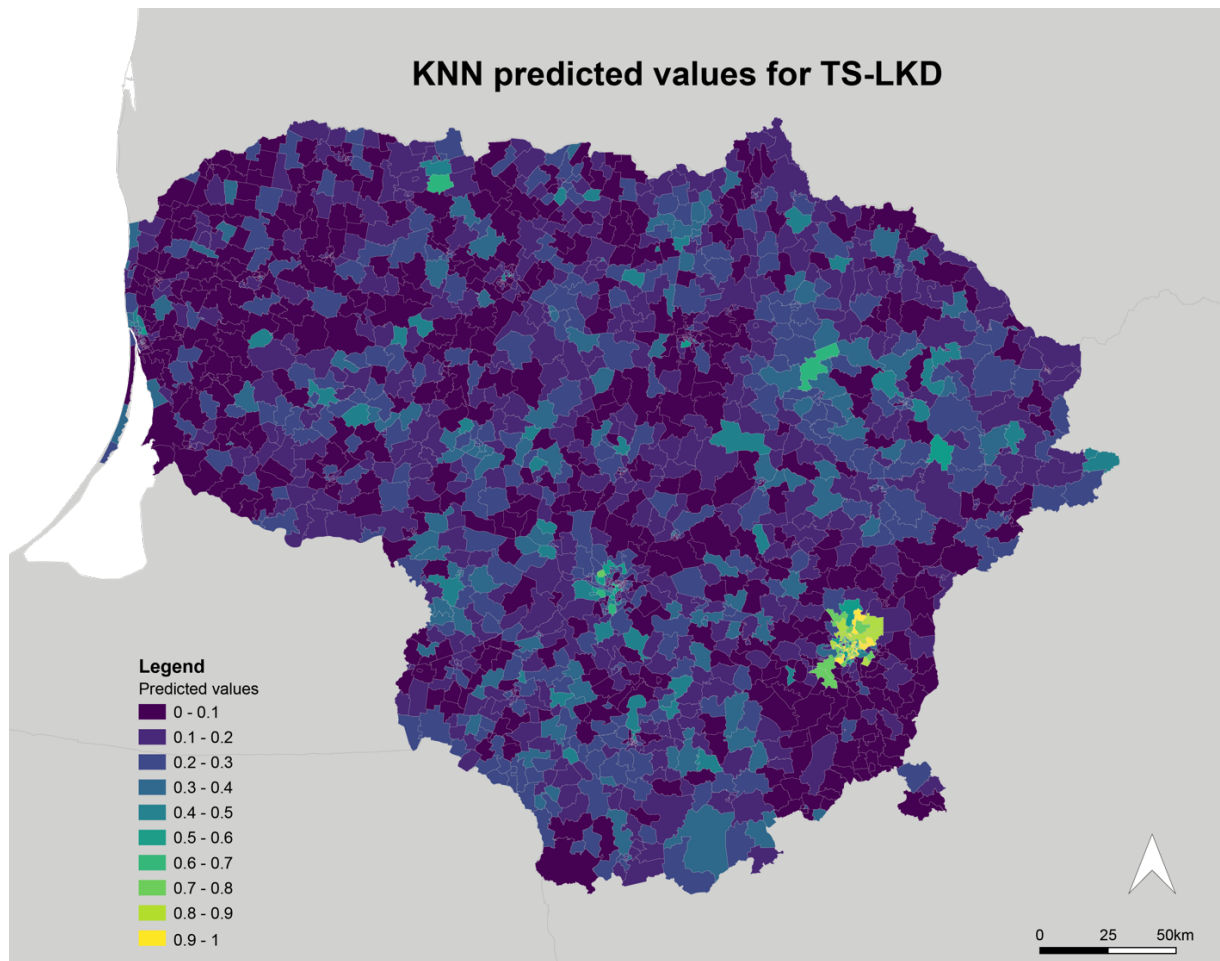


Figure 15. TS-LKD prediction map shows higher values concentrated in cities.

The diagnostic tests (Table 4) shows that The TS model exhibits a higher mean cross-validation score (0.87) compared to the LSDP model (0.73), indicating better overall performance during the training phase. This means that the model for TS is more effective. The selected hyperparameter (number of neighbours) is the same for both models (9), indicating that a similar level of complexity is preferred. The accuracy on the test set is also higher for the TS model (0.84) compared to the LSDP model (0.72), which suggests that features related to the vaccination status has higher influence and accuracy in TS model.

Model also measures the Cohen's Kappa, which indicates the level of agreement between the predicted and actual values beyond what would be expected by chance. For the TS model, a Cohen's Kappa of 0.31 implies moderate agreement between the predicted and actual values. However, for the LSDP model, a Cohen's Kappa of 0.08 indicates poor agreement between the predicted and actual values. This suggests that the model's predictions for LSDP cannot be trusted and must be improved. This could be achieved by considering other covariates or adjusting hyperparameter.

Table 4. Validation tests

Test	TS model	LSDP model
Mean Cross-Validation Score	0.87	0.73
Best Hyperparameters	9	9
Accuracy on Test Set	0.84	0.72
Cohen's Kappa	0.31	0.08

To sum up, this final chapter asks if a prediction model can be applied to foresee the factor of an individual political party's election. The results shows that KNN machine learning method can be applied to answer such questions with the accuracy of 84% for TS political party. However, the results are worse for LSDP political party, indicating that different political parties might need different set of covariates and hyperparameters to model prediction. Also, this research is limited to only one municipal election result dataset, thus the current model merely scratches the surface of the expansive analytical possibilities that could be explored to achieve a more profound and comprehensive prediction of forthcoming elections. Further exploration into intricate socio-political variables, inclusion of additional geospatial features, and model refinement could unlock a more nuanced and accurate forecasting framework.

6 Conclusion

The use of vaccination and 2023 Municipal election data allowed to investigate the spatial relationship between multiple factors within the Lithuanian context. The dataset with vaccination and infection records included all possible Covid-19 records in Lithuania's population health history, which allowed this research to be data based rather than survey based, as in other related research projects, e.g., the study by Rönn (Rönn, 2023). Having big data about Covid-19 patterns allowed us to look for specific spikes in time and understand vaccination patterns that were not seen before the data was aggregated and analysed.

The research starts with the analysis of Covid-19 related events. In this part it was identified that the data should be split in time to analyse people that were vaccinated before September 13th, 2021, when the Green Pass was implemented. The implementation of digital certificate added a new motivation for citizens to get vaccinated in order to proceed with usual social life without restrictions, therefore they could not be considered as early vaccinated population. There is a possibility that some people have vaccinated after this date due to previous infection, however, the analysis showed that it was a minor part of the population, since most Covid-19 infection peaks have happened after the Green Pass was introduced.

The events analysis was followed by the first research question that looked at the relationship between vaccination status, education levels, and voter turnout in the 2023 election. The Spearman correlation matrix revealed a strong positive correlation between early vaccinated voters and higher education levels, indicating a social pattern where those with higher education are more likely to be vaccinated early. Additionally, while differences in vaccination status were more pronounced across education levels, the variation in voter turnout between vaccinated and non-vaccinated groups was relatively small. findings illuminate complex social patterns, providing valuable insights for policymakers seeking to understand and address public health and civic engagement dynamics.

The second research question looked at the spatial distribution of the early and not vaccinated voters. Global and Local Moran's I analysis revealed the spatial clustering of early vaccinated and non-vaccinated voters. The Global Moran's I analysis confirmed significant spatial autocorrelation, particularly highlighting higher education levels and early vaccination status among voters and non-voters. Further exploration through Local Moran's I revealed that early vaccinated voters are strongly clustered in urban areas, with notable concentrations observed in Vilnius, Kaunas and Klaipeda cities. Conversely, non-vaccinated voters who participate in elections exhibit a distinct pattern of clustering around cities, challenging initial expectations of random dispersion in rural areas. These findings underscore the spatial dimension of vaccination behaviour and electoral participation, emphasizing the importance of local context.

The third research question looked at possible political preference prediction by location and the status of voters' vaccination. Employing the KNN method, the analysis focused on two major winning parties, LSDP and TS-LKD, using early vaccinated, late vaccinated, and not vaccinated voters, along with non-voters and the highest education level as independent variables. The prediction maps generated for both parties revealed spatial trends in support, with LSDP showing distribution across central Lithuania, while TS-LKD exhibited much stronger support in urban

areas, particularly in Vilnius. Diagnostic tests demonstrated better overall performance and higher accuracy for the TS-LKD model compared to LSDP, suggesting the influence of vaccination status on party support varies for different parties. However, the relatively low Cohen's Kappa values for LSDP indicate the need for model refinement and consideration of additional covariates. This research underscores the potential of machine learning methods in political prediction but also highlights the complexity and variability across different political contexts, emphasizing the need for continued exploration and refinement in future analysis.

In summary, this research offers spatial insights beyond cartographic representation, enhancing our understanding of electoral geography based on vaccination preferences and education level within distinct voting wards.

It is also worth noting that there can be so many more factors used to analyse geography of vaccination and election, such as more traditional sociological aspects like age, gender, occupation, income, which are often found as open data sources. Also, there is a great potential to use this data to analyse why people do not vote or do not vaccinate in order to target them accordingly. I agree with John Agnew (Agnew, 1996) that the practice of *mapping politics* holds the potential for providing more than just decorative cartographic representations in the realm of electoral geography. However, this potential can only be fully realised when we put in the effort to comprehend the significance of context and how it influences various aspects of this field.

7 References

- Agnew, John. 1996. "Mapping politics: how context counts in electoral geography." *Political Geography* 15 (2).
- Alfredo J. Mena Lora, MD1, PhD, MPH2 Jessica E. Long, and PhD Yunda Huang. 2023. "Rapid Development of an Integrated Network Infrastructure to Conduct Phase 3 COVID-19 Vaccine Trials." *JAMA Network Open*.
- Barney Warf, Jonathan Leib. 2011. *Revitalizing Electoral Geography*. Ashgate Publishing.
- Burneikaitė, Gerda. 2018. "ERDVINĖ RINKIMINIO AKTYVUMO ANALIZĖ VILNIAUS MIESTE." *Geografijos metraštis* 79 - 100.
- Comber, Lex. 2023. *GeoComputation and Spatial Analysis practicals*.
<https://bookdown.org/lexcomber/GEOG3195/>.
- Halim, M., Halim, A. & Tjhin, Y., 2021. COVID-19 Vaccination Efficacy and Safety Literature Review. *Journal of Clinical and Medical Research*.
- Dovydas Vidzbelis, Rolandas Tučas. 2018. "Lietuvos gyventojų rinkiminio aktyvumo teritorinė diferenciacija 2014–2016 metais." *GEOLOGIJA. GEOGRAFIJA*. 139–154.
- Ewan Mansley, Urška Demšar. 2015. "Space matters: Geographic variability of electoral turnout determinants in the 2012 London mayoral election." *Electoral Studies* 40: 322-334.
- GeoDa Center. 2023. https://geodacenter.github.io/workbook/2b_eda_multi/lab2b.html#scatter-plot-matrix.
- GIS Institute, Harvard University. n.d. *GeoDa: Spatial Regression* . https://cga-download.hmhc.harvard.edu/publish_web/GIS_Institute/2018_summer/OpenGeoDa3_2018.pdf.
- Government of the Republic of Lithuania. 2023. 22 October. <https://koronastop.lrv.lt/en/>.
- Gulnara Davud Aliyeva MD, MPH. 2022. "Infectious Disease Emergencies." *Rapid Response Situations* 163-177.
- Harvard University, GIS Institute. 2018. https://cga-download.hmhc.harvard.edu/publish_web/GIS_Institute/2018_summer/OpenGeoDa3_2018.pdf.
- Johnston, Ron. 2015. "Electoral Geography." *International Encyclopedia of the Social & Behavioral Sciences (Second Edition)* 345-348.
- Lietuvos socialdemokratų partija. n.d. Accessed October 2023. <https://www.lsdp.lt/>.
- Lithuania's Central Electoral Commission. 2022. <https://www.vrk.lt/en/2023-savivaldybiu-tarybu-ir-meru-rinkimai>.
- Lithuania's Central Electoral Commission . 2023. 22 October. <https://www.vrk.lt/atviriduomenys>.
- Lithuania's Central Electoral Commission. 2023. <https://www.vrk.lt/rinkimu-teritoriju-gis-duomenys>.
- Lithuania's State Data Agency. 2023. *COVID ir išsilavinimo statistika pagal balsavimo apylinkes*. https://open-data-ls-osp-sdg.hub.arcgis.com/datasets/25999869887f4713b98b778067e23f82_0/about.

- Lithuanian National Television and Radio. n.d. Accessed October 2023.
<https://www.lrt.lt/mediateka/irasas/2000225896/skiepijimas-nuo-covid-19-stiprinamosiomis-dozemis-poliklinikos-sako-kad-didelio-zmoniu-antpludzio-kol-kas-nera>.
- Lucas, Jack, and R. Michael McGregor. 2020. "Are city elections unique? Perceptions of electoral cleavages and social sorting across levels of government." *Electoral Studies* 66.
- Matthews, Stephen A. 2006. *GeoDa and Spatial Regression Modeling*.
https://ibis.geog.ubc.ca/~brian/workshop/GeoDa_Spatial_Regression.pdf.
- Ministry of the Economy and Innovation of the Republic of Lithuania. 2022.
<https://eimin.lrv.lt/lt/naudinga-informacija-1/informacija-verslui-del-covid-19/verslo-salygos-karantino-metu/galimybiu-pasas/dazniausiai-uzduodami-klausimai-2/kur-galiu-rasti-savo-galimybiu-pasa-kaip-ji-atsidaryti>.
- n.d. Accessed October 2023. <https://lvzs.lt/lt/>.
- Pattie, C., & Johnston, R. 2009. "Electoral Geography." *International Encyclopedia of Human Geography* 405-422.
- Robert Nisbet, John Elder, Gary Miner. 2009. "Chapter 4 - Data Understanding and Preparation." *Handbook of Statistical Analysis and Data Mining Applications* 49-75.
- Rogerson, Peter A. 2001. *Statistical Methods for Geography*. SAGE Publications, Ltd.
- Rolandas, Tučas. 2016. *Rinkimų geografija*. Vilnius: Vilnius University.
- Rönn, M. M., Menzies, N. A., & Salomon, J. A. 2023. "Vaccination and Voting Patterns in the U.S.: Analysis of COVID-19 and Flu Surveys From 2010 to 2022." *American Journal of Preventive Medicine* 65 (3): 458-466.
- State Data Agency. n.d. *Open Data Portal*. Accessed October 2023. <https://open-data-ls-osp-sdg.hub.arcgis.com/explore?collection=Dataset&tags=census2021>.
- Stephen Matthews, Tse-Chuan Yang. 2012. "Mapping the results of local statistics: Using geographically weighted regression." *Demographic research* 151–166.
- Suryadevara, M., Bonville, C. A., Cibula, D. A., Domachowske, J. B., & Suryadevara, A. C. 2019. "Associations between population based voting trends during the 2016 US presidential election and adolescent vaccination rates." *Vaccine* 37 (9): 1160-1167.
- Tėvynės sąjunga-Lietuvos krikščionys demokratai. n.d. Accessed October 2023.
<https://tsajunga.lt/>.
- University of Chicago. 2023. <https://geodacenter.github.io/>.
- Wong, D.W. 2009. "Modifiable Areal Unit Problem." *International Encyclopedia of Human Geography* 169-174.
- World Health Organization. n.d. Accessed October 2023.
<https://www.who.int/emergencies/disease-outbreak-news/item/2020-DON229#:~:text=On%2031%20December%202019%2C%20the,the%20national%20authorities%20in%20China>.

8 Appendices

8.1 Covid-19 events and media review table

Table 5. List of Covid-19 events in media

Date	Action (Lithuanian)	Action	Type	Source
2019-12-31	Kinija praneša apie nežinomos kilmės pneumonijos protrukį	China reports an outbreak of pneumonia of unknown origin	Covid-19	https://www.who.int/emergencies/disease-outbreak-news/item/2020-DON229#:~:text=On%202031%20December%202019%2C%20the,the%20national%20authorities%20in%20China
2020-01-30	PSO dėl covid plitimo paskelbė pasaulinę ekstremalią situaciją	WHO declares a global emergency due to the spread of COVID	Lock-down	https://lt.wikipedia.org/wiki/COVID-19_pandemija
2020-02-15	Šimašius pateikė rekomendacijas vilniečiams dėl koronaviruso – viskas, ką reikia žinoti	Šimašius provides recommendations to Vilnius residents regarding coronavirus - everything you need to know	Lock-down	https://www.lrt.lt/naujienos/lietuvoje/2/1145778/simasius-pateike-rekomendacijas-vilnieciams-del-koronaviruso-viskas-ka-reikia-zinoti
2020-02-26	Lietuvos vyriausybė šalyje paskelbė ekstremalią situaciją	The Lithuanian government declared a state of emergency in the country.	Lock-down	https://lt.wikipedia.org/wiki/COVID-19_pandemija
2020-02-26	Nausėda pirmas pasisakymas: asmenų patikra dėl koronaviruso vykdoma per silpnai	Nausėda's first statement: COVID testing of individuals being conducted too weakly.	Testing	https://www.lrt.lt/naujienos/lietuvoje/2/1146172/nauseda-asmenu-patikra-del-koronaviruso-vykdoma-per-silpnai
2020-02-27	Verygos (Sveikatos ministras) pirma press konferencija dėl covid panikos, trūksta priemonių	Veryga's (Minister of Health) first press conference on COVID panic, lack of measures.	Covid-19	https://www.lrt.lt/naujienos/lietuvoje/2/1146717/veryga-apie-baime-del-koronaviruso-nezinau-kaip-dar-itikintimes-neturime-jokio-intereso-slepti-informacijos
2020-02-28	pirmasis covid atvejis LT	The first COVID case in Lithuania.	Covid-19	https://www.lrt.lt/naujienos/lietuvoje/2/1146512/lietuvoje-patvirtintas-pirmas-koronaviruso-atvejis-teigiamas-39-metu-moters-meginys
2020-02-28	Malinausko (Ekstremalių situacijų koordinavimo centro vadovas) pirmasis pasisakymas	Malinauskas's (Director of the Extreme Situations Coordination Center) first statement.	Covid-19	https://www.lrt.lt/naujienos/lietuvoje/2/1146768/malinauskas-apie-pirmaji-koronaviruso-atveji-paaiskejo-kad-ir-pakankamai-gerai-jauciantis-galima-buti-viruso-nesioju
2020-03-11	PSO covid plitimą įvardijo kaip pandemiją	WHO declared COVID spread as a pandemic.	Lock-down	https://lt.wikipedia.org/wiki/COVID-19_pandemija
2020-03-15	Konservatoriai prašo pateikti atsakymus, kodėl Lietuvoje tokios mažos testavimo apimtys	Conservatives request answers as to why testing volumes are so low in Lithuania.	Testing	https://www.lrt.lt/naujienos/lietuvoje/2/1151629/konservatoriai-praso-pateikti-atsakymus-kodel-lietuvoje-tokios-mazos-testavimo-apimty
2020-03-16	Lietuvoje paskelbtas pirmasis karantinas	The first quarantine was announced in Lithuania.	Lock-down	https://lt.wikipedia.org/wiki/COVID-19_pandemija
2020-03-18	pirmasis patvirtintas antivirusinis vaistas	The first confirmed antiviral drug was announced.	Medicine	https://www.lrt.lt/naujienos/mokslas-ir-it/11/1152863/pirmoji-prosvaiste-patvirtintas-vaistas-gydyti-koronavirusa-dar-du-testuojami
2020-03-19	pradedama veikti mobilieji testavimo punktai	Mobile testing points start operating.	Testing	https://www.lrt.lt/naujienos/lietuvoje/2/1152439/mobilus-koronaviruso-patikros-punktai-tikslios-vietos-ir-darbo-tvarka
2020-03-20	Lietuvoje mirė pirmasis žmogus nuo covid	The first person in Lithuania died from COVID.	Covid-19	https://lt.wikipedia.org/wiki/COVID-19_pandemija
2020-03-26	Nausėda palaiko sprendimą įvesti karantiną, kreipėsi į ES vadovus	Nausėda supports the decision to impose quarantine and appeals to EU leaders.	Lock-down	https://www.lrt.lt/naujienos/lietuvoje/2/1151532/nauseda-palaiko-sprendima-ivesti-karantina-kreipesi-i-es-vadovus
2020-04-04	valstybės sienos su Baltarusija ir Rusija buvo uždarytos keleivių transportui	State borders with Belarus and Russia were closed for passenger transport.	Lock-down	https://lt.wikipedia.org/wiki/COVID-19_pandemija_Lietuvoje

2020-04-16	uždaryta Nemenčinė iki 2020-04-30	Nemenčinė was closed until 2020-04-30.	Lock-down	https://lt.wikipedia.org/wiki/COVID-19_pandemija_Lietuvoje
2020-06-17	Lietuvoje baigėsi pirmasis karantinas	The first quarantine in Lithuania ended.	Lock-down	https://lt.wikipedia.org/wiki/COVID-19_pandemija
2020-08-24	LRT tyrimas. Greitieji testai už 6 milijonus: už skandalingo pirkimo šmėžuoją Skvernelio komanda	LRT investigation. Rapid tests for 6 million: Skvernelis's team is under fire for a scandalous purchase.	Politics	https://www.lrt.lt/naujienos/lrt-tyrimai/5/1217763/lrt-tyrimas-greitieji-testai-uz-6-milijonus-uz-skandalingo-pirkimo-smezuoja-skvernelio-komanda
2020-09-01	Veryga pripažįsta, kad rekomendacijos dėl mokslo metų pateiktos per vėlavimą – kalta nuolat besikeičianti COVID-19 situacija	Veryga admits that recommendations for the school year were submitted too late - blames the constantly changing COVID-19 situation.	Politics	https://www.lrt.lt/naujienos/lietuvoje/2/1223041/veryga-pripazista-kad-rekomendacijos-del-mokslo-metu-pateiktos-per-velai-kalta-nuolat-besikeicianti-covid-19-situacija
2020-09-01	Koronaviruso atvejų skaičius artėja prie pavasario lygio, bet Veryga situaciją vadina stabilia	The number of coronavirus cases is approaching spring levels, but Veryga calls the situation stable.	Politics	https://www.lrt.lt/naujienos/lietuvoje/2/1223371/koronaviruso-atveju-skaicius-arteja-prie-pavasario-lygio-bet-veryga-situacija-vadina-stabilia
2020-09-09	Laikiniai stabdomi COVID-19 vakcinos bandymai: sunegalavo savanoris	COVID-19 vaccine trials temporarily halted: volunteer fell ill.	Vaccination	https://www.lrt.lt/mediateka/irasas/2000120962/laikiniai-stabdomi-covid-19-vakcinos-bandymai-sunegalavo-savanoris
2020-09-14	Žemaitaitis: koaliciją su „valstiečiais“ įsivaizduotume tik be Verygos	Žemaitaitis: we would imagine a coalition with the "farmers" only without Veryga.	Politics	https://www.lrt.lt/naujienos/lietuvoje/2/1231824/zemaitaitis-koalicija-su-valstieciais-isivaizduotume-tik-be-verygos
2020-09-15	Skvernelio pasiaiškinimai Seimui virto chaosu: užsipuolė opoziciją, klausimai dėl COVID-19 testų pirkimo liko neatsakyti	Skvernelis's explanations to the Seimas turned into chaos: he attacked the opposition, questions about the purchase of COVID-19 tests remained unanswered.	Politics	https://www.lrt.lt/naujienos/lietuvoje/2/1232607/skvernelio-pasiaiskinimai-seimui-virto-chaosu-uzsipuole-opozicija-klausimai-del-covid-19-testu-pirkimo-liko-neatsakyti
2020-09-16	Po Verygos išreikšto noro COVID-19 vakcinos klausimą perkelti į VGT – prezidentūros reakcija: ministras siekia atsikratyti atsakomybės	After Veryga expressed his desire to transfer the issue of COVID-19 vaccine to VGT - the presidential reaction: the minister seeks to evade responsibility.	Vaccination	https://www.lrt.lt/naujienos/lietuvoje/2/1233343/po-verygos-isreiksto-noro-covid-19-vakcinos-klausima-perkelti-i-vgt-prezidenturos-reakcija-ministras-siekia-atsikratyti-atsakomybes
2020-09-16	Įtampa tarp Vyriausybės ir Prezidentūros: nesutariama dėl COVID-19 vakcinos pirkimo	Tension between the Government and the Presidency: disagreement over the purchase of COVID-19 vaccine.	Vaccination	https://www.lrt.lt/mediateka/irasas/2000121830/itampa-tarp-vyriausybes-ir-prezidenturos-nesutariama-del-covid-19-vakcinos-pirkimo
2020-09-22	Skvernelis žvelgia į ateitį: tiems, kas turės skiepą nuo COVID-19, bus kitokios verslo ir keliavimo sąlygos	Skvernelis looks to the future: those who will have the COVID-19 vaccine will have different business and travel conditions.	Vaccination	https://www.lrt.lt/naujienos/lietuvoje/2/1237345/skvernelis-zvelgia-i-ateiti-tiems-kas-tures-skiepa-nuo-covid-19-bus-kitokios-verslo-ir-keliavimo-salygos
2020-09-23	Lietuva dalyvaus COVID-19 vakcinų pirkimuose: kaina – nuo 2,9 iki 18 eurų už vieną	Lithuania will participate in COVID-19 vaccine purchases: the price ranges from 2.9 to 18 euros per one.	Vaccination	https://www.lrt.lt/naujienos/lietuvoje/2/1238194/lietuva-dalyvaus-covid-19-vakcinu-pirkimuose-kaina-nuo-2-9-iki-18-euru-uz-viena
2020-09-24	Karbauskis: skiepai nuo koronaviruso nebus privalomi	Karbauskis: COVID-19 vaccines will not be mandatory.	Vaccination	https://www.lrt.lt/naujienos/sveikata/682/1239061/karbauskis-skiepai-nuo-koronaviruso-nebus-privalomi
2020-09-28	Razmuvienė apie COVID-19 židinių suvaldymą: nė viena šalis tokių priemonių netaiko	Razmuvienė on managing COVID-19 outbreaks: no country implements such measures.	Lock-down	https://www.lrt.lt/naujienos/lietuvoje/2/1241326/razmuviene-apie-covid-19-zidiniu-suvaldyma-ne-viena-salis-tokiu-priemoniu-netaiko
2020-09-30	Skvernelis apie karantiną: ir aš girdėjau apie spalio 16 dieną, bet tai yra netiesa	Skvernelis on quarantine: I also heard about October 16, but that's not true.	Lock-down	https://www.lrt.lt/naujienos/lietuvoje/2/1243073/skvernelis-apie-karantina-ir-as-girdejau-apie-spalio-16-diena-bet-tai-yra-netiesa
2020-10-08	Skvernelis: yra visos šalies karantino tikimybė, tačiau tai atneštų daug nuostolių	Skvernelis: there is a possibility of a nationwide quarantine, but it would bring many losses.	Lock-down	https://www.lrt.lt/naujienos/lietuvoje/2/1248381/skvernelis-yra-visos-salies-karantino-tikimybe-taciau-tai-atnestu-daug-nuostoliu
2020-10-11	Seimo rinkimai I turas	Seimas elections, 1st round	Election	https://www.vrk.lt/documents/10180/712974/Seimo+rinkimu+grafikas+atnaujintas+%289%29%20%283%29.pdf/a5149541-5a4d-4236-b5a2-147861e32289

2020-10-12	Veryga: Vyriausybė svarsto trumpinti privalomą izoliacijos trukmę	Veryga: Government considers shortening mandatory isolation period	Lock-down	https://www.lrt.lt/naujienos/lietuvoje/2/1251207/veryga-vyriausybe-svarsto-trumpinti-privaloma-izoliacijos-trukme
2020-10-15	Šimonytė, Armonaitė, Čmilytė-Nielsen: COVID-19 krizės valdymo modelis Vyriausybėje turėtų keistis iš esmės	Šimonytė, Armonaitė, Čmilytė-Nielsen: COVID-19 crisis management model in the Government should change fundamentally	Politics	https://www.lrt.lt/naujienos/lietuvoje/2/1253519/simonyte-armonaite-cmilyte-nielsen-covid-19-krizes-valdymo-modelis-vyriausybeje-turetu-keistis-is-esmes
2020-10-15	Veryga siūlo paankstinti vaistinėms suteiktą teisę skiepyti gyventojus	Veryga proposes to advance pharmacists' right to vaccinate residents	Vaccination	https://www.lrt.lt/naujienos/sveikata/682/1254162/veryga-siulo-paankstinti-vaistininkams-suteikta-teise-skiepyti-gyventojus
2020-10-16	Veryga ramina: apie nacionalinį karantiną diskusijų nėra	Veryga reassures: there are no discussions about a national quarantine	Lock-down	https://www.lrt.lt/naujienos/lietuvoje/2/1254640/covid-19-atveju-daugeja-bet-veryga-ramina-apie-nacionalini-karantina-diskusiju-nera
2020-10-20	Šimonytė: Vyriausybės laikysena dėl COVID-19 kelia nerimą	Šimonytė: Government's stance on COVID-19 causes concern	Politics	https://www.lrt.lt/naujienos/lietuvoje/2/1257010/simonyte-vyriausybes-laikysena-del-covid-19-kelia-nerima
2020-10-21	Vyriausybė apsisprendė dėl mokinių atostogų: jos truks savaitę, o paskui savaitę mokysis nuotoliniu būdu	The Government has decided on students' holidays: they will last a week, then a week of remote learning	Lock-down	https://www.lrt.lt/naujienos/lietuvoje/2/1258084/vyriausybe-apsisprende-del-mokiniu-atostogu-jos-truks-savaite-o-paskui-savaite-mokysis-nuotoliniu-budu
2020-10-22	Matijošaitis apie ribojimus Kaune: kažkas keisis, matyt, po rinkimų tikina, kad miestas yra suvaldęs COVID-19 situaciją	Matijošaitis on restrictions in Kaunas: something will change, probably after the elections assures that the city has managed the COVID-19 situation	Politics	https://www.lrt.lt/naujienos/lietuvoje/2/1259011/matijosaitis-apie-ribojimus-kaune-kazkas-keisis-matyt-po-rinkimu
2020-10-23	JAV patvirtino remdesivirą kaip pirmąjį vaistą nuo COVID-19, Lietuvoje jis skiriamas 6 pacientams	The US approves remdesivir as the first drug for COVID-19, it is prescribed to 6 patients in Lithuania	Medicine	https://www.lrt.lt/naujienos/sveikata/682/1259352/jav-patvirtino-remdesivira-kaip-pirmaji-vaista-nuo-covid-19-lietuvoje-jis-skiriamas-6-pacientams
2020-10-25	Seimo rinkimai II turas	Seimas elections, 2nd round	Election	https://www.vrk.lt/documents/10180/712974/Seimo+rinkimu+grafikas+atnaujintas+%289%29%20%283%29.pdf/a5149541-5a4d-4236-b5a2-147861e32289
2020-10-25	Landsbergis: laimėję rinkimus, konservatoriai tikrintų COVID-19 duomenis: ar nebuvo mėginama nuslėpti tikrąją padėtį?	Landsbergis: if elected, conservatives would check COVID-19 data: whether there was an attempt to conceal the real situation?	Politics	https://www.lrt.lt/naujienos/lietuvoje/2/1261050/landsbergis-laimije-rinkimus-konservatoriai-tikrintu-covid-19-duomenis-ar-nebuvo-meginama-nuslepti-tikraja-padeti
2020-10-26	Oksfordo universiteto vakcina nuo COVID-19 sukelia patikimą imuninę reakciją	Oxford University's COVID-19 vaccine induces a reliable immune response	Vaccination	https://www.lrt.lt/naujienos/sveikata/682/1261535/ziniasklaida-oksfordo-universiteto-vakcina-nuo-covid-19-sukelia-patikima-imunine-reakcija
2020-10-26	Veryga: Didžiosiose savivaldybėse įvedamas karantinas, griežtėja ir taisyklės: kaukių prirėks ir lauke	Veryga: Quarantine is introduced in major municipalities, rules are tightening: masks will be needed outdoors too	Lock-down	https://www.lrt.lt/mediateka/irasas/2000126725/didziosiose-savivaldybese-ivedamas-karantinas-griezteja-ir-taisykles-kaukiu-prireiks-ir-lauke
2020-10-28	Saulius Skvernelis nemano, kad šiuo metu paskelbti visos šalies karantiną būtų logiškas žingsnis	Saulius Skvernelis does not think that declaring a nationwide quarantine at this time would be a logical step	Lock-down	https://www.lrt.lt/mediateka/irasas/2000126979/saulius-skvernelis-nemano-kad-siuo-metu-paskelbti-visos-salies-karantina-butu-logiskas-zingsnis
2020-10-31	Kauno meras ragina savivaldybes padėti NVSC atlikti epidemiologinius tyrimus	Kaunas mayor calls on municipalities to help NVSC conduct epidemiological surveys	Testing	https://www.lrt.lt/naujienos/lietuvoje/2/1266897/kauno-meras-ragina-savivaldybes-padeti-nvsc-atlikti-epidemiologinius-tyrimus
2020-11-03	Prezidentūra: Sveikatos ekspertų taryba savaitės pabaigoje pateiks rekomendacijas dėl pandemijos valdymo	Presidency: Health Expert Council will provide recommendations on pandemic management by the end of the week	Politics	https://www.lrt.lt/naujienos/lietuvoje/2/1267657/prezidentura-sveikatos-ekspertu-taryba-savaites-pabaigoje-pateiks-rekomendacijas-del-pandemijos-valdymo
2020-11-03	Skvernelis: bus siūloma įvesti visuotinį karantiną	Skvernelis: universal quarantine will be proposed	Lock-down	https://www.lrt.lt/naujienos/lietuvoje/2/1267840/skvernelis-bus-siuloma-ivesti-visuotini-karantina
2020-11-05	Atleidžiamas Čaplinskas iš ULAC (Skvernelis)	Čaplinskas is dismissed from ULAC (Skvernelis)	Politics	https://www.lrt.lt/naujienos/lietuvoje/2/1270172/caplinskas-nesutinka-su-atleidimo

				argumentais-ir-zada-verygos-sprendimaiskusti
2020-11-06	KoronaStop app paleidžiamas	Launch of KoronaStop app	Covid-19	https://www.lrt.lt/naujienos/lietuvoje/2/1271004/svarbiausi-pentkadienio-ivykiai-stiprus-covid-19-suolis-koronastop-programele-ir-isauges-nedarbas
2020-11-07	Lietuvoje paskelbtas antrasis karantinas (Skvernelis)	The second quarantine declared in Lithuania (Skvernelis)	Lock-down	https://www.vz.lt/izvalgos/2020/11/04/nuo-lapkricio-7-d-vidurnakcio-lietuvoje-trims-savaitems-ivedamas-karantinas
2020-11-09	Konservatoriai, liberalai ir Laisvės partija pasirašė koalicijos sutartį	Conservatives, liberals, and Freedom Party sign coalition agreement	Politics	https://www.lrt.lt/mediateka/irasas/2000128306/lrt-radijo-zinios-konservatoriai-liberalai-ir-laisves-partija-pasirase-koalicijos-sutarti
2020-11-09	„Pfizer“: bandymų rezultatai rodo, kad gaminamos COVID-19 vakcinos efektyvumas siekia 90 proc.	Pfizer: trial results show that the COVID-19 vaccine's effectiveness is 90%	Vaccination	https://www.lrt.lt/mediateka/irasas/2000128334/zinios-pfizer-bandymu-rezultatai-rodo-kad-gaminamos-covid-19-vakcinos-efektyvumas-siekia-90-proc
2020-11-10	Europos Komisija baigė derybas su „BioNtech“ ir „Pfizer“ dėl vakcinos pirkimo	The European Commission concludes negotiations with "BioNtech" and "Pfizer" for vaccine purchase	Vaccination	https://www.lrt.lt/naujienos/mokslas-ir-it/11/1273386/europos-komisija-baige-derybas-su-biontech-ir-pfizer-del-vakcinos-pirkimo
2020-11-11	Vyriausybė pritarė 1,5 mln. koronaviruso vakcinos dozių įsigijimui iš „Sanofi“ ir GSK	The Government has approved the purchase of 1.5 million doses of coronavirus vaccine from "Sanofi" and GSK	Vaccination	https://www.lrt.lt/naujienos/sveikata/682/1274099/vyriausybe-pritare-1-5-mln-koronaviruso-vakcinos-doziu-isingijimui-is-sanofi-ir-gsk
2020-11-13	Darbą pradeda nauja seimo kadencija	Start of a new parliamentary term	Election	https://www.lrt.lt/naujienos/lietuvoje/2/1275671/parlamentarai-prisieke-lietuvaidarba-pradeda-2020-2024-metu-kadencijos-seimas
2020-11-16	Moderna“ pranešė jog jų kuriamos COVID-19 vakcinos efektyvumas – 94,5 proc	Moderna announces that the effectiveness of their COVID-19 vaccine is 94.5%	Vaccination	https://www.lrt.lt/naujienos/mokslas-ir-it/11/1277401/dar-viena-covid-19-vakcina-kurianti-kompanija-skelbia-bandymu-rezultatus-efektyvumas-94-5-proc
2020-11-18	Dulkys žada neieškoti „valstiečių“ klaidų: svarbu spręsti, kaip išeiti iš krizės	Dulkys promises not to seek "farmers'" mistakes: it is important to solve how to get out of the crisis	Politics	https://www.lrt.lt/naujienos/lietuvoje/2/1279489/dulkys-zada-neieskoti-valstieciu-klaidu-svarbu-spresti-kaip-iseiti-is-krizes
2020-11-18	Vyriausybė pritarė 1,24 mln. vakcinų nuo koronaviruso įsigijimui iš „BioNTech“ ir „Pfizer“	The Government has approved the purchase of 1.24 million vaccines against coronavirus from "BioNTech" and "Pfizer"	Vaccination	https://www.lrt.lt/naujienos/sveikata/682/1279522/vyriausybe-pritare-1-24-mln-vakcinu-nuo-koronaviruso-isingijimui-is-biontech-ir-pfizer
2020-11-19	Nausėda apie COVID-19 pandemiją: turime grįžti į civilizuotą atvejų lygį ir kovoti su dezinformacija dėl skiepu	Nausėda on the COVID-19 pandemic: we must return to a civilized level of cases and fight vaccine misinformation	Politics	https://www.lrt.lt/naujienos/lietuvoje/2/1280939/nauseda-apie-covid-19-pandemija-turime-grizti-i-civilizuota-atveju-lygi-ir-kovoti-su-dezinformacija-del-skiepu
2020-11-26	Koronavirusas nustatytas Jonavos rajone esančiame ūkyje laikomoms audinėms	Coronavirus detected in tissue farms in Jonava district	Covid-19	https://www.lrt.lt/naujienos/verslas/4/1285691/veterinarijos-tarnyba-labiausia-tiketina-kad-audines-uzsikrete-nuo-darbuotojo-nuo-ju-gali-uzsikresti-ir-zmones
2020-12-05	PSO skelbia, kad prasidedantis vakcinavimas nereiškia COVID-19 krizės pabaigos	WHO declares that the onset of vaccination does not mean the end of the COVID-19 crisis	Politics	https://www.lrt.lt/naujienos/pasaulyje/6/1292456/psa-skelbia-kad-prasidedantis-vakcinavimas-nereiškia-covid-19-krizes-pabaigos
2020-12-08	Antradienį Jungtinėje Karalystėje pradedamas skiepijimas nuo koronaviruso	COVID-19 vaccination begins in the UK on Tuesday	Vaccination	https://www.lrt.lt/naujienos/pasaulyje/6/1293791/antrasis-britanijoje-nuo-covid-19-paskiepytas-pacientas-williamas-shakespeare-as
2020-12-09	Skvernelis atsakė į Šimonytės raginimus: paskirtoji premjerė nepateikė nė vieno konkretaus siūlymo dėl karantino	Skvernelis responds to Šimonytė's calls: the designated Prime Minister did not submit any specific proposals regarding quarantine	Politics	https://www.lrt.lt/naujienos/lietuvoje/2/1295075/skvernelis-atsake-i-simonytes-raginimus-paskirtoji-premiere-nepateikene-vieno-konkreto-siulymo-del-karantino

2020-12-11	Darbą pradeda nauja Vyriausybė	Start of a new Government's work	Election	https://www.15min.lt/naujiena/aktualu/lietuva/seime-tvirtinama-ingridos-simonytes-vyriausybe-56-1422744
2020-12-12	JAV patvirtino „Pfizer-BioNTech“ vakciną nuo COVID-19	US approves "Pfizer-BioNTech" COVID-19 vaccine	Vaccination	https://www.lrt.lt/naujienos/pasaulyje/6/12/96567/jav-patvirtino-pfizer-biontech-vakcina-nuo-covid-19
2020-12-14	Karbauskis ir Širinskienė pažėrė kritikos suvaržymų planui: vadina neproporcingais ir drastiškais	Karbauskis and Širinskienė face criticism for restriction plan: call them disproportionate and drastic	Politics	https://www.lrt.lt/naujienos/lietuvoje/2/12/97002/karbauskis-ir-sirinskiene-pazere-kritikos-suvarzymu-planui-vadina-neproporcingais-ir-drastiskais
2020-12-16	II Karantino režimo sąlygos sugriežtintos	Conditions of the 2nd Quarantine regime have been tightened	Lock-down	https://www.vle.lt/straipsnis/covid-19-pandemija/
2020-12-16	Ekstremaliosios situacijos operacijų vadovu paskirtas Dulkys	Dulkys appointed as Chief of Emergency Operations	Politics	https://www.lrt.lt/naujienos/lietuvoje/2/13/00668/ekstremaliosios-situacijos-operaciju-vadovu-paskirtas-dulkys
2020-12-20	JK užfiksuota nauja covid atmaina (alpha)	New COVID variant (alpha) detected in the UK on Tuesday	Covid-19	https://www.lrt.lt/naujienos/sveikata/682/1303554/lietuvos-ekspertai-apie-nauja-koronaviruso-atmaina-jk-kol-kas-nera-duomenu-kad-ji-pavoingesne-uz-kitas-mutacijas
2020-12-21	Europos Komisija suteikė leidimą naudoti pirmąją saugią ir veiksmingą vakciną	The European Commission grants authorization for the first safe and effective vaccine	Vaccination	https://www.vle.lt/straipsnis/covid-19-pandemija/
2020-12-21	Europos vaistų agentūra patvirtino „Pfizer-BioNTech“ vakciną nuo COVID-19	European Medicines Agency approves "Pfizer-BioNTech" COVID-19 vaccine	Vaccination	https://www.lrt.lt/naujienos/mokslas-ir-it/11/1304052/europos-vaistu-agentura-patvirtino-pfizer-biontech-vakcina-nuo-covid-19
2020-12-22	Dulkys – privalomai skiepytis nereikės	Dulkys - vaccination will not be mandatory	Vaccination	https://www.lrt.lt/naujienos/sveikata/682/1303557/dulkys-apie-covid-19-vakcina-privalomai-skiepytis-nereikes-jei-viskas-vyks-sklandziai-medikai-bus-paskiepyti-sausi
2020-12-27	Lietuvoje pradėtas skiepijimas	Vaccination started in Lithuania	Vaccination	https://lt.wikipedia.org/wiki/COVID-19_pandemija_Lietuvoje
2020-12-27	EU ir LT pradeda skiepijimą (pirmiausia medikai)	EU and LT start vaccination (firstly healthcare workers)	Vaccination	https://www.lrt.lt/naujienos/pasaulyje/6/13/07456/europa-pradejo-masini-skiepijima-nuo-covid-19
2021-01-06	Vyriausybė svarsto apie „imuniteto pasą“	Government considers "immunity passport"	GP	https://www.lrt.lt/naujienos/lietuvoje/2/13/13957/vyriausybe-svarsto-apie-imuniteto-pasa-gautu-ir-pasiskiepije-ir-persirge-covid-19
2021-01-07	Nuo COVID-19 Lietuvoje pradėti skiepyti ir pacientai: pirmiausiai – sergantys sunkiomis ligomis	COVID-19 patients started to be vaccinated in Lithuania: firstly - those with severe illnesses	Vaccination	https://www.lrt.lt/mediateka/irasas/200013/6654/nuo-covid-19-lietuvoje-pradeti-skiepyti-ir-pacientai-pirmiausiai-sergantys-sunkiomis-ligomis
2021-01-12	Prasideda antrasis vakcinavimo etapas – per 5 dienas pirmuosius skiepus gaus globos namų darbuotojai ir gyventojai	The second vaccination stage begins - within 5 days, the first vaccines will be received by caregivers and residents	Vaccination	https://www.lrt.lt/mediateka/irasas/200013/6610/prasideda-antrasis-vakcinavimo-etapas-per-5-dienas-pirmuosius-skiepus-gaus-globos-namu-darbuotojai-ir-gyventojai
2021-01-28	Blinkevičiūtė: nesuprantu, kokį vaidmenį atlieka galimybių pasas	Blinkevičiūtė: I don't understand the role of the immunity passport	Politics	https://www.lrt.lt/naujienos/lietuvoje/2/16/00039/blinkeviciute-nesuprantu-koki-vaidmeni-atlieka-galimybiu-pasas
2021-02-02	Pradėti skiepyti pedagogai	Teachers start to be vaccinated	Vaccination	https://www.lrt.lt/naujienos/lietuvoje/2/13/36117/kaune-isibegejo-pedagogu-skiepijimas-nuo-covid-19-iki-rytojaus-vakcinos-sulauks-apie-2-tukst-zmoniu
2021-02-17	Pradėta vyresnių nei 80 metų gyventojų vakcinacija	Vaccination of people aged over 80 begins	Vaccination	https://www.lrt.lt/naujienos/sveikata/682/1345198/daugiau-nei-puse-savivaldybiu-sia-savaite-prades-80-ies-ir-vyresniu-gyventuju-vakcinacija-nuo-koronaviruso
2021-03-03	Pradėta vyresnių nei 70 metų gyventojų vakcinacija	Vaccination of people aged over 70 begins	Vaccination	https://www.lrt.lt/naujienos/lietuvoje/2/13/57061/vilnius-pradejo-skiepyti-vyresnius-

				nei-70-metu-gyventojus-kaune-baigiama-80-meciu-vakcinacija
2021-03-08	Pradėta vyresnių nei 65 metų gyventojų vakcinacija	Vaccination of people aged over 65 begins	Vaccination	https://www.lrt.lt/naujienos/lietuvoje/2/1360090/sam-del-covid-19-vakcinu-kai-kuriose-savivaldybese-jau-bus-skiepijami-ir-79-65-metu-asmenys
2021-03-09	Sustabdytas AstraZeneca skiepėjimas dėl šal poveikio	AstraZeneca vaccination suspended due to side effects	Vaccination	https://www.lrt.lt/mediateka/irasas/2000143766/atsivelgiant-i-gautus-pranesimus-del-vienos-astrazeneca-vakinos-serijos-salutinio-poveikio-sustabdytas-skiepijimas-ja
2021-03-17	Nausėda: Dulkio sprendimas dėl „AstraZeneca“ sudavė smūgį vakcinos patikimumui	Nausėda: Dulkys' decision on "AstraZeneca" dealt a blow to the vaccine's credibility	Vaccination	https://www.lrt.lt/naujienos/lietuvoje/2/1366666/nauseda-dulkio-sprendimas-del-astrazeneca-sudave-smugi-vakcinos-patikimumui
2021-03-19	Atnaujintas skiepėjimas AstraZeneca	AstraZeneca vaccination resumed	Vaccination	https://www.delfi.lt/sveikata/sveikatos-naujienos/po-laikiniai-sustabdyto-skiepijimo-astrazenecos-vakcina-jos-atsisako-net-ir-tie-kurie-buvo-sutike-skiepytis-86743555
2021-03-22	„AstraZeneca“ vakcina paskiepyti Nausėda, Šimonytė, Čmilytė ir Dulkys	Nausėda, Šimonytė, Čmilytė, and Dulkys vaccinated with AstraZeneca vaccine	Vaccination	https://www.lrt.lt/naujienos/lietuvoje/2/1369810/astrazeneca-vakcina-paskiepytas-nauseda-man-nekyla-abejoniu-del-mokslo
2021-03-23	Pradėti skiepyti Vyriausybės, Seimo nariai, ministrai	Government members, MPs, and ministers start to be vaccinated	Vaccination	https://news.bns.lt/63445305/
2021-03-30	Pradėti skiepyti dėstytojai	Teachers start to be vaccinated	Vaccination	https://www.lrt.lt/naujienos/lietuvoje/2/1376505/skiepai-keliasi-i-universitetus-vdu-vakcinavo-70-proc-darbuotoju-vu-laikia-savivaldybes-zinios-kyla-klausimas-del-gyvu-paskaitu
2021-04-08	vakcinuotis kviečiamos įmonės, turinčios bent 100 darbuotojų	Companies with at least 100 employees are invited to get vaccinated	Vaccination	https://www.lrt.lt/naujienos/sveikata/682/1383400/sam-paskelbus-kad-vakcinuotis-kvieciamos-imones-turincios-bent-100-darbuotoju-savivaldybe-ispeja-privaales-atitikti-ir-kitus-kriterijus
2021-04-08	vakcinuotis kviečiami pareigūnai, asmenys, kurie rūpinasi neįgaliaisiais, psichiatrines paslaugas teikiantys specialistai.	Police officers, caregivers, psychiatrists, and retail workers providing psychiatric services are invited to get vaccinated.	Vaccination	https://www.lrt.lt/naujienos/lietuvoje/2/1382246/vilniuje-treciadieni-ketinama-paskiepyti-dar-beveik-3-5-tukst-zmoniu-registruoti-kvieciama-ir-artimuosius
2021-04-13	JAV rekomendavo sustabdyti skiepėjimą „Johnson & Johnson“ vakcina nuo COVID-19	The US recommended suspending vaccination with the "Johnson & Johnson" COVID-19 vaccine	Vaccination	https://www.lrt.lt/naujienos/pasulyje/6/1388261/estija-laikiniai-nenaudos-johnson-johnson-vakcinos-nuo-covid-19
2021-04-13	Armonaitė siūlo galimybių pasą	Armonaitė proposes an immunity passport	GP	https://www.lrt.lt/naujienos/verslas/4/1386610/armonaite-siulo-galimybiu-pasaleistu-nueiti-i-renginius-sporto-klubus-maitinimo-istaigas
2021-04-15	Skvernelis pritaria galimybių pasui, Jukna ne	Skvernelis supports the immunity passport, Jukna does not	GP	https://www.lrt.lt/naujienos/lietuvoje/2/1388213/opozicijos-lyderis-teigiamai-vertina-ideja-del-galimybiu-paso-jukna-skeptiskas
2021-04-20	Vyriausybės ekspertai linkę pritarti galimybių pasui įtraukus testus	Government experts are inclined to support the immunity passport including tests	GP	https://www.lrt.lt/naujienos/lietuvoje/2/1391777/premjerės-patareja-vyriausybės-ekspertai-linkę-pritarti-galimybiu-pasui-itraukus-testus
2021-04-21	Lietuvoje pradamas skiepėjimas „Johnson & Johnson“ vakcina	Vaccination with the "Johnson & Johnson" vaccine starts in Lithuania	Vaccination	https://www.lrt.lt/naujienos/sveikata/682/1392326/lietuvoje-pradedamas-skiepijimas-johnson-johnson-vakcina-nuo-covid-19
2021-04-23	Pristatyta EP žaliojo paso idėja	EP green pass idea presented	GP	https://www.lrt.lt/naujienos/pasulyje/6/1394218/ep-nariu-nuomone-zaliojo-pasas-bus-naudojamas-tik-judejimui-tarp-es-sieniu
2021-05-03	Pradėta vyresnių nei 45 metų gyventojų vakcinacija	Vaccination of people aged over 45 begins	Vaccination	https://www.lrt.lt/naujienos/lietuvoje/2/1400415/vilnius-prades-skiepyti-45-eriu-ir-

				vyresnius-gyventojus-tikisi-kad-mazes-del-skiepo-persigalvojanciu
2021-05-03	Čmilytė-Nielsen: paaiškėjus, kad jau birželį ES gali turėti Imuniteto pasą, nebėra tikslo skubinti lietuviško atitikmens	Čmilytė-Nielsen: since it is revealed that the EU may have an Immunity Passport in June, there is no need to rush the Lithuanian counterpart	Politics	https://www.lrt.lt/naujienos/lietuvoje/2/1400424/cmilyte-nielsen-paaiskejus-kad-jau-birzeli-es-gali-tureti-imuniteto-pasa-nebera-tikslo-skubinti-lietuvisko-atitikmens
2021-05-05	Vyriausybė nutarė – Galimybių pasas pradės veikti gegužės pabaigoje	Government decides - Immunity Passport will start operating at the end of May	GP	https://www.lrt.lt/naujienos/lietuvoje/2/1402572/vyriausybe-nutare-galimybiu-pasas-prades-veikti-geguzes-pabaigoje
2021-05-17	Lietuvoje startuoja viena registracijos COVID-19 vakcinacijai platforma	One registration platform for COVID-19 vaccination starts in Lithuania	Vaccination	https://www.lrt.lt/naujienos/lietuvoje/2/1410707/lietuvoje-startuoja-viena-registracijos-covid-19-vakcinacijai-platforma
2021-05-21	Iš Blinkveičiūtės lūpų – kritika Armonaitei dėl galimybių paso	Criticism of Armonaitė for the immunity pass from Blinkveičiūtė	Politics	https://www.lrt.lt/naujienos/lietuvoje/2/1414322/is-blinkveiciutes-lupu-kritika-armonaitei-del-galimybiu-paso-ir-uzsitesusioms-rietenoms-kam-is-vadovu-vykty-i-briuseli
2021-05-24	Įsigalioja GP	The GP comes into effect	GP	https://www.lrt.lt/naujienos/verslas/4/1411752/netrukus-lietuvoje-isigalios-galimybiu-pasas-ka-tai-reiks-verslui-ir-kas-gales-naudotis
2021-05-28	Europos vaistų agentūra (EVA) leido „Pfizer“ ir „BioNTech“ sukurta vakcina nuo koronaviruso „Comirnaty“ skiepyti 12-15 metų paauglius	The European Medicines Agency (EMA) allows the Pfizer and BioNTech-developed COVID-19 vaccine "Comirnaty" to be vaccinated in 12–15-year-olds	Vaccination	https://www.lrt.lt/naujienos/pasaulyje/6/1421595/naujausia-informacija-europos-komisija-leido-skiepyti-12-15-metu-paauglius-pfizer-vakcina
2021-05-31	Masinė vakcinacija (16+)	Mass vaccination (16+)	Vaccination	https://www.lrt.lt/naujienos/lietuvoje/2/1421188/pradejusi-visuotine-vakcinacija-lietuva-gali-atsitrenkti-i-lubas-kai-kur-norinciuju-skiepytis-maziau-nei-vakcinu
2021-05-31	Europos Komisija leido skiepyti 12–15 metų paauglius „Pfizer“ vakcina	The European Commission allows vaccination of 12–15-year-olds with the Pfizer vaccine	Vaccination	https://www.lrt.lt/naujienos/pasaulyje/6/1421595/naujausia-informacija-europos-komisija-leido-skiepyti-12-15-metu-paauglius-pfizer-vakcina
2021-06-07	Pradeda veikti žaliasis pasas	The Green Pass comes into operation	GP	https://www.lrt.lt/naujienos/sveikata/682/1423442/skaitmeninis-covid-19-pazymejimas-birzelio-7-d-turetu-pradeti-veikti-lietuvoje-galima-bus-naudoti-ir-salies-viduje
2021-06-14	Lietuvoje pradamas 12–15 metų vaikų skiepimas nuo COVID-19, „Pfizer“ vakcinomis	Vaccination of children aged 12–15 against COVID-19 with Pfizer vaccines starts in Lithuania	Vaccination	https://www.lrt.lt/naujienos/sveikata/682/1430837/lietuvoje-pradamas-12-15-metu-vaiku-skiepimas-nuo-covid-19-bus-skiriamos-pfizer-vakcinos
2021-06-17	Lietuvoje – pirmas delta koronaviruso atmainos atvejis	The first case of the delta variant of coronavirus in Lithuania	Covid-19	https://www.lrt.lt/naujienos/lietuvoje/2/1434428/lietuvoje-pirmas-delta-koronaviruso-atmainos-atvejis-iveztinis-nvsc-imasi-atsargumo-priemoniu-del-plitimo
2021-07-14	Vyriausybė nutarė – privalomai testuotis dėl COVID-19 turės vežėjai, maitinimo įstaigų, pramogų, mažmeninės prekybos darbuotojai	Government decides - carriers, catering, entertainment, and retail workers will have to be tested for COVID-19	Testing	https://www.lrt.lt/naujienos/lietuvoje/2/1450804/vyriausybe-nutare-privalomai-testuotis-del-covid-19-tures-vezejai-maitinimo-istaigu-pramogu-mazmenines-prekybos-darbuotojai
2021-07-17	Lietuvoje baigėsi antrasis karantinas	The second quarantine ends in Lithuania	Lock-down	https://lt.wikipedia.org/wiki/COVID-19_pandemija_Lietuvoje
2021-07-26	Dulkys: testo galimybių pasui Vyriausybė nekompensuos	Dulkys: the Government will not compensate for the test option passport	Testing	https://www.lrt.lt/naujienos/lietuvoje/2/1457259/dulkys-testo-galimybiu-pasui-vyriausybe-nekompensuos
2021-08-04	galimybių pasą turi gauti ir atlikusieji antikūnų testą	Those who have taken an antibody test should also receive the immunity passport	GP	https://www.lrt.lt/naujienos/lietuvoje/2/1458788/armonaite-pranese-nuo-rugpjucio-4-dienos-galimybiu-pasa-turetu-gauti-ir-atlikusieji-antikunu-testa

2021-08-06	Širinskienė sako, kad nauji ribojimai nesiskiepijantiems galėtų būti patikrinti teisme	Širinskienė says that new restrictions on the unvaccinated could be tested in court	Politics	https://www.lrt.lt/naujienos/lietuvoje/2/1463993/sirinskiene-sako-kad-nauji-ribojimai-nesiskiepijantiems-galetu-buti-patikrinti-teisme
2021-08-10	Riaušės prie Seimo	Riots at the Parliament	Politics	https://www.lrt.lt/naujienos/lietuvoje/2/1466941/lrt-trumpai-riauses-prie-seimo-kaip-viskas-vyko
2021-09-07	SAM leido skiepytis trečiaja vakcinos doze	SAM allowed to be vaccinated with a third vaccine dose	Vaccination	https://www.lrt.lt/naujienos/sveikata/682/1489658/sprendimas-priimtas-registruotis-treciajai-vakcinos-nuo-koronaviruso-dozei-dalis-gyventoju-gali-nuo-siandien
2021-09-13	Vyriausybė užveria duris neturintiems galimybių paso	The Government closes the doors to those without an immunity passport	GP	https://www.lrt.lt/naujienos/verslas/4/1466732/vyriausybe-uzveria-duris-neturintiems-galimybiu-paso-negales-lankyti-didelese-parduotuvese-kavinese-gauti-kai-kuriu-paslaugu
2021-09-16	Blinkevičiūtė – apie galimybių pasą didžiosiose parduotuvėse: „Tai absurdo spektaklis“	Blinkenė - about the immunity pass in major stores: "It's an absurd spectacle"	Politics	https://www.lrt.lt/naujienos/lietuvoje/2/1497803/blinkeviciute-apie-galimybiu-pasa-didziosiose-parduotuvese-tai-absurdo-spektaklis
2021-09-28	Ramūnas Karbauskis. Pasiekėme ribą, kai krizių valdymas sukelia naujas krizes	Ramūnas Karbauskis. We reached the point where crisis management creates new crises	Politics	https://www.lrt.lt/naujienos/pozicija/679/1505547/ramunas-karbauskis-pasiekeme-riba-kai-kriziu-valdymas-sukelia-naujas-krizes
2021-10-08	Nausėda pietavo restorane, pasisakiusiame prieš galimybių pasą	Nausėda had lunch at a restaurant, spoke out against the immunity passport	GP	https://www.lrt.lt/naujienos/lietuvoje/2/1516797/nauseda-pietavo-restorane-pasisakiusiame-pries-galimybiu-pasa-prezidentas-apie-sia-pozicija-nebuvo-informuotas
2021-10-22	Sugriežtinti ribojimai parduotuvėms, aptarnaujančioms be GP	Tightened restrictions for stores serving without GP	GP	https://www.lrt.lt/naujienos/verslas/4/1526442/pasikeitus-tvarkai-prie-parduotuviu-nusidrieki-pirkeju-eiles-apsaugai-tenka-stabdyti-gudruoliuz-zmones-del-taisykliu-pikti
2021-10-25	Trečiaja doze paskiepytas Matijošaitis skambia Šimašiaus idėja sekti neskuba: tik ekspertai turi spręsti dėl papildomų ribojimų	Matijošaitis, who received a third dose of the vaccine, publicly disagrees with Šimašius's idea: only experts should decide on additional restrictions	Politics	https://www.lrt.lt/naujienos/lietuvoje/2/1528208/treciaja-doze-paskiepytas-matijosaitis-skambia-simasiaus-ideja-sekti-neskuba-tik-ekspertai-turi-spresti-del-papildomu-ribojimu
2021-11-10	Dulkys patvirtino, kad Vyriausybė svarstys siūlymą galimybių pasą taikyti nuo 12 metų	Dulkys confirmed that the Government will consider the proposal to apply the immunity passport from the age of 12	GP	https://www.lrt.lt/naujienos/lietuvoje/2/1538197/dulkys-patvirtino-kad-vyriausybe-svarstys-siulyma-galimybiu-pasa-taikyti-nuo-12-metu
2021-11-17	Vyriausybė nutarė – galimybių pasas turės galiojimo laiką, jo reikės ir 12-mečiams	Government decides - the immunity passport will have a validity period, and it will be required even for 12-year-olds	GP	https://www.lrt.lt/naujienos/lietuvoje/2/1543432/vyriausybe-nutare-galimybiu-pasas-tures-galiojimo-laika-jo-reikes-ir-12-meciams
2021-11-18	Veryga: galimybių paso reikalavimas nuo 12 metų gali paskatinti vaikų patyčias	Veryga: the requirement of an immunity passport from the age of 12 may encourage bullying	GP	https://www.lrt.lt/naujienos/lietuvoje/2/1545275/veryga-galimybiu-paso-reikalavimas-nuo-12-metu-gali-paskatinti-vaiku-patycias
2021-11-24	Omicron pradžia PAR	Omicron begins in PAR	Covid-19	https://en.wikipedia.org/wiki/SARS-CoV-2_Omicron_variant
2021-12-01	Testavimas tampa mokamas	Testing becomes paid	Testing	https://www.lrt.lt/naujienos/lietuvoje/2/1553246/testavimas-del-covid-19-nuo-gruodzio-1-osios-taps-mokamas-kaip-reikes-testuoti-darbuotojams
2021-12-03	Trečią vakcinos nuo COVID-19 dozę gavęs Nausėda: galimybių pasas vaikams kelia papildomų iššūkių ir problemų	Nausėda, after receiving a third dose of the vaccine: the immunity passport for children poses additional challenges and problems	Vaccination	https://www.lrt.lt/naujienos/lietuvoje/2/1556251/trecia-vakcinos-nuo-covid-19-doze-gaves-nauseda-galimybiu-pasas-vaikams-kelia-papildomu-issukiu-ir-problemu

2021-12-06	Prie Seimo – mitingas prieš „segregaciją“: susirinkusieji neigia koronavirusą, tiki Dievo ir angelų apsauga	A rally against "segregation" is held at the Parliament: participants deny the coronavirus, believe in God and angel protection	Politics	https://www.lrt.lt/naujienos/lietuvoje/2/15/57614/prie-seimo-mitingas-pries-segregacija-susirinkusieji-neigia-koronavirusa-tiki-dievo-ir-angelu-apsauga
2021-12-15	prasideda 5–11 metų vaikų skiepijimas	vaccination of children aged 5-11 begins	Vaccination	https://www.lrt.lt/mediateka/irasas/200019/0495/vaiku-skiepijimas-nuo-covid-19-tiketasi-daugiau-atzalas-registruojanciu-tevu-taciau-tai-tik-pirmos-dienos
2021-12-21	Po susitikimo su basomis mamomis prezidentas svarstys, ar kreiptis į Konstitucinį Teismą	After meeting with barefoot mothers, the president will consider whether to appeal to the Constitutional Court	Politics	https://www.lrt.lt/naujienos/lietuvoje/2/15/69382/po-susitikimo-su-basomis-mamomis-prezidentas-svarstys-ar-kreiptis-i-konstitucini-teisma
2021-12-23	Nuo sausio parlamentarai į Seimą galės įeiti tik su galimybių pasu	From January, MPs will only be able to enter the Parliament with an immunity passport	GP	https://www.lrt.lt/naujienos/lietuvoje/2/15/70729/nuo-sausio-parlamentarai-i-seima-gales-ieiti-tik-su-galimybiu-pasu
2021-12-29	Prezidentui įteiktas kreipimasis su 112 tūkst. parašų dėl galimybių paso stabdymo	112,000 signatures handed over to the President regarding the suspension of the immunity passport	Politics	https://www.lrt.lt/naujienos/lietuvoje/2/15/72386/prezidentui-iteiktas-kreipimasis-su-112-tukst-parasu-del-galimybiu-paso-stabdymo
2021-12-30	Šimonytė: nematome pagrindo siūlyti masinio privalomojo skiepavimo	Šimonytė: we see no reason to propose mass compulsory vaccination	Vaccination	https://www.lrt.lt/naujienos/lietuvoje/2/15/75578/simonyte-nematome-pagrindo-siulyti-masinio-privalomojo-skiepavimo
2022-01-11	Premjerė: reikalavimas vaikams iki 16 metų turėti galimybių pasą bus laikinai stabdomas	Prime Minister: the requirement for children under 16 to have an immunity passport will be temporarily suspended	GP	https://www.lrt.lt/naujienos/lietuvoje/2/15/85418/premjere-reikalavimas-vaikams-iki-16-metu-tureti-galimybiu-pasa-bus-laikiniai-stabdomas
2022-01-13	Sausio 13 švilpimai prie Seimo	January 13 whistles at the Parliament	Politics	
2022-02-05	stabdomas GP	GP suspended	GP	https://www.registrucentras.lt/p/1420
2022-04-20	nutraukta ekstremalioji situacija	extreme situation terminated	Lock-down	https://www.lrt.lt/naujienos/lietuvoje/2/16/75955/simonyte-apie-nutraukiama-ekstremalioji-situacija-del-covid-19-pacientu-skaicius-ligonese-mazeja-bet-ragina-ruostis-rudeniiui
2022-08-01	Vakcinuotis kviečiama stiprinamąja ketvirtąją vakcinos doze	Vaccination invited with the fourth strengthening dose	Vaccination	https://www.lrt.lt/mediateka/irasas/200022/5896/skiepijimas-nuo-covid-19-stiprinamosiomis-dozemis-poliklinikos-sako-kad-didelio-zmoniu-antpludzio-kolkas-nera

8.2 List of all variables used for the analysis

apl_id - voting county id

pavad - voting county name

apg_nr - voting county number

apl_id- voting ward id

apg_pav - voting ward name

mix_apgapl - mix of voting county and ward name

V_num - number of people that voted in ward

V_vac_pre - number of people that voted and got vaccinated before 2021 September 13th in ward

V_vac_post - number of people that voted and got vaccinated after 2021 September 13th in ward

V_vac_not - number of people that voted and never got vaccinated in ward

V_inf_pre - number of people that voted and got infected before 2021 September 13th in ward

V_inf_post - number of people that voted and got infected after 2021 September 13th in ward
V_inf_not - number of people that voted and never got infected in ward
V_gpass - number of people that voted and were eligible for Green pass (got vaccinated or were infected before 2021 September 13th) in ward
V_edu_1 - number of people that voted and have higher education in ward
V_edu_2 - number of people that voted and have post-secondary tertiary education in ward
V_edu_3 - number of people that voted and have secondary education in ward
V_edu_4 - number of people that voted and have post-secondary tertiary education in ward
V_edu_5 - number of people that voted and have basic education in ward
V_edu_10 - number of people that voted and have primary education in ward
V_edu_null - number of people that voted and there is no data about their education in ward
NV_num - number of people that didn't vote in ward
NV_vac_pre - number of people that didn't vote and got vaccinated before 2021 September 13th in ward
NV_vac_post - number of people that didn't vote and got vaccinated after 2021 September 13th in ward
NV_vac_not - number of people that didn't vote and never got vaccinated in ward
NV_inf_pre - number of people that didn't vote and got infected before 2021 September 13th in ward
NV_inf_post - number of people that didn't vote and got infected after 2021 September 13th in ward
NV_inf_not - number of people that didn't vote and never got infected in ward
NV_edu_1 - number of people that didn't vote and have higher education in ward
NV_edu_2 - number of people that didn't vote and have post-secondary tertiary education in ward
NV_edu_3 - number of people that didn't vote and have secondary education in ward
NV_edu_4 - number of people that didn't vote and have post-secondary tertiary education in ward
NV_edu_5 - number of people that didn't vote and have basic education in ward
NV_edu_10 - number of people that didn't vote and have primary education in ward
NV_edu_null - number of people that didn't vote and there is no data about their education in ward
VRK_r_sk - number of people from Election committee that have right to vote in ward
VRK_turn - voting turnout from Election committee
w_party_sh - political party name acronym that won in 2023 March 5th Municipal election 1st tour

8.3 Global Moran's I table

Table 6. Global Moran's I table for all variables

Variable	Queen 1st order
V_vac_pre	0.694
V_vac_post	0.621
V_vac_not	0.586
V_gpass	0.695
V_edu_1	0.788
V_edu_2	0.531
V_edu_3	0.572
V_edu_4	0.428
V_edu_5	0.218
V_edu_10	0.090
NV_vac_pre	0.693
NV_vac_post	0.647
NV_vac_not	0.648
NV_edu_1	0.792
NV_edu_2	0.664
NV_edu_3	0.624
NV_edu_4	0.517
NV_edu_5	0.386
NV_edu_10	0.024
VRK_turn	0.521

8.4 KNN codes and reports

8.4.1 KNN model for TS / LSDP

```
import geopandas as gpd
import matplotlib.pyplot as plt
from sklearn.model_selection import cross_val_score, train_test_split,
GridSearchCV
from sklearn.neighbors import KNeighborsClassifier
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score, cohen_kappa_score
from matplotlib.colors import BoundaryNorm
from matplotlib.colorbar import ColorbarBase
import numpy as np

geojson_path = '/content/drive/MyDrive/Colab
Notebooks/results_dummy.geojson'
gdf = gpd.read_file(geojson_path)

selected_columns_model = ['V_vac_pre', 'V_vac_not', 'V_vac_post',
'NV_vac_pre', 'NV_vac_not', 'NV_vac_pos', 'V_edu_1', 'LSDP']

data_model = gdf[selected_columns_model]

X_model = data_model.drop('LSDP', axis=1)
y_model = data_model['LSDP']

X_train_model, X_test_model, y_train_model, y_test_model =
train_test_split(X_model, y_model, test_size=0.2, random_state=42)

scaler_model = StandardScaler()
X_train_scaled_model = scaler_model.fit_transform(X_train_model)
X_test_scaled_model = scaler_model.transform(X_test_model)

knn_classifier_model = KNeighborsClassifier(n_neighbors=9)
knn_classifier_model.fit(X_train_scaled_model, y_train_model)

cv_scores_model = cross_val_score(knn_classifier_model,
X_train_scaled_model, y_train_model, cv=5)
print("Cross-Validation Scores:", cv_scores_model)
print("Mean Cross-Validation Score:", np.mean(cv_scores_model))

param_grid_model = {'n_neighbors': [3, 5, 7, 9]}
```

```

grid_search_model = GridSearchCV(knn_classifier_model, param_grid_model,
cv=5)
grid_search_model.fit(X_train_scaled_model, y_train_model)

best_params_model = grid_search_model.best_params_
print("Best Hyperparameters:", best_params_model)

best_knn_classifier_model = grid_search_model.best_estimator_

y_pred_test_model = best_knn_classifier_model.predict(X_test_scaled_model)
accuracy_test_model = accuracy_score(y_test_model, y_pred_test_model)
print("Accuracy on Test Set:", accuracy_test_model)

kappa = cohen_kappa_score(y_test_model, y_pred_test_model)
print("Cohen's Kappa for LSDP:", kappa)

gdf['LSDP_probability'] =
best_knn_classifier_model.predict_proba(scaler_model.transform(X_model))[:
, 1]

fig, ax = plt.subplots(figsize=(10, 7))

cmap = plt.get_cmap('viridis')
norm = BoundaryNorm(np.linspace(0, 1, 11), cmap.N)
gdf.plot(column='LSDP_probability', cmap='viridis', linewidth=0.1, ax=ax,
edgecolor='0.8', legend=True, norm=norm, legend_kwds={'label': "LSDP
Probability"})

cb = ColorbarBase(ax.inset_axes([1.05, 0.1, 0.03, 0.8]), cmap=cmap,
norm=norm, ticks=np.linspace(0, 1, 11))
cb.set_label("Probability Bins")

plt.title('LSDP Probability Map')
plt.show()

```

8.4.2 Actual results of election for TS-LKD and LSDP political parties

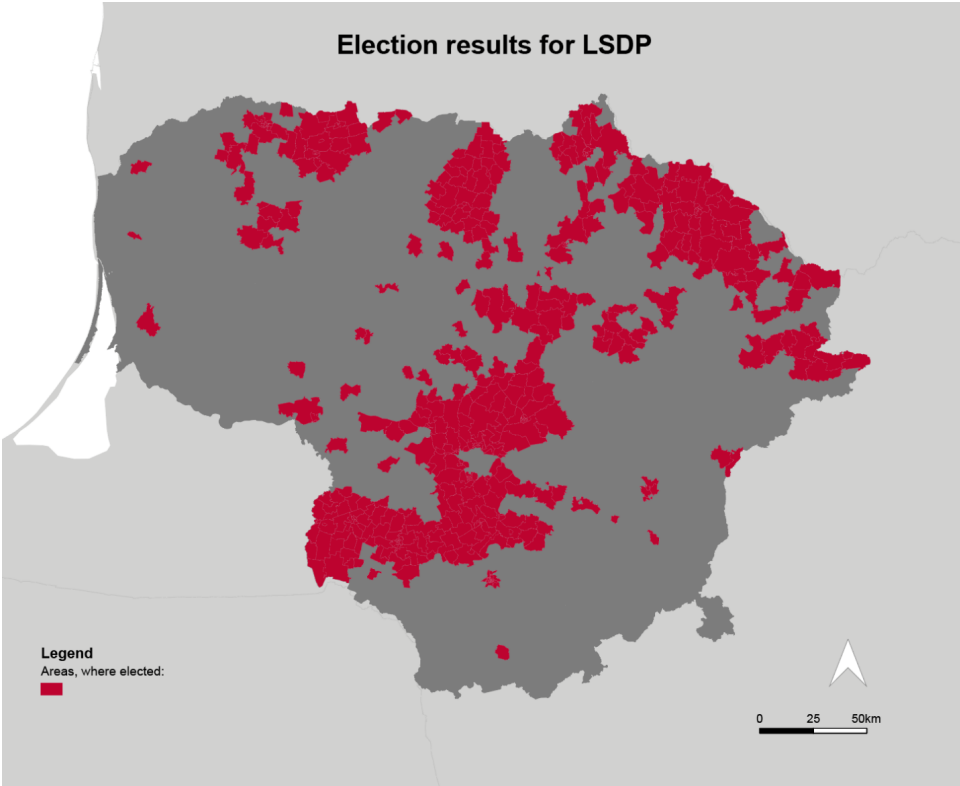


Figure 16. Actual election results for LSDP

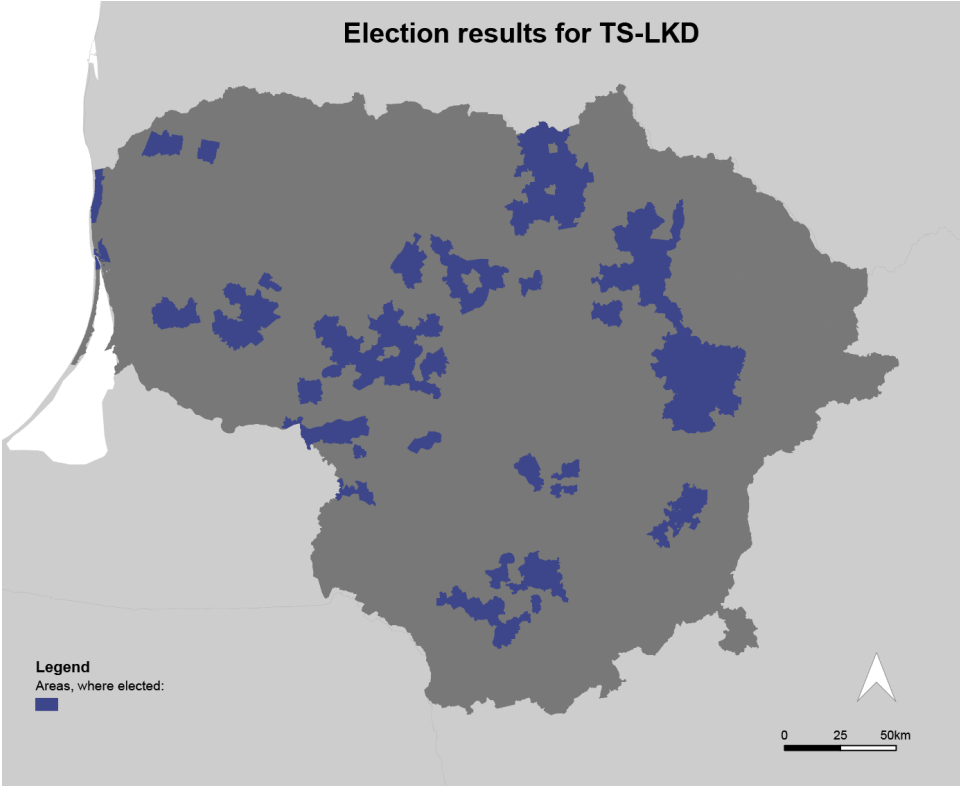


Figure 17. Actual election results for TS-LKD

8.5 Political parties' abbreviations

Table 7. Lithuania's Political parties' abbreviations (2023 March Municipal election)

Political party name	Abbreviation
Politinis komitetas „Vardan Šilalės krašto“	KOM-VŠK
Partija „Laisvė ir teisingumas“	PLT
Demokratų sąjunga „Vardan Lietuvos“	DSVL
Politinis komitetas „Atsinaujinančiam Panevėžiui“	KOM-AP
Politinis komitetas Ištikimi Klaipėdai	KOM-IK
Lietuvos valstiečių ir žaliųjų sąjunga	LVŽS
Politinis komitetas „Kartu už Utenos kraštą“	KOM-KUUK
Lietuvos lenkų rinkimų akcija-Krikščioniškų šeimų sąjunga	LLRA-KŠS
Lietuvos socialdemokratų partija	LSDP
Vieningas Kaunas	KOM-VK
Lietuvos regionų partija	LRP
Liberalų sąjūdis	LRLS
Laisvės partija	LP
Tėvynės sąjunga-Lietuvos krikščionys demokratai	TS-LKD
Politinis komitetas „Jaunoji Kazlų Rūda“	KOM-JKR
Politinis komitetas „Drauge su Jumis“	KOM-DSJ
Politinis komitetas Nepartinis sąrašas „Dirbame miestui“	KOM-DM
Politinis komitetas „Už Druskininkus“	KOM-UD
Politinis komitetas Kretingos kraštas	KOM-KK
Darbo partija	DP
Išsikėlę patys	PATYS
Šilalės centristai	KOM-ŠC
Tautos ir teisingumo sąjunga (centristai, tautininkai)	TTS
Biržų atgimimas	KOM-BA
Krikščionių sąjunga	KS
Lietuvos žaliųjų partija	LŽP
Politinis komitetas „Siekime kartu“	KOM-SK
Politinis komitetas „Naujas startas Vilkaviškio kraštui“	KOM-NSVK

Politinis komitetas „Stipri Utena“	KOM-SU
Žemaičių partija	ŽP

8.6 Additional charts

8.6.1 Covid-19 vaccination timeline

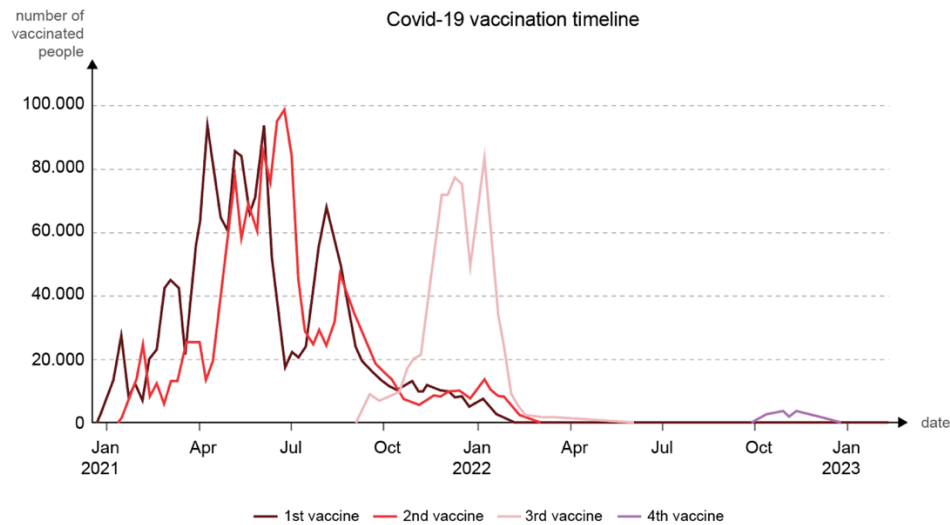


Figure 18. Vaccination timeline shows that the 4th vaccination appears to be too irrelevant to consider. It is visually obvious that the 2nd vaccination pattern follows the 1st vaccination, with the 3rd vaccination being less popular. Data: Lithuania's Data Agency

8.6.2 Covid-19 infection timeline

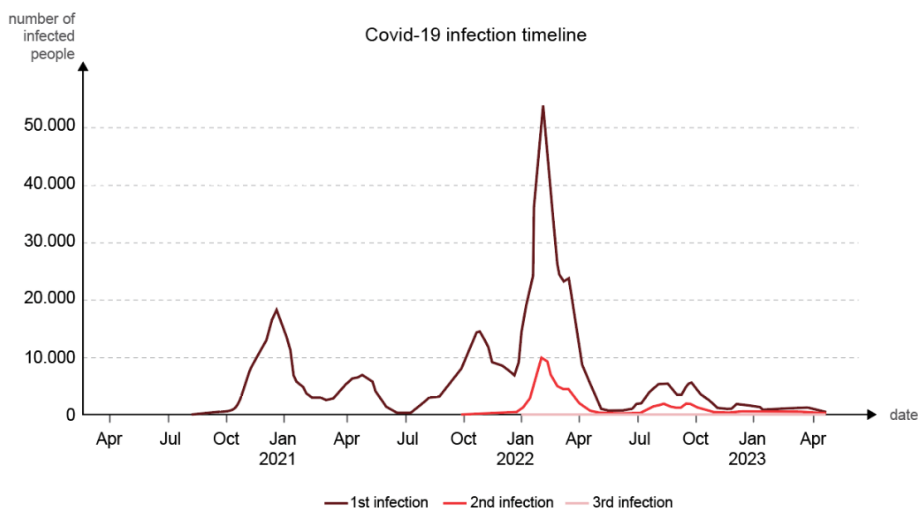


Figure 19. Infections timeline revealed that from the 3rd infection volumes become irrelevant for the research, since the highest peaks are for the 1st time and the 2nd time infections. Data: Lithuania's Data Agency

8.6.3 Volume of people that voted within each education category

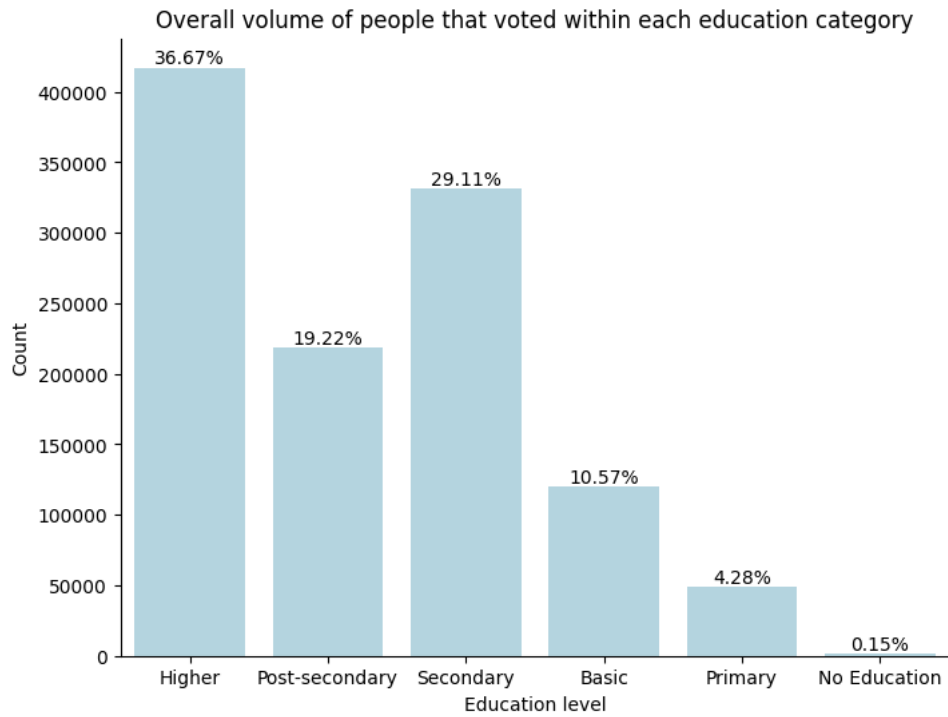


Figure 20. Volume of people that voted in each education category reveals that primary and no education categories are the minority in population

8.6.4 Early infected and vaccinated people between voters with the GP

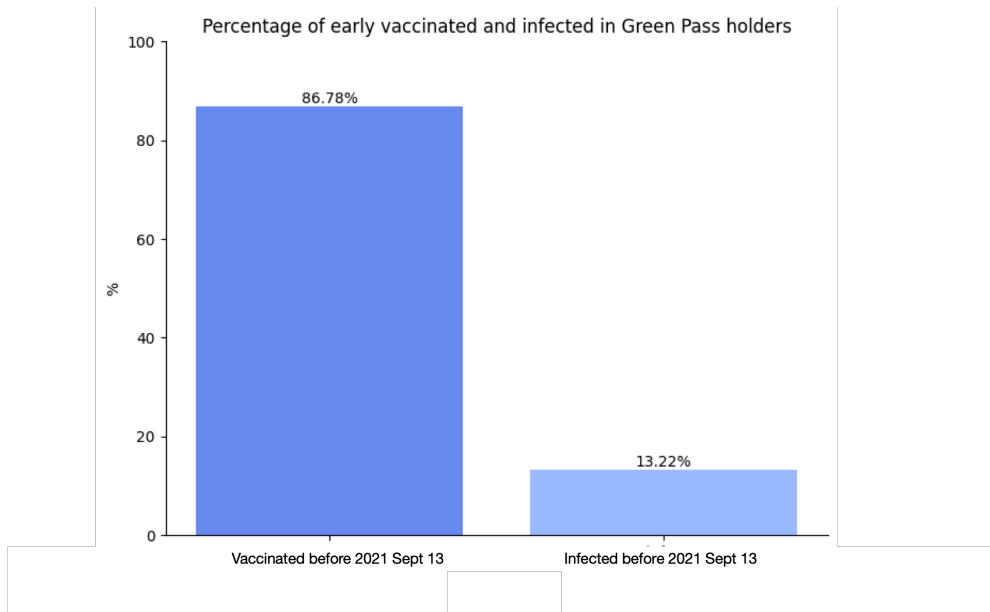


Figure 21. Percentages of early infected and vaccinated people between voters with the Green Pass

8.7 Variables distribution analysis

The distribution of variables had to be inspected in order to select the best method for data analysis. To do so it was decided to both visually inspect and run through Shapiro-Wilk statistical test (code below) on the people, that voted and have GP variable. The Shapiro-Wilk test returns a p-value, and if the p-value is greater than 0.05 it suggests that the data follows a normal distribution. In this case, p-value is $1.29e^{-40}$, meaning that the data does not follow a normal distribution. The test was run (and confirmed the non-normal distribution) for all variables, but it was decided to visually represent only the main research variable (Figure 22).

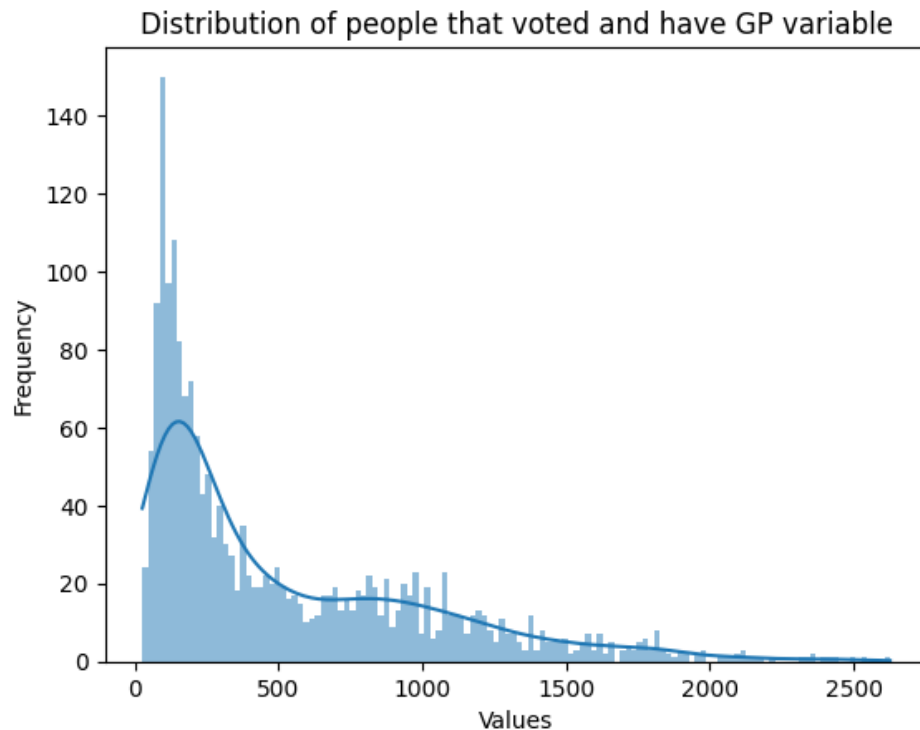


Figure 22. The distribution of people, that voted and have GP variable confirmed its non-normal distribution.

The code used to inspect Shapiro-Wilk test and create histogram:

```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from scipy.stats import spearmanr, shapiro, anderson
import numpy as np

from google.colab import drive
drive.mount('/content/drive')

file_path = '/content/drive/MyDrive/Colab
Notebooks/wards_results_vacc.csv'
```



```

df = pd.read_csv(file_path)

stat, p_value = shapiro(df['V_gpass'])
print(f'Shapiro-Wilk Test - Statistic: {stat}, p-value: {p_value}')
if p_value > 0.05:
    print('Data appears to be normally distributed based on Shapiro-Wilk
test.')
else:
    print('Data does not appear to be normally distributed based on
Shapiro-Wilk test.')
sns.histplot(df['V_gpass'], kde=True, edgecolor='none', binwidth=20)
plt.title('Distribution of people that voted and have GP variable')
plt.xlabel('Values')
plt.ylabel('Frequency')
plt.show()

```

8.8 Spearman Rank code

The code used to create Spearman rank correlation matrix:

```

import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from scipy.stats import spearmanr
import numpy as np
from google.colab import drive
drive.mount('/content/drive')
file_path = '/content/drive/MyDrive/Colab
Notebooks/wards_results_vacc.csv'
df = pd.read_csv(file_path)
df = df.rename(columns={
    'V_gpass': 'Green Pass',
    'VRK_turn': 'Voting Turnout',
    'V_edu_1': 'Higher',
    'V_edu_2': 'Post-secondary',
    'V_edu_3': 'Secondary',
    'V_edu_4': 'Basic',
    'V_edu_5': 'Primary',
    'V_edu_10': 'No Education',
    'V_vac_not': 'Not vaccinated',
    'V_vac_pre': 'Early vaccinated',
    'V_vac_post': 'Late vaccinated',
    'V_num' : 'Number of voters'

```

```

}))
selected_columns = ['Early vaccinated', 'Late vaccinated', 'Not
vaccinated', 'Higher', 'Post-secondary', 'Secondary', 'Basic', 'Primary',
'No Education', 'Number of voters', 'Voting Turnout' ]

selected_df = df[selected_columns]
spearman_matrix, pval_matrix = spearmanr(selected_df)
spearman_matrix_subset = spearman_matrix[:3, 3:11]
pval_matrix_subset = pval_matrix[:3, 3:11]
print("\nSpearman Rank Correlation Matrix (selected variables):")
print(spearman_matrix_subset)
print("\nP-values Matrix:")
print(pval_matrix_subset)
plt.figure(figsize=(10, 4))
sns.heatmap(spearman_matrix_subset, annot=True, cmap='Reds', fmt='.2f',
linewidths=.5, cbar_kws={'label': 'Correlation'})
plt.title('Spearman Rank Correlation Matrix')
plt.xticks(np.arange(len(selected_columns[3:11])) + 0.5,
selected_columns[3:11], rotation=45)
plt.yticks(np.arange(3) + 0.5, ['Early vaccinated', 'Late vaccinated', 'Not
vaccinated'], rotation=0)
plt.xlabel('Variables of interest')
plt.ylabel('Voter vaccination status')
plt.show()
plt.figure(figsize=(10, 4))
sns.heatmap(pval_matrix_subset, annot=True, cmap='Reds', fmt='.2f',
linewidths=.5, cbar_kws={'label': 'P-value'})
plt.title('P-values Matrix')
plt.xticks(np.arange(len(selected_columns[3:11])) + 0.5,
selected_columns[3:11], rotation=45)
plt.yticks(np.arange(3) + 0.5, ['Early vaccinated', 'Late vaccinated', 'Not
vaccinated'], rotation=0)
plt.xlabel('Variables of interest')
plt.ylabel('Voter vaccination status')
plt.show()

```

8.9 Spearman Rank for more variables

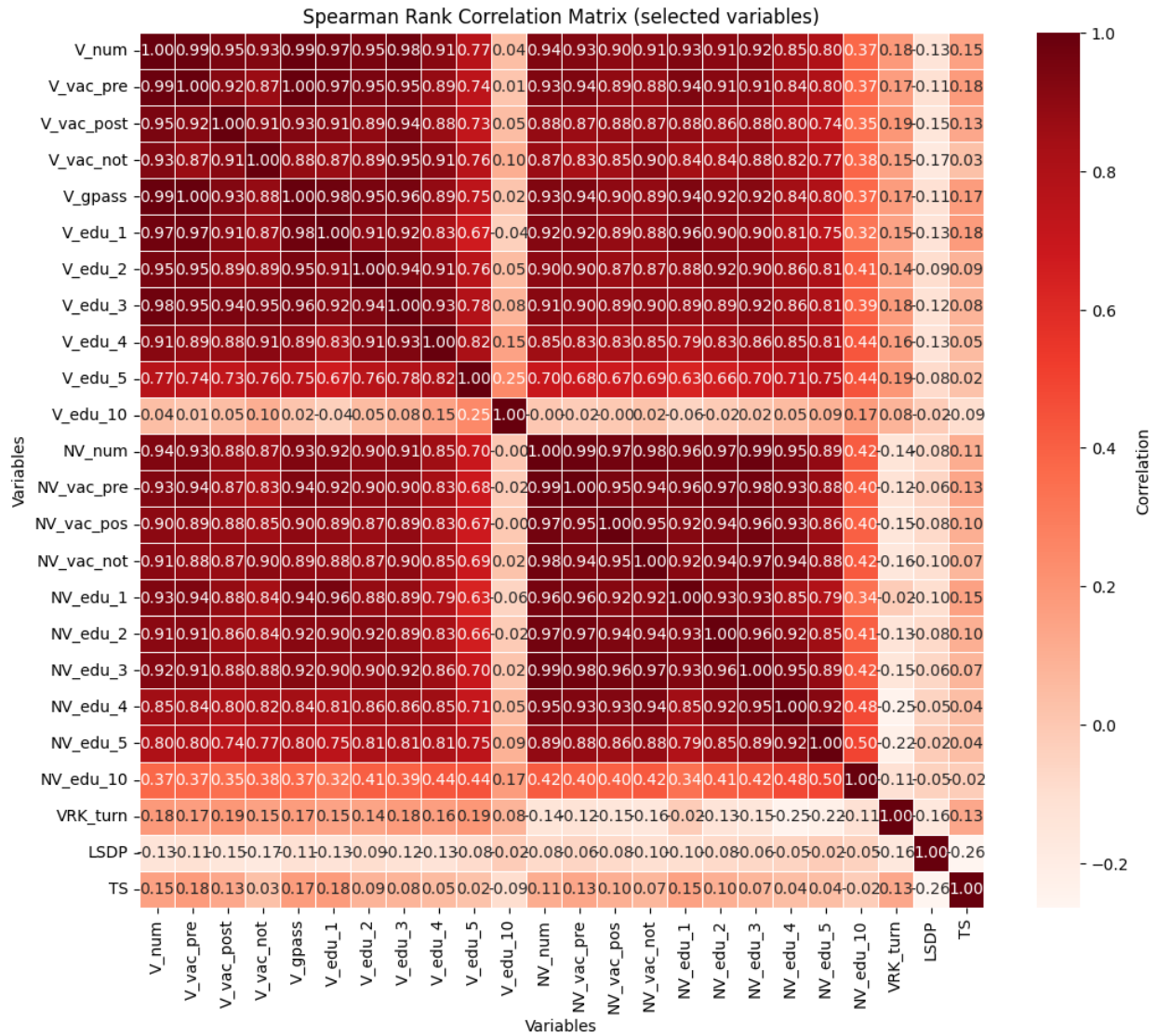


Figure 23. Spearman Rank correlation Matrix for extended list of variables

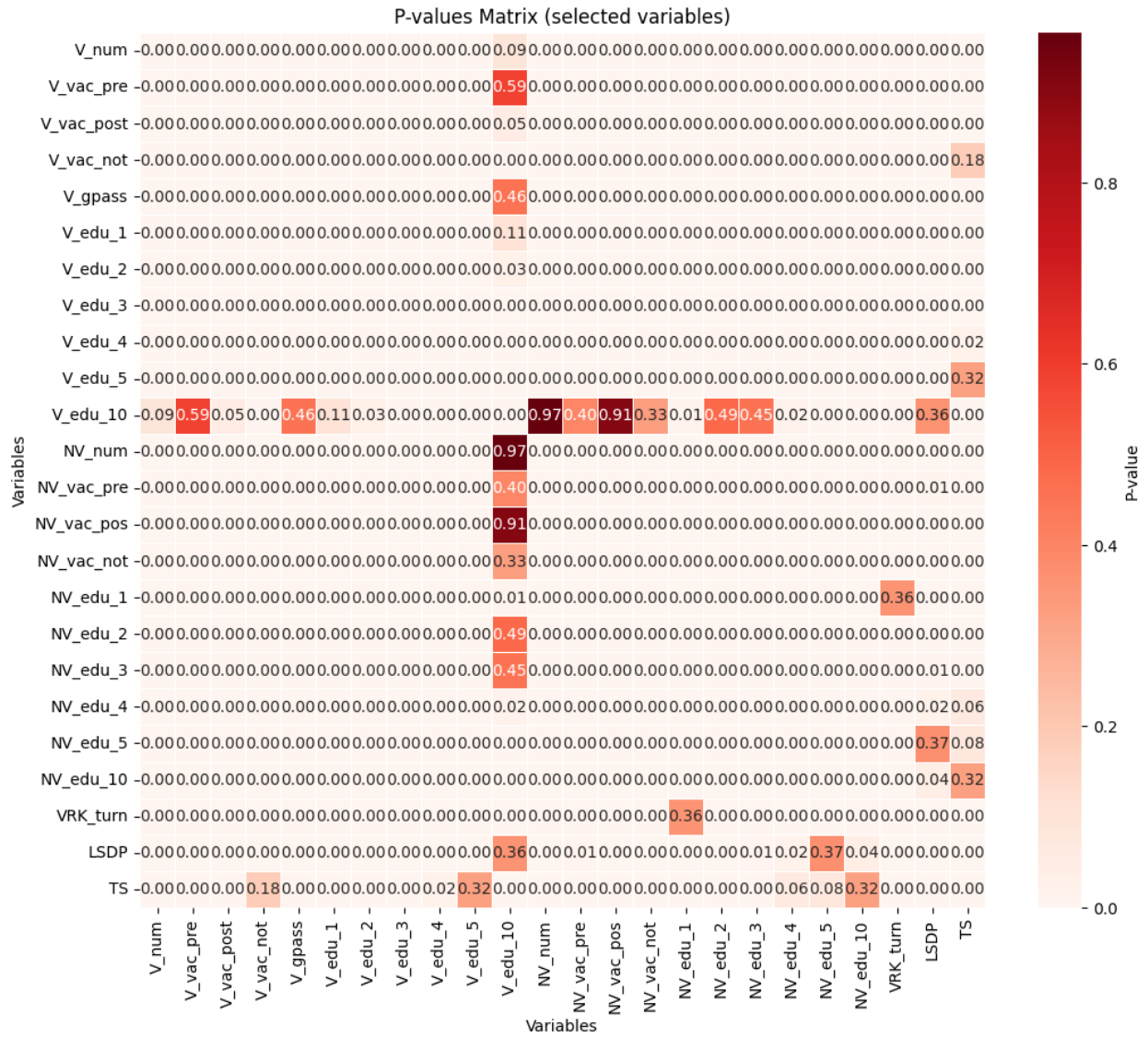


Figure 24. Spearman Rank P-values Matrix for extended list of variables

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