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FACULTY OF SOCIAL SCIENCES
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The geography of the populist vote in Slovakia

Diploma thesis

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Declaration of Authorship

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Prague, May 2, 2023

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Abstract

The success of populist political parties depends on a complex system of factors that influence the voters. Researchers connect the phenomenon to several socio-demographic characteristics such as age, income, or education. It is insufficient to only study individuals and predict their decisions based on the metrics we know about them and the place they live in. It is also beneficial to examine the regions' influence on each other. This is why we turn not only to OLS, but also to multiple spatial models with various demographic and economic variables at the county and municipality levels to explain support for populist parties in Slovakia. Data from the two most recent parliamentary elections, in years 2016 and 2020, are analyzed and we zoom on local election results of two Slovak populist parties: SMER and ĽSNS. Analysis results point towards existence of significant spillover effects among Slovak regions - directly in support for both parties, as well as coming from observed and unobserved vote share determinants.

Keywords populism, populist political parties, spatial analysis, spatial models, vote share, Slovakia

Title The geography of the populist vote in Slovakia

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Abstrakt

Úspech populistických politických strán závisí od zložitého systému faktorov, ktoré ovplyvňujú voličov. Výskumníci spájajú fenomén s niekoľkými sociodemografickými charakteristikami, ako je vek, príjem alebo vzdelanie. Nestačí len skúmať jednotlivcov a predpovedať ich rozhodnutia na základe metrík, ktoré o nich a o mieste ich žitia vieme. Je tiež dôležité skúmať vzájomné pôsobenie regiónov. Preto sa obraciame nielen na OLS, ale aj na viaceré priestorové modely s rôznymi demografickými a ekonomickými premennými na úrovni krajov a obcí, aby sme vysvetlili podporu populistickým stranám na Slovensku. Analyzujeme dáta z posledných dvoch parlamentných volieb v rokoch 2016 a 2020 a priblížime výsledky komunálnych volieb dvoch slovenských populistických strán: SMER a ĽSNS. Výsledky analýzy poukazujú na existenciu významných prelievacích efektov medzi slovenskými regiónmi – priamo na podporu oboch strán, ako aj z pozorovaných a nepozorovaných determinantov podielu hlasov.

Klíčová slova populizmus, populistické politické strany, priestorová analýza, priestorové modely, volebný podiel, Slovensko

Název práce Geografia populistickej voľby na Slovensku

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Acronyms

AIC Akaike Information Criteria

HZDS People's Party - Movement for a Democratic Slovakia

LISA Local Indicators of Spatial Association

LM Lagrange Multiplier Tests

ĽSNS People's Party - Our Slovakia

MLR Multiple Linear Regression

OLS Ordinary Least Squares

SAC Spatial Autocorrelation model

SDM Spatial Durbin model

SDEM Spatial Durbin Error model

SEM Spatial Error model

SLM Spatial Lag model

SLX Spatial Lagged X model

SMER Smer - Social Democracy

SNS Slovak national party

VIF Variance Inflation Factor

Master's Thesis Proposal

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Proposed topic	The geography of the populist vote in Slovakia

Motivation Populist parties are trying to obtain a greater vote share of ordinary people by telling what they want to hear and by promising what they desire. Even though populism gained a lot of attention after Donald Trump´s election, it has been an issue since the 19th century. Research suggests that certain factors contribute to the higher success of populist political parties. As Rodriguez-Pose (2018) suggests, populist politicians are successful in places with periods of declining agricultural productivity, crises in the industrial sectors, brain drain or even thoughts about a hopeless future. In this kind of environment, they gain a lot of power. In Slovakia, there are significant differences among regions in terms of economic and industrial development. These factors influence the support of populism. Klamár (2018) focuses specifically on Slovakia, on the country as a whole and also on regional disparities. He monitors various fields (e.g., economic structure, labour market, technical and social infrastructure) and concludes that regions in the west of Slovakia are significantly better off than the regions in the east. Even though the research was written in 2006, the author predicts that these differences will deepen in the future. Rijevova and Klimko (2016) obtain similar results by analyzing regional differences in the labour market in Slovakia. The differences are exacerbated by foreign investments focused on the western regions, weak infrastructure in the eastern and southern regions and their insufficient connections with the capital. My bachelor thesis, defended in 2021, focuses on exploring voting patterns in Slovak counties. The OLS analysis reveals that counties with lower average wages and higher unemployment were more likely to support populist political parties, whereas counties with a higher share of the Hungarian minorities are voting for different political parties. These results point towards strong regional disparities within Slovakia. The empirical analysis conducted in my bachelor thesis assumes that individual counties are independent of each other and ignores relationships between them. However, neighbouring regions share difficulties, and these connections cannot be ignored. Therefore, the OLS model might not be sufficient enough for such analysis, and it requires spatial econometrics. Therefore, in my master's thesis, I would like to focus on the characteristics of Slovak counties and the connections between them in relation to the support of two populist political parties, SMER-SD and ĽSNS, obtained in the parliamentary elections of 2016 and 2020. Moreover, I would like to see how the demographic and socio-economic characteristics of one county affect the neighbouring counties. Additional value added to the master's thesis is the use of the new census (2021) data allowing for the inclusion of the most up-to-date regional characteristics in the analysis.

Hypotheses: Maps of electoral results from 2016 and 2020 reveal that neighbouring districts share similar patterns of voting for populist political parties and the counties with the highest vote share given to such parties are clustered. What is driving these patterns? Is this because these districts are so similar or is it because in one of these districts the characteristics have spillover effects?

1. Hypothesis 1: Big towns have spillover effects on neighbouring regions, in other words voting results in counties located close to big towns are affected by these big towns' characteristics.
2. Hypothesis 2: Support for populist political parties is clustered due to the similarity of demographic and economic characteristics of neighbouring counties.
3. Hypothesis 3: Education structure is one of the most important county characteristics affecting election results.
4. Hypothesis 4: The relationships from previous hypotheses are stable over time.

Methodology I will analyze voting results of the two populist political parties SMER-SD and ĽSNS in the two most recent parliamentary elections in Slovakia, taking place in March 2016 and February 2020. I will use the census data of 2011 to relate regional characteristics to voting results in 2016 and the new census data of 2021 to relate regional characteristics to voting results in 2020. Additionally, there will be municipal elections taking place in October 2022, which I might consider in the analysis as well. As the baseline, I will perform an OLS analysis, that will indicate which economic or demographic characteristics of Slovak counties are influential on the vote share given to these parties. Additionally, I will analyze a first-differencing model to examine how differences in regional development affect changes in political support. As I focus on examining individual variables influencing the electoral decision of voters in favour of populists, I want to explain the regional variations of electoral behavior. The aim is to reveal the influence of spatial phenomena as well as spatial autocorrelation of election results. For that reason, I will work with models specially designed for spatial data. I will detect spatial autocorrelation using the Moran´s I statistic, which is used as an indicator of spatial clusters/space dependence (Florino, 2016). Working with spatially clustered data creates a high possibility of the existence of error autocorrelation, therefore we can solve the issue by the usage of models that have the ability to control for spatial effects (Kouba, 2007). Regarding spatial econometrics there are usually two types of models used in the related literature: the spatial interval model and the spatial error model. These methods use residual spatial correlation assumption in the regression model. However, while the interval model uses the spatial effects of the dependent variable directly as another independent variable, the error model uses the spatial autoregressive process in the residuals (Kouba, 2007). Since I assume a connection between the individual counties, I expect existence of autocorrelated errors among them. In this thesis, I will rely on the usage of the spatial error model. Furthermore, I will compare the results of the baseline model with the spatial error model. I predict that results of the spatial model will reveal that fluctuations in one county will affect other counties in the choice of voting for populist political parties. This analysis enriched by spatial econometrics might be very helpful in exploring additional voting patterns in Slovakia.

Expected Contribution This thesis will be an extension of the bachelor thesis defended at IES in 2021. I will use more sophisticated and adequate tools of spatial econometrics. It is supposed to refine the results of the OLS analysis, which has the aforementioned shortcoming of ignoring the connections between neighbouring counties. The spatial analysis enables me to examine these links. I aim to discover the effect of characteristics of a county to adjacent counties. For example, whether a strong minority in a specific county influences also voting sentiment of people living in neighbouring counties, eventually how far this influence reaches. Similarly, in case of an economically important cities, I would like to examine whether there is a spillover effect on the whole region. In my bachelor thesis, I used two sources of data: yearly data coming from sample surveys and data from the 2011 census (minorities, religion). The yearly survey data does not provide information on the demographic structure of population on county-level. Data coming from the census covers the whole Slovak population and provides detailed information about population structure at county-level. However, at the time of writing my bachelor thesis the newest census was ten years old. Therefore, I could not use all of the suitable regional characteristics, such as education structure of local population, as they were rendered unusable due to their rapid development over the years. Since there was only one relevant census for both elections, I used the same data in analysis of both, 2016 and 2020 populist parties vote share. For that reason, the OLS results could be inaccurate. Furthermore, I could not use the census data in First-Differencing at all, I performed the analysis by using the yearly data. The new census taking place after 10 years, in 2021, allows me to analyze potential new determinants of support for populism and update the already used ones. I expect more accurate results of econometric analyses. Additionally, to the best of my knowledge, the new census data have not yet been analyzed in the context to 30.6.2022.

Outline

1. Introduction
2. Literature review
3. Advantages of spatial econometrics
4. Methodology
5. Data
6. Results
7. Conclusion

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Author

Supervisor

Chapter 1

Introduction

Democracy gives ordinary people the power to decide who will lead their country. The power, however, comes with a responsibility to choose the leaders or parties that will support the voters' interests and align with their ideas. Many people take the hard road - they study and evaluate the party programs, check facts, and learn about the politicians' history to make the best possible decision. Others rely only on their feelings or the information they effortlessly receive from the media, banners in public transport, friends or family. This phenomenon allows for gaining political support by encouraging hatred or fear, making impossible commitments, and spreading half-truths or lies. It can give hope to people in need, create common enemies or discredit opponents or authorities. Such tools are widely used by populists, a type of politicians that promote themselves as aligned with ordinary people and promise to fight for them against enemies or elites who either do not care about them or outright want to harm or control them.

In this thesis, we ask why populist parties succeed in some regions while losing in others. What makes it easier for populism to thrive, and why do certain parties succeed in some regions while losing in others? We try to answer these questions in the context of the political scene in Slovakia. As a post-communist country with huge disparities between regions and turbulent political development in recent years, it provides a appropriate dataset for our research. First, we identify which regional socio-demographic characteristics predict support for populist countries. Research suggests that age, income and education have high explanatory power - Dijkstra et al. (2019) coin the term "holy trinity" for them.

Similar results are confirmed by the research of Dusková (2021) but using a limited dataset available at that time. The work can be improved by incorporating inter-regional relationships. People often travel from one city to another to work or meet relatives, sharing their worldviews and influencing each other's political preferences. Universities or large companies shape not only their county but also adjacent counties. Clusters of counties sharing similar issues like lack of work opportunities or underdeveloped infrastructure can magnify the sentiment. We believe in the importance of considering spatial relationships when analysing data with a geographical component.

"Everything is related to everything else, but near things are more related than distant things." – Tobler (1970)

Kim et al. (2003) suggest that using spatial data and geographical connections knowledge can be helpful in better understanding election results. We study three types of spatial effects on the observed variable - the effect of the other counties' independent variables, election outcome and the effect of unobservables.

We analyse two Slovak parliamentary elections in 2016 and 2020 to examine the stability of the support over time. To investigate the phenomenon, we use the regional data from election years and conduct a spatial analysis to reveal direct and indirect relationships between examined variables. The most widely used models are spatial error and spatial lag models; however, the analysis reveals the importance of using multi-factor spatial models, specifically the Spatial Durbin and Spatial Autocorrelation models. Results confirm spatial spillovers in the vote share, various independent variables and errors, which underscores the importance of measuring spatial interactions.

The thesis is structured as follows: Chapter 2 presents the political situation in Slovakia since its beginning, focusing on the last two parliament elections. Chapter 3 explains the definition of worldwide and Slovak populism and its characteristics. In Chapter 4, we present the worldview of Slovak citizens from two international surveys. Further, Chapter 5 describes the voting geography and usage of spatial analysis. Chapter 6 is devoted to the data description used in our empirical analysis. Chapter 7 explains the theory behind a variety of spatial models. We discuss the results in Chapter 8. The last chapter Chapter 9 provides the findings of the thesis.

Chapter 2

The political situation in Slovakia

The aim of this chapter is to give a comprehensive understanding of the political situation in Slovakia. The study focuses on the historical backdrop of parliamentary elections and political parties to achieve this objective. Additionally, the chapter delves into the contemporary political atmosphere prevailing in the country.

2.1 The history

Slovakia was part of several state groupings in Central Europe, and its history is closely connected to the political and territorial changes in the area and shares political sentiments with surrounding coutries to this day. The history of Czechoslovakia began after the disintegration of the Austro-Hungarian Empire. Between 1948 and 1989, the state was communist until Czechoslovak citizens suppressed communism in the Velvet Revolution, and democracy substituted the previous regime. Subsequently, in 1993, Czechoslovakia peacefully disintegrated, and two independent states were created, namely the Slovak Republic and the Czech Republic. Slovakia afterwards joined the European Union and NATO in 2004. Slovakia became part of the Eurozone in 2009. However, as Mesežnikov and Gyárfášová (2018) explain, "Yet since its split from the Czech Republic in the 1993 Velvet Revolution, Slovakia has been—and remains—an arena of sharp political competition between advocates of liberal-democratic values and those who prefer illiberal and authoritarian approaches." Despite having representative parliamentary democracy with a multiparty system, there were two types of parliamentary parties. The first group was trying to make Slovakia a full-fledged European country, a liberal democracy with a direction to the West. On the other side was a group of political parties with authoritarian leaders using populism to achieve their goals [Gyárfášová and Mesežnikov, 2018].

During the period from 1992 to 1998, the Slovak Republic was governed by the Movement for a Democratic Slovakia (HZDS), led by Vladimír Mečiar. This period, referred to as "Meciarism," is notable for several reasons, including the privatisation of state property at below-market prices to individuals closely connected to HZDS party members. Such actions resulted in the bankruptcy of many of these enterprises due to the incompetence of new owners and financial mismanagement [Cigáňová, 2007] . The Mečiar administration was also marked by several conflicts, including a dispute between Mečiar and President Michal Kováč, which was followed by the kidnapping of the president's son and the death of police officer Robert Remiáš in a car bombing. Mečiar infamously stated, "The act did not happen" in reference to these events. Additionally, Mečiar issued amnesties that halted criminal prosecution in connection to the kidnapping and murder. Despite winning the subsequent elections in 1998 and 2002, the HZDS could not form a ruling coalition.

The era of democratic parties followed when a coalition of SDK (Party of Democratic Coalition), SOP (Party of Civic Understanding), SMK (Party of the Hungarian Coalition) and SDĽ (Party of Democratic Left) was formed. Their government purpose aimed to get Slovakia into the EU and NATO, which was finally achieved in 2004. In the 2006 elections, the Direction - Social Democracy (SMER-SD) party emerged as the winner. The first government of Róbert Fico began. Despite criticising Mečiar, Fico formed the first coalition with the HZDS and the Slovak National Party (SNS). SMER won the subsequent elections in 2010 but was unable to form a coalition, leading to the SDKÚ-DS (previously SDK) party taking the lead with three other parties. This coalition failed to govern for the full electoral period and disintegrated due to disagreement over supporting European Financial Stability.

In the 2012 parliamentary elections, SMER obtained 44.4% of the votes. The massive triumph gave them a majority in the parliament and enabled them to form a ruling coalition on their own. It is worth mentioning that the far-right political party, ĽSNS (People's Party - Our Slovakia), was established before these elections in 2010.

2.2 The last two parliamentary elections

In 2016, SMER emerged victorious in the elections for the fourth consecutive time, with Róbert Fico as its leader. A total of eight parties obtained the mandatory 5% of the vote to be represented in government (as indicated in Table 2.1). The ĽSNS party obtained the first seats in the parliament. SMER formed a ruling coalition with three other parties. However, in late February of 2018, Ján Kuciak, an investigative journalist focused on exposing corruption within the state, and his fiancée Martina Kušnírová were shot and killed at their home. This murder shook society. The attack on democracy and its principles triggered the biggest protests in Slovakia since 1989. At that time, the demonstrators demanded the resignation of Prime Minister Robert Fico as well as Minister of the Interior Robert Kaliňák. After the murder, party preferences dropped significantly, as did citizens' trust in the state. Subsequently, the Minister of Culture, the Minister of the Interior, the next Minister of the Interior, and the Chief of Police resigned, as well as Robert Fico resigned from the post of Prime Minister. These events deeply disturbed Slovakia and the election was won by the anti-corruption movement OĽANO, while SMER was the second most popular party in the election, going into opposition. A total of six parties obtained the mandatory 5% of the vote to be represented in government, displayed in Table 2.1. Even though SMER is in the opposition, it remains a highly visible party due to its vocal criticism of the government and calls for early elections. In January 2023, the party initiated a referendum on shortening the current electoral term in conjunction with other opposition parties. The referendum did not achieve its desired outcome as voter turnout was low, with only 27.24% of eligible voters participating.

Table 2.1: Results of the 2016 and 2020 Slovak parliamentary elections

Party	**2016 Vote Share (%)**	**2020 Vote Share (%)**
SMER	28.28	18.29
SAS	12.10	6.22
OĽANO	11.02	25.02
SNS	8.64	-
ĽSNS	8.04	7.97
SME RODINA	6.62	8.24
MOST-HID	6.50	-
SIEŤ	5.60	-
Za Ľudí	-	5.77

Chapter 3

Populism

Nowadays, society has been facing an increasing amount of influential topics in daily lives, such as the refugee and migrant crisis, climate change, the COVID-19 pandemic and vaccination efforts, as well as the Russian invasion of Ukraine. Besides, more people have access to media and social networks than ever before, making that huge amount of information available to individuals. However, the quantity of information can make it challenging for individuals as they might face problems verifying the accuracy of certain news and facts, which politicians can leverage. These politicians, referred to as populists, often appeal to popular sentiments by making promises that align with the desires of their target audience, consequently gaining significant support and achieving their political objectives.

3.1 Leaders and followers

Leaders of populist political parties are often considered charismatic due to their tendency to make personal and radical decisions [Pappas, 2016]. Their communication style is typically direct and aimed at appealing to the general public. To be effective, these leaders must be perceived as relatable and capable of protecting voters and giving them hope. Building a connection between the leader and followers is considered crucial [Albertazzi and McDonnell, 2008]. Populists often position themselves as the defenders of the "ordinary people" against perceived enemies such as "financial tycoons, intellectuals, and journalists" [Pasquino, 2008], as these groups are not seen as being part of the general population.

Despite their criticism of the media, populist leaders rely on media attention to make themselves visible and attract mass support. They often benefit from the media's preference for sensational stories over mundane speeches and bureaucratic explanations [Mazzoleni, 2008]. Charismatic populist leaders often tap into people's fears by attacking marginalised groups such as national minorities, the LGBTI community, or migrants during their impassioned speeches. Therefore, an important question is who is more likely to vote for populist parties and in which regions they tend to be more successful.

Populist parties tend to enjoy the greatest support among men, the older population, and people living in majority-population areas. The so-called "holy trinity" of age, income and education are considered the three most important variables when analysing populist voter demographics [Dijkstra et al., 2019]. Education is also important, with less educated individuals more likely to trust populists. Populist voters are often unemployed or manual workers, farmers, or owners of small family businesses [Mastropaolo, 2008]. Algan et al. (2017) also suggest a direct correlation between voting for anti-establishment parties and unemployment.

In Rodrigues-Pose (2018) analysis, regions grappling with economic and social issues, often labelled as "places that do not matter," have shown a higher likelihood of success for populist political groups. The 2016 US presidential election is a notable example, where Donald Trump emerged victorious in states like Ohio, Iowa, and Wisconsin, which were facing a decline in their manufacturing industries. Notably, urban areas with high populations, like Columbus, Des Moines, and Milwaukee within those states tended to favour the opposing candidate, Hillary Clinton. Similarly, in France, Marine le Pen did not gain significant support in large cities but rather in industrial regions such as Picardie, France-Comté, and Champagne-Ardenne, which are facing economic decline. This trend highlights the correlation between populist movements and areas experiencing economic and social challenges [Poes, 2018].

3.2 Populism and COVID-19

The COVID-19 pandemic has not only had a significant impact on public health but also led to the expansion of misinformation and conspiracy theories. Populist political parties have frequently taken advantage of fabricated accounts, resulting in the propagation of disinformation like the notion that 5G networks transmit the virus, the pandemic is Bill Gates' responsibility, or that disinfectants can treat the virus [Ahmed et al., 2020; Enders et al., 2020]. The academic community has extensively studied this phenomenon, and scholars have emphasised the hazards of spreading misinformation and its effects on public health and confidence in governmental organisations.

Eberl et al. (2021) point correlation between the expansion of populist ideologies and decreased trust among citizens towards state institutions and scientific expertise. The authors attribute this phenomenon to the implementation of controversial measures by state institutions aimed at protecting citizens during the COVID-19 pandemic, which were subsequently criticised by populist political entities. Additionally, the authors note that populist leaders have frequently espoused conspiracy theories that have been at odds with scientific findings, potentially contributing to mistrust in vaccines and other scientific recommendations. Furthermore, the study highlights that populist leaders, such as Boris Johnson, Jair Bolsonaro, Donald Trump, and Nicolás Maduro, have often downplayed the severity of the COVID-19 pandemic, with the United States and Brazil being among the countries most heavily impacted by the virus. For example, Johnson suggested a quick return to everyday life. Bolsonaro considered the viral disease a media trick; Trump suggested Hydroxychloroquine treatment without scientific evidence and suggested drinking lemongrass and elderberry tea.

Despite a lack of formal education or expertise on the subject, government officials were vocal in their discourse surrounding COVID-19 and received significant media attention. It is evident that opinions on COVID-19 are tied to the voting preferences of people and whom people vote for [McKee et al., 2021].

3.3 Slovak populism

Populism has been influencing the everyday life of ordinary people in Slovakia since its beginning. Bútora et al. (2008) argue that populism has had a pervasive impact on the daily lives of individuals in Slovakia since the emergence of the first ruling party, the HZDS. The HZDS is considered an example of an authoritarian and hard populist party, positioning itself as a strongly pro-Slovak entity and heavily criticising the Party of Hungarian Community (SMK) and the Hungarian minority population as a whole. The party often blamed *"elites"* for not understanding the true needs of Slovak citizens, and it gained support from voters who were dissatisfied with the post-communist transformation of Slovakia. Initially, the HZDS's voter base was primarily composed of individuals residing in smaller towns and regions with a high concentration of religious and older populations and individuals with lower levels of education. The party was particularly successful in certain areas of Slovakia, such as the northern and eastern regions. However, support for the HZDS gradually decreased, and the party was dissolved in 2014 [Spáč, 2012].

The baton of populism was passed to left-oriented SMER. The party became dominant, building its position on citizens frustrated by the political polarisation caused by HZDS and the evolution of democracy after the communist era. It is considered a soft populist political party cooperating with national parties. Their main goal was the creation of social policy and the building of a welfare state. They focused on creating a national feeling among people or improving the relationship with the state and its symbols by defining themselves against the Hungarian and Roma minorities. SMER instilled in citizens a rosy retrospection for the period of communism when they highlighted the regime's social security. Also, the party claimed international corporations negatively influenced and ruled Slovakia [Mesežnikov, 2008]. Firstly, SMER attracted young voters living in western and central areas of Slovakia; however, afterwards, they received support from previous HZDS voters, and their voter base became older [Spáč, 2012].

The hostile environment created by SMER's rhetoric against national and ethnic minorities, as well as their blaming of elites, has enabled the rise of far-right political parties in Slovakia. One such example is the ĽSNS party, founded in 2010 and widely considered a far-right party. The ĽSNS's political platform, 'Desatoro' - Ten Commandments, prior to the 2020 elections, calls for introducing drug tests in schools, abolishing Brussels' "dictate", withdrawing from NATO and promoting traditional marriage between a man and a woman. The party has a strong anti-minority and homophobic view, targeting migrants and claiming that Slovaks are second or third-class citizens [Kluknavska, 2012]. The party is critical of other political parties, all coalition, opposition, and non-parliamentary parties. Alongside SMER, ĽSNS has been vocal in its opposition to COVID-19 measures, refusing to wear masks, opposing the closing of restaurants, schools, and churches, and considering movement restrictions as bullying. They supported anti-government protests, criticised vaccination, and distributed anti-vaccination leaflets.

Chapter 4

The worldview of Slovak citizens

The European Union periodically creates numerous surveys focused on diverse topics such as values, politics, environment or financial situation. These surveys can be utilised to exhibit that Slovak citizens might share opinions that are attractive to expanding of populist parties, as demonstrated in the previous chapter. The respondents of these surveys represent a diverse range of ages, education levels, and regions, providing a comprehensive representation of the general public opinion among Slovak citizens.

4.1 Joint EVS/WVS

A Joint study EVS/WVS, conducted by the European values study and the World values survey, researched 88 countries, including Slovakia. The fieldwork period for this study was from September 26th, 2017, to December 1st, 2017. The survey sample consisted of 1431 respondents. The study contains a great variety of fields, including social values, well-being, corruption, migration, and political culture.

The graphs displayed in the figure 4.1 below show various questions, such as the justifiability of some events, unwanted neighbours, desired child qualities, and evaluating their values and traditions. We display two bars, one for Slovakia and the other represents the EU value.

The first graph shows what characteristics the respondents would like to develop in their children. The graph shows that for Slovak respondents, the two most important characteristics of children are hard work and a sense of responsibility, while the two least important values are considered to be obedience and selflessness. As we can see, there are significant differences between

SK and the EU. As already mentioned, hard work (77%) is number one in Slovakia, whereas only 41% of EU respondents perceive the importance of quality. The second biggest difference is in tolerance for others, which is number two among EU respondents (76%); in SK, only 32% of respondents believe in its importance.

In the second set of questions, respondents were asked to identify groups of people they would not like to have as neighbours. The results show that the majority of respondents, 83%, would not want to have drug addicts as neighbours, whereas 78% would not like to have heavy drinkers as neighbours. Additionally, 39% of respondents stated that homosexuals are considered unwanted neighbours, and 30% would avoid having people of different races as neighbours. Compared to the EU value, we can see higher values of unwanted neighbours among all groups. The biggest difference is shown in foreign workers (45% vs. 22%) and people of different races (30% vs. 12%).

The third graph shows to what extent abortion, capital punishment, divorce, euthanasia, political violence, suicide and casual sex are morally acceptable to respondents. Abortion is legal in Slovakia, and the death penalty has been abolished since 1990. The survey reveals further differences between Slovakia and the EU. For respondents from the EU, abortion, divorce, euthanasia and casual sex are more justifiable than for Slovaks. Among Slovak respondents, the most justifiable are divorces and abortions, with a value slightly above the median (5).

The last set of questions focuses on the social values, attitudes, and stereotypes, which might reveal outlook among Slovak citizens. One of the most decisive opinions is that people who do not work turn lazy, which might also be connected with the most meaningful child quality - hard work. Also, people agree that work should come first, even if it means less spare time. Regarding the stereotypes, most respondents disagree that university education is more important for boys than girls; however, the value is lower in comparison to the EU value. We can see similar behaviour in the case of the question of whether men make better business executives than women. Slovak respondents are indecisive about whether men are better political leaders, while EU values show disagreement with the statement. Additionally, respondents tend to disagree that homosexual couples are as good parents as heterosexual ones. Respondents strongly agree that nation people should be prioritised over immigrants by employers, whereas EU value is somewhere in the middle.

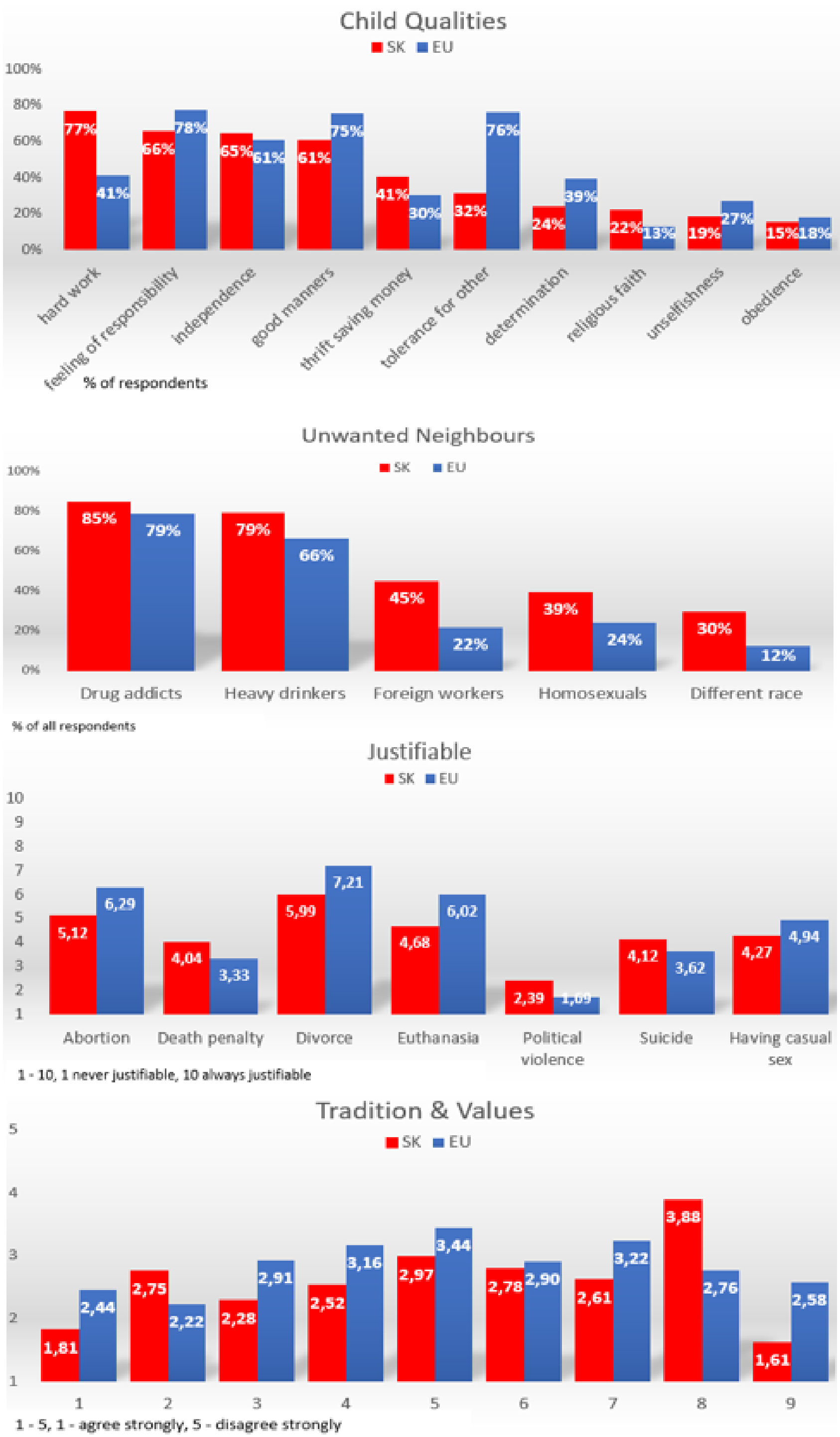

Figure 4.1: Joint EVS/WWS results

Legend:

1 - People who do not work turn lazy

2 - Duty towards society to have children
3 - Work should come first even if it means less spare time
4 - Men make better political leaders than women do
5 - University is more important for a boy than for a girl
6 - Pre-school child suffers with working mother
7 - Men make better business executives than women do
8 - Homosexual couples are as good parents as other couples
9 - Employers should give priority to (nation) people than immigrants

4.2 European Social Survey

The European Social Survey (ESS) is a cross-national research effort aimed at comprehending public attitudes and values throughout Europe. Its scope is extensive, containing subjects such as social trust in media, politics, fairness, and the timing of life. Although the survey is conducted biennially, this investigation compares two sets of data from the ESS: ESS Round 6 (gathered in 2018) and ESS Round 9 Slovakia (gathered in 2021). The sample size for ESS Round 6 is 1083 respondents, while ESS Round 9 Slovakia consists of 1847 respondents.

It is important to note that the results of ESS Round 6 may have been affected by the murder of Slovak journalist Ján Kuciak and his fianceé Martina Kušnírová. As previously mentioned, this event led to a significant decrease in citizens' trust in the state. On the other hand, the results of ESS Round 9 may have been influenced by the ongoing COVID-19 pandemic. The pandemic began when the survey was conducted, and populist parties, such as SMER and ĽSNS, had recently moved to the opposition. These parties used controversial government decisions related to the pandemic, such as restrictions and mandatory mask-wearing, to disrupt stability and gain popularity among voters. Their anti-government rhetoric may have decreased trust in governmental institutions and lowered overall satisfaction. Same as before, we compare SK and EU values. The comparison is displayed in the figure 4.2.

The first set of graphs shows trust in legal systems, the police, politicians, etc. and respondents' interest in politics. As we can see, trust values are increasing over the years, and the greatest trust is in the police, while the lowest is in politicians. All SK values are below the EU average. In the case of interest in politics, there has been an increase in value over the years, and overall this value is significantly higher than the trust values and is higher than the EU's interest in politics. It shows that although people are interested in politics, they do not trust it.

In the case of public involvement in public affairs, we see whether the respondent voted in the previous national elections and whether the respondent participated in a public demonstration in the last 12 months (1 = yes, 0 = no). Since there were restrictions on demonstrating during COVID-19 and people were forbidden to gather, most people did not participate in demonstrations. On the other hand, in 2018, there were massive protests in Slovakia, and many people participated. Higher voter turnout in the 2020 parliamentary elections is demonstrated in the graph as well.

Regarding the satisfaction of Slovaks with the government and the current state of the economy, we have seen the opposite trend over the years. While satisfaction with the economy has decreased, satisfaction with the national government is higher. These values are also relatively low, as the median value is 5. The satisfaction with the national government is even lower on the EU level.

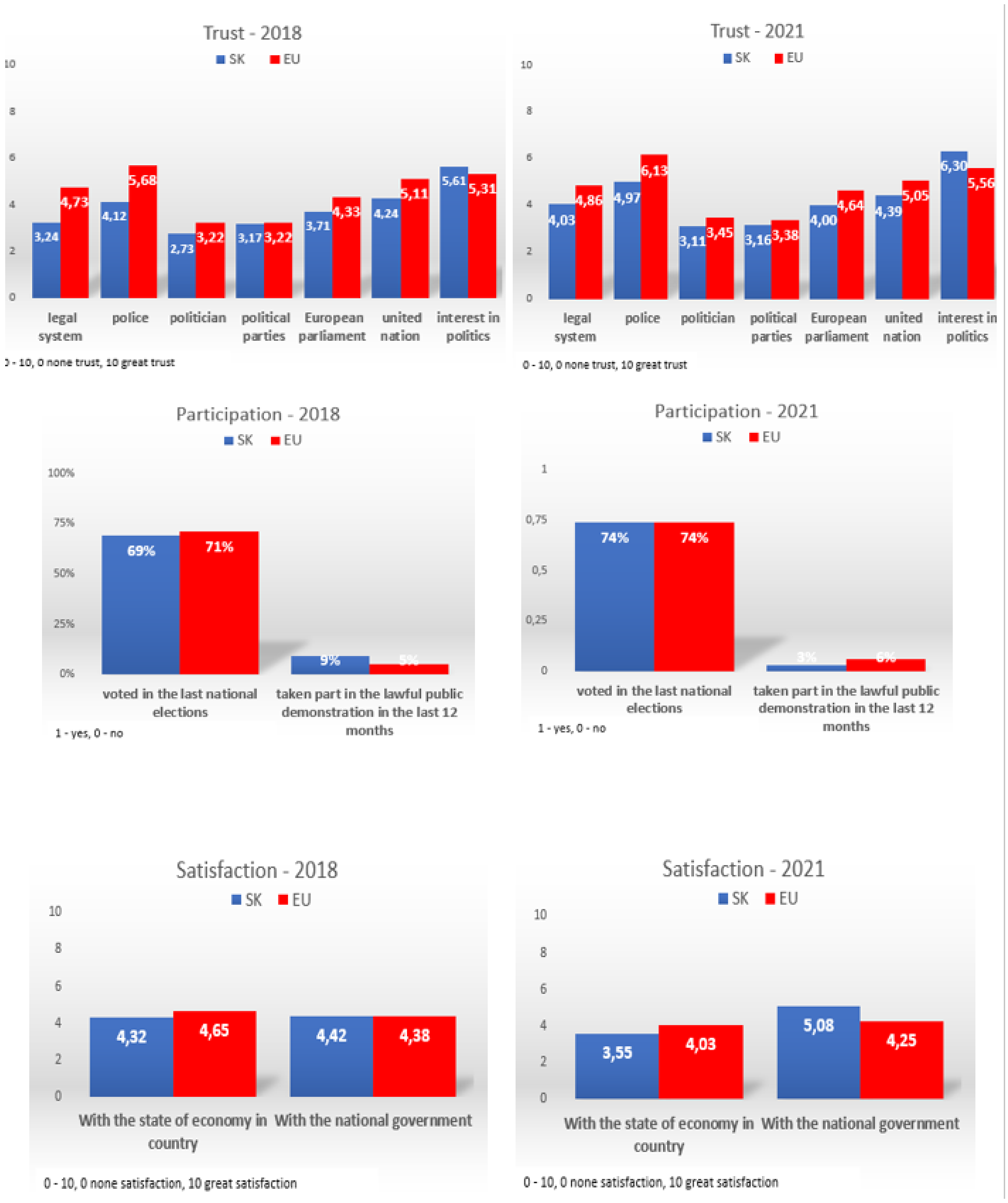

Figure 4.2: European Social Survey results

To conclude, surveys indicate that Slovak respondents have a lower level of trust in political and governmental institutions; they maintain traditional views on gender roles and refuse the unknown such as homosexuals and immigrants. This makes them an easy target of populist political campaigns.

Chapter 5

Voting's geography

5.1 Spatial analysis

Maps have been used essentially throughout history. Initially, they were primarily utilised for navigation, but also by those seeking to gain and maintain power [Chapin et al., 2005]. The increasing importance of maps in contemporary society directly results from spatial technologies' proliferation, as Shekhar and Xiong (2007) explain. Spatial analysis, a method of studying and interpreting phenomena spatial relationships and patterns, are utilised extensively across various disciplines, including criminology, epidemiology, archaeology, and social studies. Goodchild et al. (2000) argue that this trend results from transforming society in space, which significantly impacts the spatial organisation of social, economic, political, and cultural spheres - critical domains within the social sciences. Additionally, applying a spatial approach in election analysis is gaining recognition as a valuable tool in understanding electoral outcomes. Understanding the reasons behind political changes is crucial in voting geography, combining insights from political science with information obtained from natural sciences such as geography. The ability to explain vote share by describing the dependencies between different social or economic conditions is possible through spatial analysis. The importance of spatial analysis is particularly evident in explaining local factors [Kerekeš, 2018].

The research examining election results and seeking to explain them has two predominant theoretical approaches: composite and contextual [Thrift, 1983]. The composite approach explains election outcomes by analysing socioeconomic characteristics, such as the proportion of religious, educated, or aged individuals within a given population. In contrast, the contextual approach focuses on understanding the relationship between individuals and the environment in which they reside, taking into account factors such as population density and the proportion of immigrants in a given area Maškarinec et al. (2013). This approach recognises that the characteristics of specific neighbourhoods or issues that arise in particular regions can significantly impact voting decisions. Within the framework of voting geography, these theories are primarily applied to examining electoral outcomes at the country or regional level.

5.2 Usage of voting geography

Voting results demonstrate areas where political parties or candidates have more considerable support as well as areas with weaker support. Traditional cross-sectional models can recognise factors that influence voting habits, such as socio-economic traits, demographics, or the presence of cultural or historical landmarks. They can also trace how voting patterns have evolved over time by scrutinising voting data from distinct elections. In the real world, the relationships are more complex, so it is necessary to consider the location of observations. Therefore, we aim to investigate the spatial models, which allow for investigating inter-regional relationships.

Spatial models are advantageous specifically in voting geography because they allow us to analyse and understand patterns of voting behaviour concerning geographical location. They can be employed to interpret the impact of diverse factors on voting trends by factoring in the location. Kim et al. (2003) used spatial analysis to explain the results of US Presidential elections from 1988 to 2000 at the county level. The analysis involved defining the spatial proximity between individual districts and using spatially weighted matrices to create overall measures of Moran's statistics and local indicators of spatial association (LISA) for descriptive statistics. The results revealed a division of America into the East, which is predominantly Democratic, and the West, which is predominantly Republican, with the Mississippi River serving as the dividing line. The spatial error model confirmed the regional distribution of voters, and the authors noted increased polarisation, with Democrats being more successful in counties with higher unemployment or heavily populated counties. At the same time, Republicans gained support among counties in rural areas.

In Europe, specifically the European Union, Fiorino et al. (2021) conducted a spatial analysis of voter turnout in EU member countries from 1999 to 2014 at the regional level. Using Moran's statistics and Hierarchical Linear Modelling, the authors found that regions with lower (or higher) voter turnout are surrounded by areas with similar voter turnout, confirming that location plays a significant role in voter turnout. The study also found that the variability between countries decreased over time, and the regions had similar voter turnout. Similarly, Pagliacci and Bonacini (2022) conducted a spatial analysis of the success of the right-wing Lega party in Italy in the 2019 election to the European Parliament. The study found that inner municipalities were more likely to vote for Lega, with a 1.86 percentage point higher vote share than non-inner areas. Additionally, the study found that the larger the municipality, the lower the support for the Lega party.

Michaud et al. (2021) conducted a spatial analysis of parliamentary elections in Sweden over the last three decades, from 1985-2018. It revealed voting characteristics specific to different regions in Sweden, such as North, Urban, Rural South, and Far South. Using Jensen-Shanon similarities, the study found a correlation in voting in larger cities.

In Eastern Europe, Hinich et al. (1999) conducted a spatial analysis of the 1998 parliamentary elections in Ukraine by surveying 1149 respondents. The study revealed different electoral behaviour in the east and West of Ukraine, with the eastern part rejecting reforms and being pro-Russian. In contrast, the western part has Ukrainian national feelings and a Ukrainian-speaking population. Eastern parts of Ukraine, such as Donetsk, Kharkiv, or Zaporizhzhya, were more likely to vote for pro-communist parties, while the capital, Kyiv, and western parts, such as Ivano-Frankivsk, Rivne, or Lviv, preferred democratic leaders.

There has been extensive spatial analysis research on voting behaviour in the Czech Republic. Kouba et al. (2007) analysed the Czech party system and factors that influence it, using Moran's statistics and LISA to find that voting support for individual parties is clustered, meaning that regions with similar voting behaviour surround regions with higher vote share for a specific party.

Maškarinec (2017) conducted a spatial analysis of Czech parliamentary elections from 2006 to 2013, using the same tools as Kouba et al. (2007) and finding support for the theory of geographic dependence on voting behaviour. Another research by Maškarinec et al. (2013) focused on the spatial analysis of presidential elections in the Czech Republic in 2013, discovering that a shock in one region would cause a ripple effect in neighbouring regions. Limited spatial analyses are performed in Slovakia, and this thesis will fill the gap by analysing parliamentary elections with the focus on the geographical element.

Insight into voting trends can be gleaned using spatial models to analyse the influence of various factors and track changes over time by comparing data from different elections. This understanding can benefit researchers and policymakers in making better-informed decisions, creating effective strategies for engaging with voters, and boosting voter turnout.

Chapter 6

Data

The dataset used in this study is composed to capture significant societal behaviour. We analyse the voting results from the 2016 and 2020 parliamentary elections at the county and municipality levels. The dataset containing the voting data is supplemented with regional socio-demographic characteristics. We use characteristics collected annually, complemented by the data from the population census that takes place every decade, with the last one taking place in 2021.

We extend the work of Dusková (2021) by applying the models also on the municipality-level data and by using the more recent census. We believe it provides more information about the country's inhabitants allowing for a more comprehensive understanding of the factors that may influence the election outcome. At lower levels of aggregation (county and municipality levels), the populist parties' vote share determinants are more evident.

This chapter outlines the variables employed in the thesis, focusing on the dependent variable, followed by the explanatory variables measured at the level of 79 Slovak counties and 2927 Slovak municipalities. The analysis is conducted mainly at the county level due to the fact that some data are unavailable at the municipality level - some variables are collected yearly only at the county level. In contrast, we can rely only on the census in the case of the municipality level.

When interpreting counties' or municipalities' data, it is crucial to be aware of the ecological inference fallacy, which refers to making incorrect assumptions about individuals based on aggregate results about the group, such as assuming that unemployed people vote for populist parties. Since we are analysing data at the county and municipality levels, we need to acknowledge the fallacy and avoid making assumptions about individuals based on aggregated data. It is essential to interpret the outcomes by considering the significance of neighbourhood effects, which results in a more accurate portrayal of the population. These variables are publicly available on the Statistical Office of the Slovak Republic. We also work with shapefiles downloaded from Geoportal.

6.1 Explained variable

In this analysis, we are looking at how populist parties are able to gain support and take votes away from non-populist parties in different counties and identify any trends or patterns in this behaviour. For the purpose of this analysis, we measure populist support as the percentage of votes cast in the parliamentary elections for the populist political parties SMER and ĽSNS. The reason for selecting these two parties is explained in the previous chapter. We analyse their election results and obtained vote share on the local level (NUTS-3) in the last two parliamentary elections, 2016 and 2020. Parliamentary elections take place every four years, and citizens vote for the National Council of the Slovak Republic. We do not choose presidential elections because there are elected individual candidates, also municipality elections are not suitable since people can vote based on their acquaintances.

We utilise maps from Dusková (2021) to visualise the electoral support for these parties. We provide two sets of maps displayed in figures 6.1, 6.2, 6.3. Firstly we display the vote share for SMER and ĽSNS of the 2016 and 2020 parliamentary elections at the county level. As a robustness check, we also provide the obtained vote share of these parties on the municipality level. However, the municipality level is only provided for the 2020 election year, which will be explained later.

It is evident that support for these parties is consistent over the examined years, with only a slight decrease in the share of votes obtained. The maps of SMER's vote share reveal a clustering of counties where the support is strong, particularly in the northern and eastern Slovakia. At the same time, districts in the south and west, particularly around the capital city of Bratislava, have minimal support. The visualisation provides an initial understanding of the spatial clustering of neighbouring counties of vote share.

Concerning the ĽSNS party, we can see they were the most successful in the southern central part of Slovakia. Like SMER, they received minimal support in the areas surrounding the capital and in the southern parts with a higher population of the Hungarian minority. By investigating electoral data in this manner, we expect to be able to identify patterns and trends in the behaviour of populist parties and their ability to gain support in different counties.

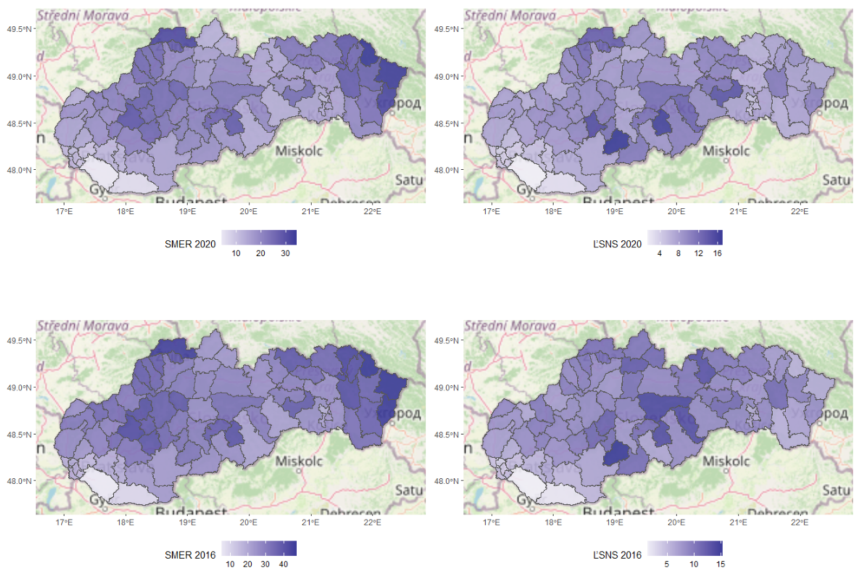

Figure 6.1: Vote share of parties on the county level

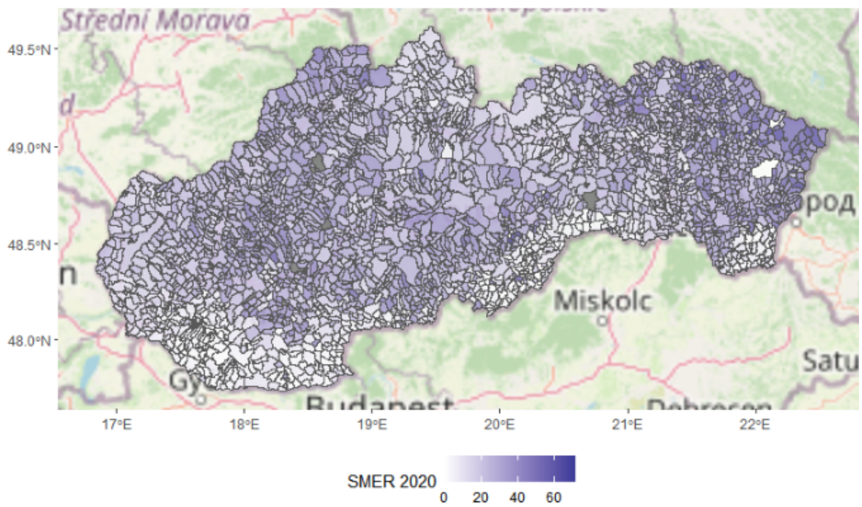

Figure 6.2: Vote share SMER on the municipality level

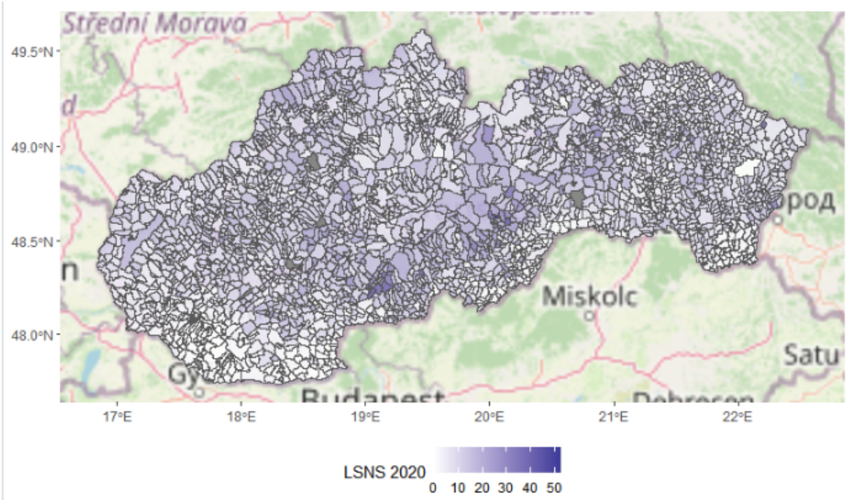

Figure 6.3: Vote share ĽSNS on the municipality level

6.2 Explanatory variables

In our analysis, we relate election results to several regional socio-demographic characteristics. Our data come from two distinct sources: output statistics that are collected annually and census data. Compared to Dusková (2021), our study benefits from the availability of the newest census data, allowing us to incorporate essential information from counties. Additionally, we provide variables on the municipality level.

Our primary objective is to investigate which regional characteristics can explain voting behaviour and determine which elements are crucial to consider when analysing the electoral support for populist political parties. Dijkstra et al. (2019) argue that socio-demographic characteristics such as age, income and education constitute the "holy trinity" of populist voter profiles. Furthermore, Rodrigues-Pose (2018) suggests that unskilled individuals with lower-income jobs and limited educational attainment are more likely to support populist parties. In order to gain a deeper understanding of these factors, we include demographic variables such as the share of productive age and pre-reproductive age inhabitants, average regional wage adjusted for inflation, and the percentage of individuals with a university degree. We do not include the variable average age since Dusková (2021) has revealed that the variable is highly correlated with other variables. We expect counties with higher average wages and higher levels of educational attainment should have less support for populist parties.

The job structure is also an essential factor to consider when examining the vote share of populist parties. Analysing the employment composition of a population in the county can provide a valuable understanding of a county's economic health and well-being, which can indicate the level of support for populist parties. Skill level is a commonly used classification for the workforce, including skilled, semi-skilled, and unskilled workers (according to the occupation they are employed in). Examining the percentage of jobs that fall into these categories, such as a high concentration of low-skilled or low-paying jobs, can offer important information in comprehending the level of support for populist parties. It is especially relevant since populist parties frequently target working-class and low-income individuals, who may face economic instability and a lack of opportunities. On the other hand, Inglehart and Norris (2016) observe that populist parties generally do not receive support from unskilled workers but rather from self-employed individuals such as proprietors of small family-owned businesses, plumbers, and owners of small-scale stores. Our analysis includes variables for skilled and unskilled workers while excluding semi-skilled workers due to perfect collinearity.

In addition to job structure, the unemployment rate in a county can also be a significant variable to consider when analysing the vote share of populist parties. According to Algan et al. (2017), there is a correlation between unemployment and voting for anti-establishment and populist parties. High unemployment levels may indicate economic insecurity and a lack of opportunities, leading to dissatisfaction with the status quo and a desire for change. Furthermore, unemployment is a relatively easy variable to measure and compare across different counties. Therefore, in our analysis, we utilise an adjusted measure of unemployment that accounts for factors such as "Education and preparation for the labour market", "Temporary incapacity for work and care of a family member", and "Graduate practice". We expect unemployment to correlate positively with the vote share for SMER and ĽSNS parties.

Now, we shift our focus to other factors influencing the vote share of populist parties. Specifically, we aim to explore the role of religiosity, ethnicity and nationality. In particular, we examine the relationship between the presence of Hungarian and Roma populations in the county and the vote share of populist parties. These variables are of interest as the two examined parties are often hostile against them. The populist parties share nationalistic views, and Hungarians are considered enemies for historical reasons. The usual problems of the Roma community, such as a high unemployment rate, low education, high crime rate and bad hygiene in the settlements, are used to make them the enemies of ordinary Slovak citizens. We predict counties with a higher population of non-Slovak people negatively correlate with the vote share for populist political parties.

Religiosity, specifically Roman Catholicism, is an essential factor to consider in this analysis as it can strongly indicate traditional values and beliefs. Populist parties often position themselves as defenders of traditional values and Christianity, making religious individuals more exposed to their messages and more likely to support them. We choose the variable Roman Catholics, the region's predominant religion and the most conservative one. Therefore, we assume that Roman Catholics favour voting for populist parties.

Census data is necessary to collect certain variables like religiosity, nationality, and the proportion of individuals with a university degree. Census data are collected every decade. Thus, we use the 2021 census data when analysing the 2020 elections and the 2011 census data when analysing the 2016 elections. Variables such as the average wage, unemployment rate, the proportion of skilled and unskilled workers and the proportion of people in pre-productive and productive age have been collected annually; however, only on the county level (we employ the census data on the municipality level). Unfortunately, the average wage is unavailable at the municipality level; therefore, models utilising the average wage can be estimated only at the county level. Other variables are available at the municipality level. For the municipality level, we use data from the 2021 census, and thus we work with these variables only for examining vote share in the 2020 parliamentary elections. The detailed descriptive statistics of variables is available in the Appendix A.

We anticipate that the variables of unemployment, average wage, and those with a university degree could be the most significant factors in this analysis. To demonstrate the significance of these variables, we present maps that display their values in the counties of Slovakia in 2020 displayed on figure 6.4. The map depicting unemployment rates clearly demonstrates a distinct split across the country, with lower rates in the western regions and higher rates in the central and eastern regions, except for the area encompassing the second largest city in Slovakia, Košice, and its adjacent counties. A similar pattern can be observed in the map of average wages, although the division is not as pronounced. On the other hand, the map of university degree holders does not show a significant division throughout the country, with notable concentrations only around the capital and in the Košice region.

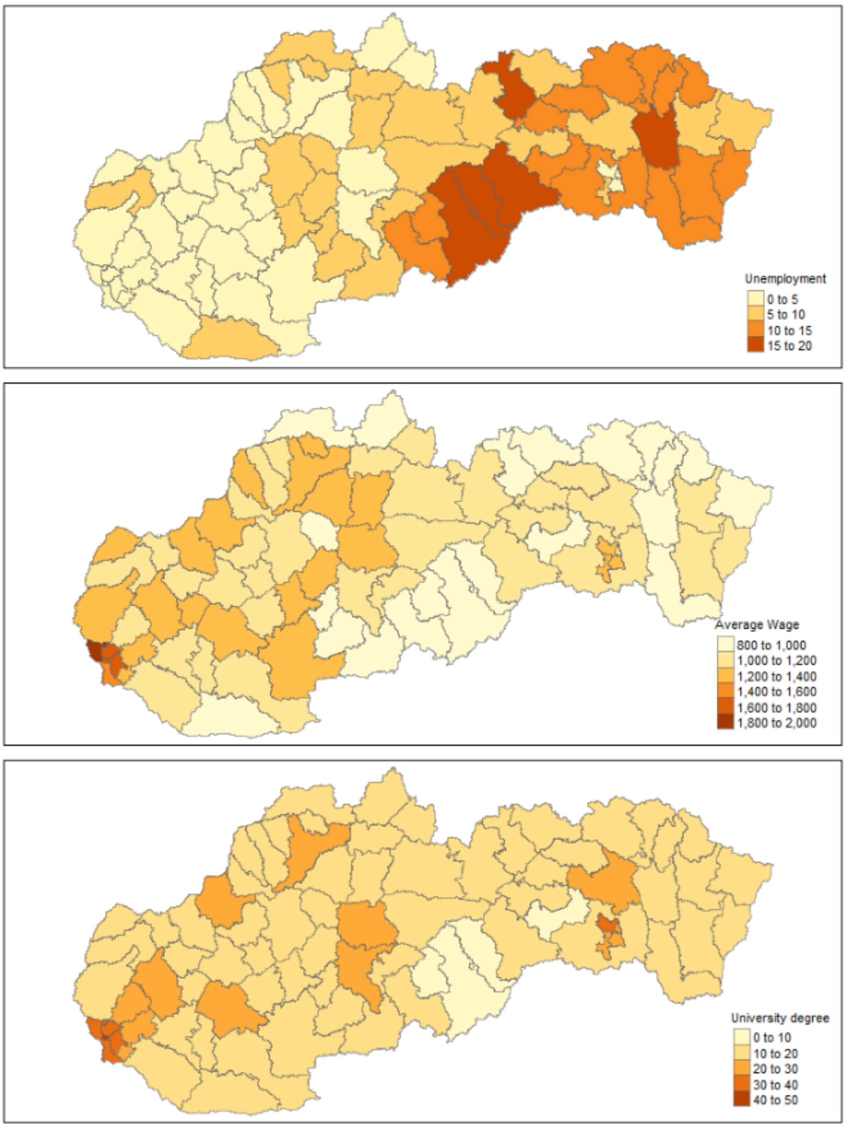

Figure 6.4: Variables' distribution

6.2.1 Correlation between variables

In order to demonstrate the relationship between these variables, we present a correlation plot 6.5 of variables on the county level. The plot's colour represents the correlation's strength, with blue indicating a positive correlation and red indicating a negative correlation. To ensure the validity of our analysis, we avoid correlations that exceed 0.65 or fall below -0.65. We observe a significant positive correlation between the variables of the average wage and university degree, as well as between unemployment and the share of Roma people. Given the importance of these variables, we use two separate models to examine further their relationship with the vote share of populist parties. The correlation between variables on the municipality level is very similar and included in the Appendix B.

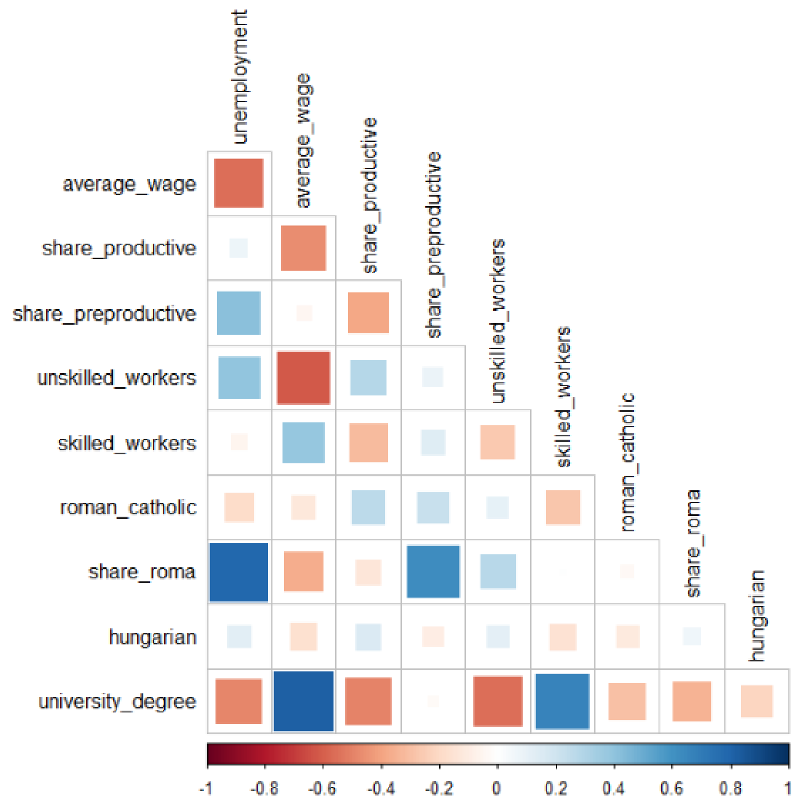

Figure 6.5: Correlation matrix - counties

6.2.2 Hypotheses

Analyses of electoral result maps from the 2016 and 2020 elections reveal that neighbouring districts exhibit remarkably similar voting patterns for these parties, with clusters of counties showing a high percentage of votes in their favour. This finding raises important questions about the underlying drivers of such trends. Are these patterns solely due to the similarities between these districts, or is there evidence of spillover effects from specific characteristics in one district to its neighbours? This thesis aims to explore and provide insights into the factors that contribute to the geographical clustering of populist voting patterns. We analyse these districts' demographic, socio-economic, and political characteristics to understand this phenomenon and its implications for democratic governance comprehensively.

- Hypothesis #1: Education structure is an essential county characteristic affecting its election results.
- Hypothesis #2: Support for populist political parties is clustered due to the spillovers in the outcome - vote share.
- Hypothesis #3: Support for populist political parties is clustered due to the similarity of demographic and economic characteristics of neighbouring counties.
- Hypothesis #4: Vote share is affected by spillovers in unobservables.
- Hypothesis #5: The relationships from previous hypotheses are stable over time.

Chapter 7

Methodology

This chapter describes the theoretical background of the econometric approach used in this analysis. Firstly, the basic model applied in the analysis is introduced. The following section focuses on hypothesis testing, beginning with an explanation of the hypotheses and subsequently detailing the techniques employed to address them. We include an overview of the Global Moran's Indicator and Local Indicators of Spatial Association (LISA) and a description of the spatial models, such as Spatial Error, Spatial Lag, Spatially Lagged X, Spatial Durbin, Spatial Durbin Error and Spatial Autocorrelation Model. The analysis is estimated in the R software with various packages. We used package *stargazer* for importing results.

7.1 Baseline Model

This thesis investigates the relationship between the vote share of populist political parties and various characteristics in counties. To achieve this, we propose a multiple regression model, which is given by:

$$y_{i,t} = \alpha_0 + X1_{i,t-1}\beta + X2_{i,t-1}\gamma + X3_{i,t-1}\sigma + u_{i,t},$$

where $y_{i,t}$ is the dependent variable, representing the vote share of populist political parties (either SMER or ĽSNS) in county i in the election year t (t=2016 and t=2020), $X1_{i,t-1}$ is a vector of demographic characteristics i in year $t-1$, $X2_{i,t-1}$ is the vector of ethnic and religious characteristics i in year $t-1$, $X3_{i,t-1}$ is the vector of labour-market related characteristics i in year $t-1$ and $u_{i,t}$ is the disturbance term.

Based on the literature, we have categorised several potential explanatory variables into three groups - demographic, ethnic/religious and labour-market characteristics, including unemployment, average wage, level of education, the skill level of the job (skilled and unskilled), and the age of voters (measured by the share of productive and pre-productive age groups in the county). Ethnic and religious characteristics are represented by the share of minorities, specifically Roma and Hungarian, as well as the share of Roman Catholics.

Specification 1:

$$\begin{aligned}\text{vote\_share}_{i,t} = & b_0 + b_1\text{unemployment}_{i,t} + b_2\text{university\_degree}_{i,t} \\ & + b_3\text{share\_productive}_{i,t} + b_4\text{share\_preproductive}_{i,t} \\ & + b_5\text{unskilled\_workers}_{i,t} + b_6\text{roman\_catholics}_{i,t} \\ & + b_7\text{hungarian}_{i,t} + u_{i,t}\end{aligned} \tag{7.1}$$

Specification 2:

$$\begin{aligned}\text{vote\_share}_{i,t} = & b_0 + b_1\text{average\_wage}_{i,t} + b_2\text{share\_productive}_{i,t} \\ & + b_3\text{share\_preproductive}_{i,t} + b_4\text{skilled\_workers}_{i,t} \\ & + b_5\text{unskilled\_workers}_{i,t} + b_6\text{roman\_catholics}_{i,t} \\ & + b_7\text{share\_roma}_{i,t} + b_8\text{hungarian}_{i,t} + u_{i,t}\end{aligned} \tag{7.2}$$

By estimating these models and analysing their coefficients, we aim to identify which characteristics are most strongly associated with the vote share of populist political parties in counties. This analysis provides valuable insights into the underlying drivers of populist voting patterns and contribute to a better understanding of the implications of these trends for democratic governance.

7.2 Global Moran's I

We start by conducting exploratory spatial analysis. This allows us to visualise our data and observe spatial clustering. Global Moran's I is an indicator of spatial autocorrelation that determines whether the values of a particular variable are randomly distributed or clustered in a pattern across a examined area. This statistic measures the similarity of values between neighbouring observations compared to the similarity among all pairs of observations. The Global Moran's I is:

$$I = \frac{N}{S} \cdot \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(y_i - \bar{y})(y_j - \bar{y})}{\sum_{i=1}^{n} (y_i - \bar{y})^2},$$

where N represents the number of observations, S represents the sum of weights, $w_{i,j}$ represents an element of the spatial weights matrix W, y_i and y_j represent the values of the random variable at locations i and j.

The spatial weight matrix, symbolised as W, is the critical component in the formula for Global Moran's I [Maškarinec, 2013]. This matrix captures the connections between the observations studied in the dataset. The matrix elements, $w_{i,j}$, indicate the strength of the relationship between observations i and j, and can be calculated through techniques such as the queen or rook contiguity, distance-based methods, or other methods. Regarding the contiguity matrix, there are two methods to use: the queen and rook contiguity. The queen method defines a relationship between two observations if they have a common edge or vertex. If two observations are neighbours on a chessboard and can be connected diagonally, horizontally, or vertically, they are considered queen neighbours. On the other hand, rook contiguity only takes into account vertical and horizontal connections between observations [Anselin, 1995]. Choosing between the queen and rook neighbours depends on the aim of the analysis. Since our purpose is to examine the vote share of political parties based on some counties' characteristics, it may be more appropriate to use "queen" neighbours. We expect the relationships between counties to be complex and require different forms of spatial dependence to be captured. The queen criteria of neighbour in Slovakia is displayed on the map 7.1 below.

The other type of matrix is the inverse distance matrix which measures the spatial association between observations. Its construction involves computing the inverse of the distance between each pair of observations in the dataset. We first generate a distance metric, Euclidean distance. Subsequently, the distances between every pair of observations are calculated, and then the inverse is computed, resulting in a matrix

$$w_{ij} = \frac{1}{d_{ij}},$$

where each element in row i and column j represents the inverse of the distance between observation i and observation j. Spatial autocorrelation denotes the inclination of observations that are close to each other to be more alike than observations that are far away. Using the inverse distance matrix, spatial econometricians can account for this spatial autocorrelation and ensure their models are accurately specified.

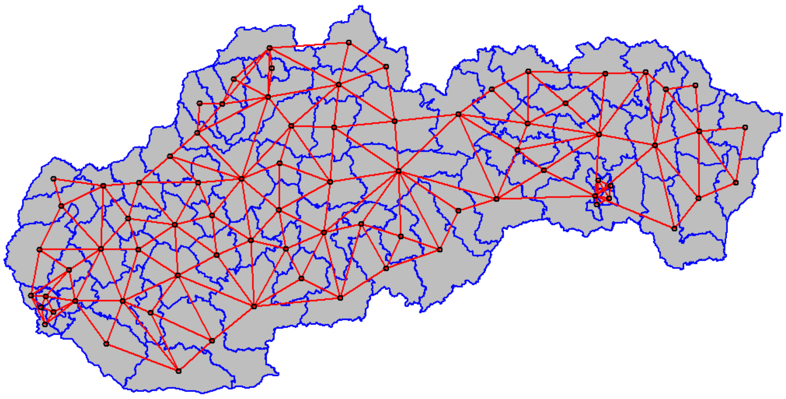

Figure 7.1: Queen criteria

The values of Moran's I range from -1 to 1, where a value close to 1 suggests strong positive spatial autocorrelation, a value close to -1 indicates strong negative spatial autocorrelation, and values close to 0 suggest no spatial autocorrelation. If neighbouring observations have similar values, the statistic is positive, reflecting positive spatial autocorrelation. Conversely, if neighbouring observations tend to have distinct values, the statistic is negative, reflecting negative spatial autocorrelation [Anselin, 1995]. One limitation of Moran's I is that it only measures global spatial autocorrelation and does not provide information about local patterns or clusters of similar values. To overcome this limitation, we can use other measures of spatial autocorrelation, such as the Local Indicator of Spatial Association, providing information about local patterns of spatial autocorrelation.

7.2.1 Local Moran's I

Local Indicators of Spatial Association (LISA), also known as "local Moran's I," is a set of measures for identifying and analysing local patterns of spatial autocorrelation in a study area. This tool helps to identify clusters of high or low values and outliers of a variable of interest. The indicator is widely used in similar papers [Maškarinec, 2013]. According to Hypothesis 1, we should be able to observe clusters around the big cities. LISA calculates the statistic for each location in the study area based on the values of the variable of interest and its neighbouring locations. This calculation is made by comparing the variable's value at a given location with the average value of the variable in its neighbouring locations. LISA requires a spatial weight matrix to define the spatial relationships among observations and a threshold to define significant clustering. The form of the Local Moran's I is:

$$I_i = \frac{\sum_{j=1}^{n} w_{ij}(y_i - \bar{y})(y_j - \bar{y})}{\sum_{i=1}^{n}(y_i - \bar{y})^2},$$

with the exact notation as in the Global Moran's I. The local Moran's I statistic is positive when the variable's value at a given location is greater than the average value of its neighbouring locations, indicating the presence of a high-high cluster. On the other hand, it is negative when the variable's value is lower than the average value of its neighbouring locations, indicating a low-low cluster. Additionally, the statistic can identify outliers or "not significant spots" in the form of high-low or low-high clusters [Anselin, 1995]. However, the Global Moran's I and LISA indicators serve more for a descriptive analysis of the observed phenomenon, and their explanatory possibilities are limited.

7.3 Spatial models

Spatial models are used to analyse spatially interrelated data, where geographically close observations are more likely to be similar than those far apart. The usual statistical models, such as the OLS, assume that each observed unit is independent, may bring biased results and/or undermine inference if spatial interrelations are strong. Spatial econometric models account for this kind of dependence by incorporating information about the spatial relationships among observations. Overall, spatial econometrics provides a robust framework for analysing and understanding data with a geographical component. We display all models below based on Cook et al. (2015).

$$\begin{aligned}
\text{Spatial Error Model:} \quad & y = X\beta + u \qquad u = \lambda W u + e \\
\text{Spatial Lag Model:} \quad & y = \rho W y + X\beta + e \\
\text{Spatially Laged X Model:} \quad & y = X\beta + WX\theta + e \\
\text{Spatial Durbin Model:} \quad & y = \rho W y + X\beta + WX\theta + e \\
\text{Spatial Autocorrelation Model:} \quad & y = \rho W y + X\beta + u \qquad u = \lambda W u + e \\
\text{Spatial Durbin Error Model:} \quad & y = X\beta + WX\theta + u \qquad u = \lambda W u + e
\end{aligned}$$

As Burkey (2018) explains, there are three distinct ways in which regions may be related to their neighbouring regions.

- The value of **y** in a particular region may be associated with the value of **y** in a neighbouring region. Vote share in one region itself influences the vote share in adjacent regions regardless of the explanatory variables.
- The values of **X** variables in a region may impact the value of **y** in a neighbouring region. The various aspects of the economic situation in adjacent regions influence vote share in one region.
- The errors **e** from a statistical model may be correlated with the errors of a neighbouring region. This happens when spatially autocorrelated errors are clustered.

Spatial econometrics considers two types of data properties: correlation among spatial units (spatial clustering), and causal relations among spatial units (spatial spillovers or interactions). The former appears *"when the level, presence, or change of an observed (unobserved) determinant in one unit is correlated with but not a function of (not caused by) the value of that factor in other (spatially proximate) units"* [Cook et al., 2015]. Such correlation is caused only by similarities between units, and there is no interaction required. The latter means that the outcome, observable and unobservable of one or more region unit affects the outcomes of other unit/s. Whenever there is a causal relationship (not just correlation) among spatial units, we discuss spillovers.

Most of the developments in spatial econometrics are related to two of the mentioned sources of spatial relationships, the correlation of **y** and the correlation of **e**, which are the core assumptions of the two most widely applied models - the **Spatial Lag Model** (SLM) and the **Spatial Error Model** (SEM). Although these models share some mathematical similarities, their underlying logic and interpretations differ significantly. The spatial error model specifies that the error terms of the regression model are spatially autocorrelated, meaning that they are correlated with the errors of neighbouring observations. The model assumes the existence of omitted variables that follow spatial patterns, leading to spatial autocorrelation of error terms. This model is employed when spatial autocorrelation is considered a noise that requires correction in the regression. The purpose of the model is to filter out spatial autocorrelation in the data, even if the model itself is not explicitly spatial [Anselin, 2001]. If spatial errors are ignored, OLS is unbiased and consistent, but β is inefficient and standard errors wrong. Typically, the model assumes a spatial autoregressive process and is expressed as:

$$y = X\beta + u \qquad u = \lambda W u + e,$$

Here, λ represents the spatial autoregressive parameter that reflects the degree of interdependence among the errors. The nxn matrix **W** represents the spatial weight matrix, while the nx1 vector denotes the error term **e**. If the model does not involve a spatial error, then $\lambda = 0$. On the other hand, the spatial lag model, includes a spatially lagged dependent variable as an additional explanatory variable in the model. This captures the effect of neighbouring observations on the dependent variable. The model declares that a dependent variable is influenced by both its own structural, locational, and neighbour characteristics (direct effects) and the spatially weighted average of its neighbouring dependent variable (indirect effects) [Anselin, 2001]. To conclude, the dependent variable is assumed to be influenced by its **X** value and neighbouring units' **y** values. OLS is, in this case, biased and inconsistent. The equation representing the SLM can be represented as

$$y = \rho W y + X\beta + e,$$

where **y** is a vector of the dependent variable with n elements, ρ is the spatial autoregressive coefficient ($-1 \leq \rho \leq 1$), **W** is the nxn spatial weights matrix that defines the connections between observations, **X** is the nxk matrix of explanatory variables, β is the k element vector of coefficients, and **e** is the n element error term vector. We can use the Lagrange Multiplier tests to help decide whether to employ spatial error or spatial lag models. There are four LM tests:

- LMerr test: tests for spatial error dependence, happening when the model errors show spatial autocorrelation.
- LMlag test: tests for spatial lag dependence, occurring when the dependent variable is spatially autocorrelated.
- RLMerr test: tests for spatial error dependence using a robust version.
- RLMlag test: tests for spatial lag dependence using a robust version.

As Burkey (2018) explains, there is one more occurrence of spatial patterns since the above models ignore the regional interrelation caused by X. The **Spatially Lagged X model** explains the spillovers of independent variables. This source of spatial correlation can be modelled as follows:

$$y = X\beta + WX\theta + e$$

Compared to the previous model, the difference is that we use the spatial term $WX\theta$ where **W** is the spatial weight matrix, **X** is the matrix of the explanatory variables, and θ is the spatial autoregressive term measuring the degree of spatial spillovers. So far, we have described models that deal with spatial correlation driven by a single channel or mechanism. However, it is conceivable that multiple factors may cause spatial dependence. Therefore, we present two-factor models, specifically the Spatial Durbin (SDM), Spatial Error Durbin (SDEM), and Spatial Autocorrelation models (SAC) that might be valuable in exploring spatial correlation.

$$\begin{aligned} SDM &: y = \rho Wy + X\beta + WX\theta + e \\ SAC &: y = \rho Wy + X\beta + u \qquad u = \lambda Wu + e \\ SDEM &: y = X\beta + WX\theta + u \qquad u = \lambda Wu + e \end{aligned}$$

The SDM incorporates the spatial autocorrelation present in both the **y** and the **X**. Additionally, the SAC method combines the spatially autocorrelated errors and **y**, whereas the SDEM takes into account the spatial autocorrelation in **y** and spatially autocorrelated errors. It is not possible to decide which model is the best in general, the researchers pick one or another based on what appears to be the source of spatial correlation according to their research question and intuition [Cook et al., 2015].

7.4 Analytical approaches used to test research question

So far, this chapter illustrates several approaches used to model spatial relationships. Now, we propose how they can be used to test the hypothesis introduced in chapter 6.4.

7.4.1 Hypothesis 1

Hypothesis #1: Education structure is an essential county characteristic affecting its election results.

The literature suggests that various demographic and economic factors are critical in shaping voting patterns. In chapter 6.2, we mention that according to Dijkstra et al. (2019), education, age, and income are the "holy trinity" of the populist voter. Dusková (2021) could not include this variable because the latest available data were from 2011. The fast growth of the education level in Slovakia makes such data unreliable. However, in this thesis, we already have much more recent data from the 2021 census, allowing us to include education in our model.

Given its simplicity and ability to interpret coefficients straightforwardly, we propose a multiple regression model to investigate this relationship. However, when certain forms of regional interrelationships are present, the OLS gives biased estimates. Since we have expectations of county clustering and the existence of relationships between neighbouring counties, we employ spatial econometrics.

7.4.2 Hypotheses 2 & 3 & 4

Hypothesis #2: Support for populist political parties is clustered due to the spillovers in the outcome - vote share.
Hypothesis #3: Support for populist political parties is clustered due to the similarity of demographic and economic characteristics of neighbouring counties.
Hypothesis #4: Vote share is affected by spillovers in unobservables.

First, we compute the Global Moran statistics and visualise local clusters through the LISA to confirm the spatial autocorrelation level. As we described in the previous chapter 7.3, there are three options when exploring the occurrence of spatial autocorrelation.

Hypothesis #2 explains that spatial autocorrelation is caused by spillovers in the dependent variable, which is, in our case, the vote share of populist political parties. It means that the vote share itself influences the vote share in the surrounding counties regardless of the socio-economic factors. It could apply in our case since relatives in the neighbouring counties might discuss the elections and political situation and influence each other. Also, when one party is successful in one particular county, it can increase its trustworthiness in neighbouring counties. The SLM can be used to test this hypothesis, which focuses on explaining only the spatial autocorrelation. Furthermore, the SDM and SAC are combined two-factor models that explain the spatially autocorrelated vote share.

Hypothesis #3 suggests that the features of particular counties may spill over the voting outcomes to nearby counties. Specifically, we expect that counties near big towns may be impacted by the traits of these urban centres, leading to comparable voting patterns for populist parties. Given their economic prosperity, low unemployment rates, and high average wages, we expect these cities to demonstrate relatively low levels of support for populist parties. On the other hand, the opposite effect might happen in underdeveloped clusters of counties. We believe that counties in close proximity share these factors; hence they may lead to similar support patterns for populist political parties. Therefore, we estimate the SLX, SDM and SDEM models that take into account the spatial autocorrelation of independent variables. Hypothesis #4 proposes that there might be unobservables in our model which are spatially autocorrelated. SEM, SAC and SDEM are ideal with such autocorrelation.

Based on the literature, the two most commonly utilised spatial methods are the spatial lag and spatial error model. We use Lagrange Multiplier tests as diagnostic tools [Anselin, 1998]. However, other spatial models like the SLX, SDM, SDEM and SAC do not have any single test like Lagrange Multiplier that would discriminate among these models. Therefore we must rely on our intuition. After estimating the models, Akaike Information Criteria (AIC) becomes a valuable tool. AIC is a significant statistical measure that we use to compare various models based on their ability to explain a specific data set. The principle of parsimony, which suggests that the simplest model that adequately explains the data should be used, underlies the statistic [Akaike, 1974]. By utilising AIC, we can prevent overfitting our models, and we should consider the model with the lowest AIC. Even though a great variety of models could be applied to our research question, we expect to estimate the combined two-factor models (SAC, SDM, SDEM). The reasoning behind the expectation is that single-channel models cannot capture the complexity of the vote share's explanation.

7.4.3 Hypothesis 5

Hypothesis #5: The relationships from previous hypotheses are stable over time.

In our analysis, we aim to detect the changes and trends in voting behaviour. To do so, we estimate the same relationship between the vote share and independent variables for two election years, 2016 and 2020. This allows us to compare whether findings in one election year align with those from the second.

Chapter 8

Empirical results

8.1 OLS Estimation

The present study begins with the OLS results. Given that OLS relies on five key assumptions explained in the Appendix C, we undertake tests to ensure that our estimates are consistent and efficient. In particular, we investigate the presence of multicollinearity by employing the Variance Inflation Factor (VIF), and we test for heteroskedasticity by applying the Breusch-Pagan test. However, OLS assumptions are violated when data are spatially correlated. First, the error structure might be affected, meaning that OLS is inefficient but unbiased. Second, there might be endogeneity caused by spatial spillovers; in this case, the traditional cross-sectional model would be biased.

The first Specification relates to the vote share given to the party SMER in the 2020 parliamentary elections to the following independent variables: unemployment, university_degree, share_productive, share_preproductive, unskilled_workers, roman_catholic, hungarian.

The coefficients estimated from the model provide information on the direction and magnitude of the relationship between each predictor variable and vote share of the party SMER.

OLS estimation results for Specification 1 are reported in table 8.1. The results show that unemployment has a significant positive relationship with SMER vote share, meaning that higher levels of unemployment in a county are associated with higher SMER vote share. The share of people with a university degree, the share of the population in pre-productive age and the share of the Hungarian minority show a significant negative relationship with the vote share of the party SMER, meaning that higher values of mentioned variables cause lower vote share. Variables are able to explain more than 70% of the variation in SMER support (applies to both specifications). In Specification 2 reported in column 2 of table 8.1, we still aim to explain the variation in the vote share of the party SMER, but using a different set of explanatory variables. The results show that the average wage, the share of the population in the pre-productive age, the share of skilled workers, and the share of Roma and Hungarian minority are significant predictors of the party's support, with p-values less than 0.05.

Specifically, an increase in the average wage, in the share of skilled workers, and the share of the Roma population is associated with a decrease in vote share given to the SMER party, while an increase in the share of the population in pre-productive age and share of Hungarian population is associated with increased support for the SMER party. The other independent variables, such as the share of productive, unskilled workers and the share of Roman Catholics, do not significantly impact the party's vote share.

In both specifications, we can see that share of unskilled workers and Roman Catholics in the county do not appear as important correlates of vote share given to the SMER party, whereas the share of people of productive age, the share of skilled workers and Hungarian minority appear to be important correlates.

We similarly provide the same two specifications visible in column 3 and column 4 of the table 8.1 to estimate the relationship between ĽSNS vote share and a set of explanatory variables. The dependent variable represents the share of votes received by the ĽSNS party in the 2020 Slovak parliamentary election. Interpreting our results, the only insignificant variable is the share of unskilled workers; otherwise, all variables are significant. The model estimates that variables positively and significantly influencing the vote share are unemployment and the share of Roman Catholics. In contrast, variables that might negatively impact the vote share negatively are the share of people with a university degree, the share of productive/pre-productive people and the share of Hungarians. Used variables are able to explain more than 70% in Specification 1 and more than 55% of the variation in support for ĽSNS in Specification 2. This indicates that in the case of ĽSNS, the first Specification is probably more suitable. Specification 2 shows the negative relationship between the average wage, the share of the population of pre-productive age, skilled workers and the share of Hungarian. On the other hand, counties with a share of Roman Catholics and Roma show positive effects in voting for the party ĽSNS.

Next, we report OLS results for 2016 displayed in table 8.2. In the case

Table 8.1: Variables describing the vote share of SMER and ĽSNS in 2020

	OLS			
	Dependent variable:			
	SMER_voteshare		*ĽSNS_voteshare*	
	(1)	(2)	(1)	(2)
unemployment	0.532***		0.341***	
	(0.149)		(0.074)	
university_degree	−0.321***		−0.183***	
	(0.088)		(0.044)	
average_wage		−0.009***		−0.004**
		(0.003)		(0.002)
share_productive	0.381	0.655*	−0.480**	−0.173
	(0.365)	(0.371)	(0.181)	(0.227)
share_preproductive	−1.152***	−1.137***	−0.519***	−0.350**
	(0.239)	(0.254)	(0.119)	(0.155)
skilled_workers		−0.212***		−0.110***
		(0.066)		(0.040)
unskilled_workers	−0.055	−0.039	0.078	0.185
	(0.179)	(0.188)	(0.089)	(0.115)
roman_catholic	0.004	−0.020	0.076***	0.052***
	(0.033)	(0.029)	(0.016)	(0.018)
hungarian	−0.322***	−0.322***	−0.109***	−0.105***
	(0.031)	(0.031)	(0.015)	(0.019)
share_roma		1.025***		0.408**
		(0.288)		(0.176)
Constant	15.976	12.184	46.107***	29.596*
	(26.291)	(27.870)	(13.057)	(17.020)
Observations	79	79	79	79
R^2	0.729	0.728	0.715	0.568
Adjusted R^2	0.703	0.697	0.687	0.518
F Stat	27.313***	23.430***	25.470***	11.483***
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 8.2: Variables describing the vote share of SMER and ĽSNS in 2016

	OLS			
	Dependent variable:			
	SMER_voteshare		*ĽSNS_voteshare*	
	(1)	(2)	(3)	(4)
unemployment	0.342***		0.199***	
	(0.124)		(0.042)	
university_degree	−0.763***		−0.132***	
	(0.134)		(0.046)	
average_wage		−0.018***		−0.005***
		(0.005)		(0.002)
share_productive	0.101	−0.071	0.139	0.111
	(0.359)	(0.423)	(0.123)	(0.158)
share_preproductive	−1.031***	−1.357***	−0.131	−0.153
	(0.295)	(0.332)	(0.101)	(0.124)
skilled_workers		−0.325***		−0.040
		(0.087)		(0.033)
unskilled_workers	0.181	0.194	−0.006	−0.002
	(0.243)	(0.267)	(0.083)	(0.100)
roman_catholic	−0.029	−0.018	0.056***	0.052***
	(0.038)	(0.040)	(0.013)	(0.015)
hungarian	−0.453***	−0.437***	−0.117***	−0.109***
	(0.038)	(0.040)	(0.013)	(0.015)
share_roma		0.392***		0.130***
		(0.129)		(0.048)
Constant	47.518*	83.235**	−2.789	6.388
	(27.358)	(33.818)	(9.361)	(12.653)
Observations	79	79	79	79
R^2	0.757	0.736	0.707	0.620
Adjusted R^2	0.733	0.706	0.678	0.576
F Stat	31.646***	24.450***	24.498***	14.265***
Note:				*p<0.1; **p<0.05; ***p<0.01

of models describing the SMER vote share, we exhibit statistically significant unemployment, university degree, and the share of pre-productive and Hungarian. Specification 2 shows the significance of the share of pre-productive, skilled workers, Roma and Hungarians. ĽSNS Specification 1 shows the significance of the unemployment share of the people with a university degree, Roman Catholics and Hungarian. On the other hand, Specification 2 demonstrates the significance of the average wage, Roman Catholics, Roma and Hungarian. Comparing the 2016 results with the 2020 results, we can conclude that the majority of the variables show similar significance, and the relationship has been quite stable over the years.

8.2 Global Moran's I

We first examine the spatial autocorrelation of the **dependent variable**, the vote share. As described in the methodology section, defining the spatial weight matrix is essential. We are utilising two types of matrixes; a neighbouring contiguity matrix and an inverse distance matrix.

The output 8.3 shows the test results, including the Moran I statistic (a measure of spatial autocorrelation) and its p-value for both types of matrices. The p-value is, in all cases, very small, suggesting strong evidence against the null hypothesis of no spatial autocorrelation.

The alternative hypothesis is that there is greater spatial autocorrelation. It means that neighbouring counties tend to have similar values of SMER vote share, and this similarity is greater than what we would expect if the data were randomly distributed. The sample estimate of the Moran I statistic is in the case of the contiguity matrix 0.52, which is the observed value of the Moran I statistic in the data. This positive value indicates positive spatial autocorrelation in the SMER vote share variable. Regarding the inverse distance matrix, we see a notably lower Global Moran's I, which is still significant and positive.

In order to assess the statistical significance of the Moran I statistic, we provide the Monte Carlo method that involves generating random permutations of the data to create a null distribution of the Moran I statistic (the distribution under no spatial autocorrelation). The observed Moran I statistic is then compared to this null distribution to determine its statistical significance. In our case, the p-value is very small, indicating strong evidence against the null hypothesis and favouring the alternative hypothesis of spatial autocorrelation. Therefore, the Monte Carlo simulation confirms the Moran I test results and

Table 8.3: Moran's I statistics for SMER, and ĽSNS using contiguity and inverse distance matrices

	SMER				*ĽSNS*			
	contiguity		inverse		contiguity		inverse	
	Moran	p-value	Moran	p-value	Moran	p-value	Moran	p-value
Moran	0,52	0,00	0,05	0,01	0,46	0,00	0,05	0,01
MC	0,52	0,01	0,05	0,03	0,46	0,01	0,05	0,01

strengthens the conclusion that there is spatial autocorrelation in the SMER vote share.

In the case of the ĽSNS, the estimates of the Moran I statistic are 0.462 and 0.464 for the contiguity and inverse distance matrices, respectively. The statistic suggests positive spatial autocorrelation in the variable. The p-value is statistically significant; we can reject the null hypothesis of no spatial autocorrelation and conclude there is evidence of spatial autocorrelation in the data. The Monte Carlo simulation confirms the spatial autocorrelation.

8.3 LISA

The LISA identifies spatial clusters of electoral results for political parties; we focus on the dependent variables. As in the previous case, we provide a comparison of results when using two types of spatial weight matrices. In the case of the contiguity matrix displayed in figure D.1, for the 2020 election year, the LISA analysis for SMER identified seven districts with high-high clustering, implying that districts with high electoral results were surrounded by neighbouring districts with similarly high electoral results. These clusters are primarily located in the eastern part of the country, with one county in the north. Additionally, one county is found to have a low-high clustering, indicating a low electoral result, while surrounded by districts with high results. Also, it revealed spatial clusters of low-low electoral results in 11 counties located primarily in the surrounding area of the capital city with an overlap in southern Slovakia, which has a high concentration of Hungarians.

When using the inverse distance matrix (figure D.2), we can see only one low-low cluster located in the capital's surroundings. Otherwise, the results do not show any significant findings. The explanation may be that the coordinates of the district are given according to the district city, and also, some counties are significantly larger than others. This can cause that there is a long distance between neighbouring districts, which can influence each other's voters. Therefore, they are taken as remote when using the inverse matrix and may not correctly depict reality. A better calculation of the distance between districts would be the distance between the borders, that is, the closest distance between the counties' borders, which is difficult to implement and calculate.We tried various options for computing inverse distance, such as $\frac{1}{d^2}$ and $\frac{1}{\log(d+1)}$. However, there were no significant differences, so we decided to use the basic one, $\frac{1}{d}$.

We use the same approach to calculate and interpret LISA for ĽSNS. The contiguity matrix revealed a similar trend in the western and southern parts of the country. Notably, in the eastern part of the country, there are no local clusters of vote share. The inverse-distance matrix explores clusters in Slovakia's western, northern and southern parts. LISA displayed for 2016 can be found in Appendix D.

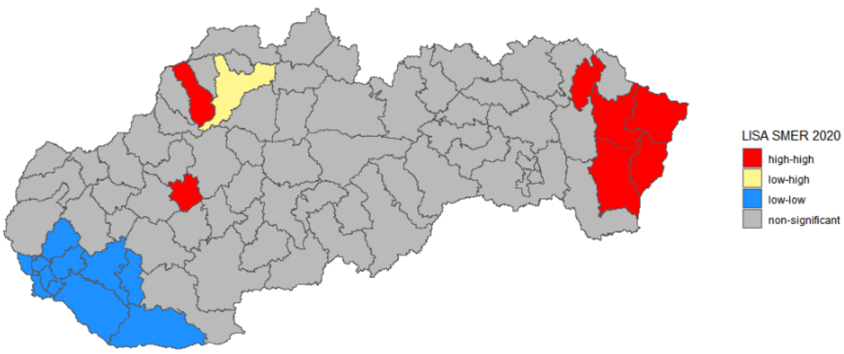

Figure 8.1: LISA SMER Contiguity 2020

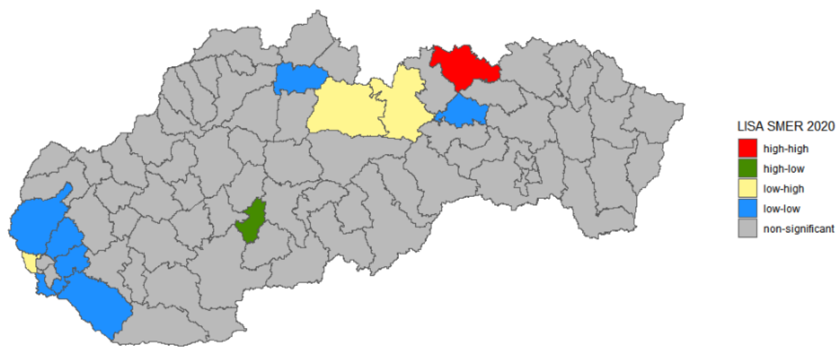

Figure 8.2: LISA SMER Inverse 2020

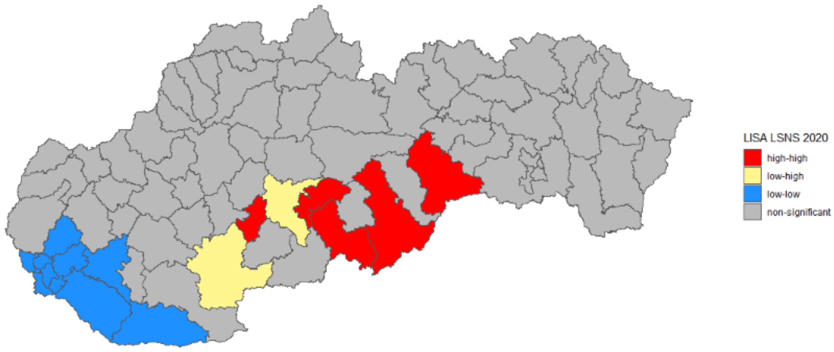

Figure 8.3: LISA ĽSNS Contiguity 2020

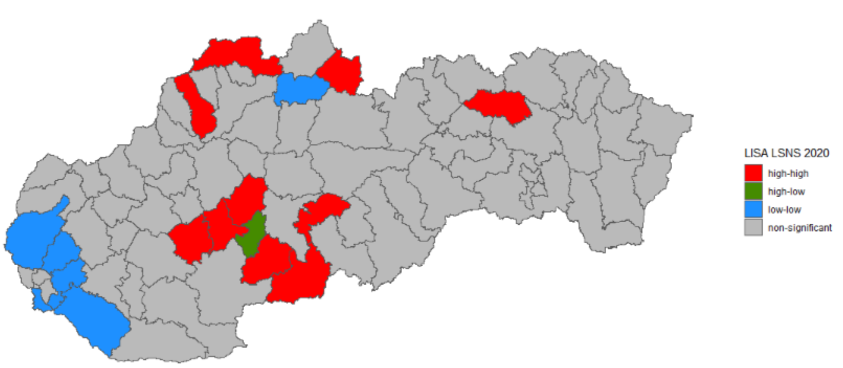

Figure 8.4: LISA ĽSNS Inverse 2020

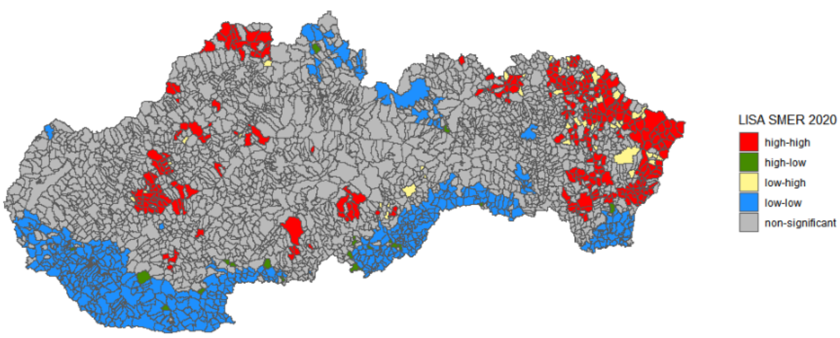

Figure 8.5: LISA SMER Municipality Contiguity 2020

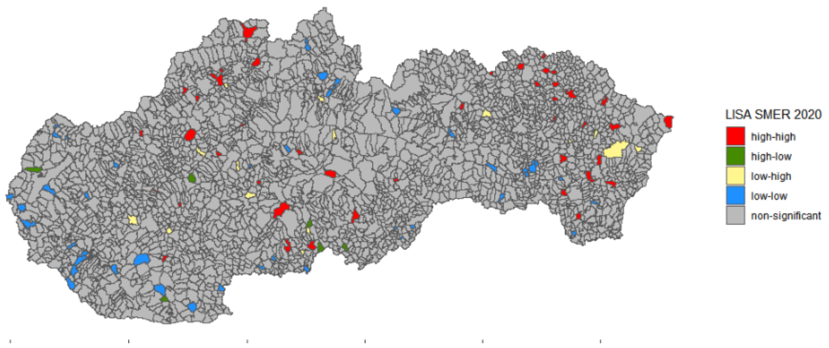

Figure 8.6: LISA SMER Municipality Inverse 2020

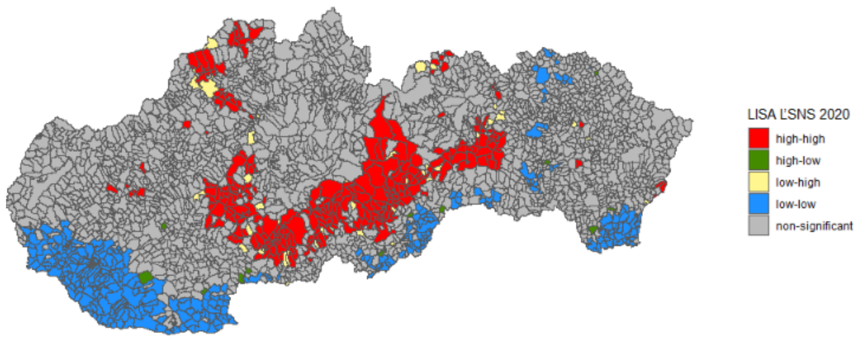

Figure 8.7: LISA ĽSNS Municipality Contiguity 2020

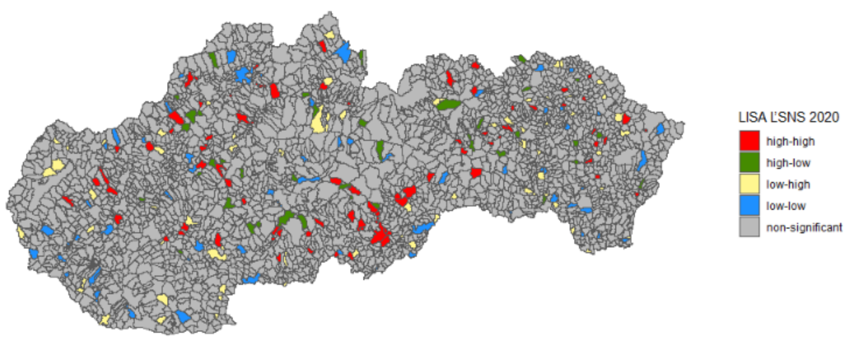

Figure 8.8: LISA ĽSNS Municipality Inverse 2020

Spatial analysis involves identifying spatial autocorrelation, which is essential in determining areas with distinct characteristics. Through the use of the LISA indicators map, we can observe how the distribution of electoral support for individual parties is regionally structured and concentrated in specific regions. However, it is important to note that the Global Moran's I and LISA indicators used are primarily for descriptive analysis, and their explanatory capabilities are limited Maškarinec, 2013].

Our analysis on the county level reveals areas with low values covering a large part of the capital city, Bratislava, while Košice and its surrounding areas are non-significant. In the analysis of election results for the year 2020, LISA essentially identifies cores or concentrations of voter support for SMER in the eastern part of Slovakia, which is not the case for 2016, when this area is insignificant. Most of the counties in other parts of Slovakia seem not to be interrelated. We can see similar results at the municipality level. In order to select a suitable spatial model, we explore the relationship between variables by utilising models that consider both dependent and independent variables. The findings allows us to make informed decisions and draw more accurate conclusions from our analysis.

8.4 Spatial models

8.4.1 Comparing single-channel models

Lagrange-Multiplier tests are employed to make an informed choice regarding the model since they are able to indicate whether we should use one of the two most used spatial models; SEM or SLM. The tables 8.4 and 8.5 below show the results for four different Lagrange-Multiplier tests performed on both models of both parties: LMerr, LMlag, RLMerr and RLMlag, with corresponding test statistics and p-values.

Table 8.4: Comparison of SMER Specifications 2020

	SMER Specification 1				SMER Specification 2			
	Contiguity		Inverse		Contiguity		Inverse	
	stat	p-value	stat	p-value	stat	p-value	stat	p-value
Moran I	−0.002	0.42	0.12	0	−0.008	0.45	0.13	0
LMerr	0.01	0.97	17.09	0	0.01	0.91	19.87	0
LMlag	3.48	0.06	12.82	0	3.67	0.05	19.97	0
RLMerr	3.15	0.14	5.60	0.02	1.99	0.16	3.89	0.05
RLMlag	5.63	0.02	1.33	0.25	5.67	0.02	3.92	0.05

Tests for both matrices show the test statistics and p-value of the Global Moran I, LMerr, LMLag and their robust versions for both parties' models. The results of the Moran's indicate that the null hypothesis of zero spatial autocorrelation cannot be upheld for any of the models tested. Therefore, it is necessary to employ spatial econometrics methods in the analysis. Based

Table 8.5: Comparison of ĽSNS Specifications 2020

	ĽSNS Specification 1				ĽSNS Specification 2			
	Contiguity		Inverse		Contiguity		Inverse	
	stat	p-value	stat	p-value	stat	p-value	stat	p-value
Moran I	−0.09	0.86	0.11	0	−0.07	0.80	0.13	0
LMerr	1.68	0.21	14.02	0	1.08	0.29	20.34	0
LMlag	1.35	0.25	10.3	0	0.54	0.46	29.30	0
RLMerr	0.43	0.51	5.01	0.02	0.59	0.46	0.38	0.53
RLMlag	0.18	0.67	1.29	0.25	0.02	0.91	9.34	0.01

on our analysis, it appears that the inverse distance matrix is a more accurate measure of spatial interactions for both of our models. This is supported by the fact that the statistics in spatial diagnostics are more significant when using the inverse-distance matrix. Therefore, we can conclude that an inverse-distance matrix is a superior tool for measuring the presence of spatial interactions in our models. Based on the obtained results from Lagrange Multipliers, SMER's Specification 1 guides us to estimate the spatial error model, but in the case of Specification 2, all of our tests are significant.

In the case of the ĽSNS models, we can see inconsistencies in both Specifications since the Specification 1 tests suggest using the spatial error model, and in Specification 2, we can see a significant RLMlag model. We can see similar values obtained from the LM test estimated on models with the dataset from 2016 displayed in tables 8.6 and 8.7. Since there is no definitive choice between the two most commonly used models, the SEM and the SLM, it is necessary to implement advanced spatial models such as SDM, SDEM, and SAC. As Cook et al. (2015) explains, even if the Moran I and LM tests point towards using SLM or SEM, additional precautions are needed to avoid inefficiencies and possible bias in our parameter estimates. These tests are only indicative of the spatial process and are have limited applicability in selecting specifications from a wide class of possible spatial models.

Table 8.6: Comparison of SMER Specifications 2016

	SMER Specification 1				SMER Specification 2			
	Contiguity		Inverse		Contiguity		Inverse	
	stat	p-value	stat	p-value	stat	p-value	stat	p-value
Moran I	−0.001	0.44	0.16	0	0.01	0.34	0.15	0
LMerr	0.01	0.94	28.75	0	0.06	0.80	26.08	0
LMlag	2.94	0.08	13.30	0	0.15	0.67	39.15	0
RLMerr	1.31	0.25	15.51	0	0.42	0.51	1.82	0.17
RLMlag	4.24	0.04	0.06	0.79	0.52	0.47	14.89	0

Table 8.7: Comparison of ĽSNS Specifications 2016

	ĽSNS Specification 1				ĽSNS Specification 2			
	Contiguity		Inverse		Contiguity		Inverse	
	stat	p-value	stat	p-value	stat	p-value	stat	p-value
Moran I	−0.01	0.47	0.11	0	−0.01	0.47	0.15	0
LMerr	0.02	0.87	14.68	0	0	0.94	26.66	0
LMlag	0.51	0.47	11.95	0	0.93	0.33	33.52	0
RLMerr	0.74	0.39	4.37	0.03	1.35	0.24	2.53	0.11
RLMlag	1.21	0.27	1.34	0.20	2.28	0.13	9.38	0

8.4.2 Interpretation of spatial models

As mentioned in the hypothesis section, various models apply to our research question. We estimate all the models to determine the most suitable model and compare their performance. In this regard, we present the AIC values for each model variation and spatial model in two separate tables. The first table 8.8 showcases models at the county level, while the second table 8.9 compares models at the municipality level.

To begin with, we comment on the AIC of models estimated at the county level. As the table depicts, there is no single model that works the best in all cases. Selecting different models for different specifications and years would not be consistent. Also, Burkey (2018) asserts that no single technique can comprehensively compare all spatial models and identify the optimal one with certainty. Rather, the author suggests that researchers must rely primarily on their own expertise to choose the appropriate method and, secondarily, use a variety of statistical measures to obtain some indication of the model's goodness of fit. So, even if we include a comparison of AIC, we must focus on our intuition.

Regarding the table comparing models at the municipality level, the analysis indicates that the SAC model exhibits the lowest AIC value for both parties,

Table 8.8: AIC comparison models on the county level

	2020				2016			
	SMER		ĽSNS		SMER		ĽSNS	
specification	1	2	1	2	1	2	1	2
OLS	427,1	429,5	316,5	351,5	470,7	479,2	301,2	323,9
SLM	416,1	413,5	308,1	334,3	460,3	457,3	291,9	307,1
SEM	417,1	418,0	306,0	338,3	456,0	465,3	290,5	310,5
SDM	414,1	408,7	290,2	335,6	461,5	457,2	291,3	311,9
SDEM	415,8	412,8	291,9	337,7	462,9	462,8	291,4	315,3
SAC	409,6	409,6	306,6	333,4	451,9	452,7	290,3	305,4
SLX	426,0	412,7	290,2	337,7	474,3	464,3	295,2	316,1

Table 8.9: AIC comparison models on the municipality level - 2020

	SMER 1	ĽSNS 1
OLS	20 125	17 336
SLM	19 766	17 336
SEM	19 837	16 998
SDM	19 658	16 846
SDEM	19 659	16 866
SAC	19 583	16 769
SLX	19 801	16 997

making it the most appropriate model for this scenario. However, since we employ SDM for models on the county level, we decided to provide results for both these models. The SAC model results on the county level can be found in the Appendix E.

Interpretation of SMER - counties

Table 8.10 below shows the SDM model for both specifications and years of the party SMER. The coefficient ρ captures the spatial lag effect, indicating that the values of the dependent variable in neighbouring counties affect the dependent variable in a particular county. A positive value indicates a positive correlation between vote shares in neighbouring districts, while a negative ρ value implies a negative correlation. The ρ is positive and statistically significant in our case, with values of 0.89 and 0.87 for Specification 1 and 0.75 and 0.76 for Specification 2. It implies that closer proximity observations tend to have similar values for the dependent variable, indicating a high degree of spatial autocorrelation in both years. A significant values of the LR test confirms the result. Findings suggest that spatial relationships between variables are essential to understanding their effects.

The Nagelkerke pseudo-R-squared is a goodness-of-fit measure for models that lack a directly interpretable R-squared value. It indicates the proportion of the dependent variable's variation explained by the model and ranges from 0 to 1, with higher values indicating a better fit. The Nagelkerke is 0.81 and 0.82 for models of Specification 1 and 0.83 for Specification 2 models, suggesting that the models explain over 80% of the variation in the dependent variable.

We firstly start with interpretation od Specification 1 coefficients. Regarding the coefficients in 2020, we can see that unemployment and its lagged value are positive and statistically significant. The significance suggests that an increase in the unemployment rate in a particular county is associated with an increase in the vote share and an increase in the unemployment rate in neighbouring counties is also associated with an increase in the vote share. Other significant but negative variables are the share of people with a university degree, the share of the population in pre-productive age and the share of Hungarians, meaning that the increase of these variables in the county cause a negative influence on the vote share of the party SMER. The share of unskilled workers in the surrounding counties negatively impacts the vote share of the party SMER. On the other hand, the increase in the share of Roman Catholics and Hungarians in the neighbouring counties positively impacts the vote share of the party SMER in the particular county.

When interpreting the 2016 results, we can see similar results in the case of the counties with the higher share of university people, the share of people in pre-productive age and the share of Hungarians as well as the indirect effect of the share of unskilled workers. Otherwise, other variables are insignificant.

Secondly, we describe the coefficients of the Specification 2. Even though there are certain variables, such as the share of people in pre-productive age, the share of skilled workers and the share of Roma and Hungarian minorities, which are significant in both years, we observe that the share of people in productive age is significant only in 2020. All these significant variables have negative signs, indicating that increasing their value in the county decreases the vote share for the party. The only variable with the opposite effect is the share of Roma people, implying that an increase in its value can lead to an increase in the vote share.

Concerning the lag variables displaying the indirect effect, we can see more differences between the years; hence we interpret them separately and start

Table 8.10: Estimated SDM model - SMER

	SDM - SMER			
	Specification 1		*Specification 2*	
	(2020)	(2016)	(2020)	(2016)
unemployment	0.463***	0.215	-	-
	(0.160)	(0.162)		
university_degree	−0.226**	−0.815***	-	-
	(0.091)	(0.179)		
average_wage	-	-	−0.001	−0.007
			(0.003)	(0.005)
share_productive	0.231	0.115	0.818**	0.189
	(0.334)	(0.432)	(0.344)	(0.436)
share_preproductive	−0.838***	−0.638**	−0.893***	−1.042***
	(0.231)	(0.319)	(0.245)	(0.349)
skilled_workers	-	-	−0.178***	−0.347***
			(0.058)	(0.075)
unskilled_workers	−0.151	−0.041	0.101	0.017
	(0.152)	(0.229)	(0.156)	(0.266)
roman_catholic	−0.009	−0.023	−0.035	−0.011
	(0.027)	(0.035)	(0.024)	(0.035)
share_roma	-	-	1.155***	0.403***
			(0.275)	(0.116)
hungarian	−0.323***	−0.436***	−0.312***	−0.392***
	(0.031)	(0.043)	(0.030)	(0.039)
lag.unemployment	2.156**	1.196	-	-
	(1.080)	(0.851)		
lag.university_degree	0.134	0.315	-	-
	(0.442)	(0.922)		
lag.average_wage	-	-	0.057***	0.022
			(0.021)	(0.037)
lag.share_productive	1.336	−0.248	5.491***	3.987
	(1.483)	(2.336)	(1.465)	(2.916)
lag.share_preproductive	−1.528	−1.821	0.462	0.743
	(1.424)	(1.966)	(1.148)	(1.688)
lag.skilled_workers	-	-	−1.091***	−1.245***
			(0.310)	(0.439)
lag.unskilled_workers	−5.610***	−6.051**	0.146	−4.970
	(1.964)	(2.739)	(1.654)	(3.508)
lag.roman_catholic	0.485*	0.339	−0.108	−0.069
	(0.271)	(0.225)	(0.198)	(0.408)
lag.share_roma	-	-	4.025**	0.975
			(1.675)	(0.750)
lag.hungarian	0.600**	0.458	0.280	0.019
	(0.298)	(0.338)	(0.288)	(0.331)
Constant	−66.355	63.729	−438.177***	−207.723
	(124.877)	(214.520)	(135.049)	(266.228)
ρ	0.879 ***	0.841***	0.764**	0.737**
Nagelkarke R^2	0.81	0.82	0.83	0.83
Log Likelihood	−190.124	−214.029	−185.294	−185.420
Wald Test (df = 1)	120.217***	66.598***	27.566***	21.410***
LR Test (df = 1)	13.715***	14.242***	6.126**	5.874**

Note: *p<0.1; **p<0.05; ***p<0.01

with 2020. In the case of the average wage, the output reveals that the local area's average wage does not exhibit a significant relationship with the vote share. However, the average wage in neighbouring spatial units, denoted as lag.average_wage, displays a positive and statistically significant correlation with the party vote share. The finding suggests that the economic conditions in surrounding counties significantly impact the support of the party SMER more than the local average wage. A possible reason for this outcome is that individuals living in a specific locality may compare their economic circumstances with those of their neighbours in nearby counties. If the average wage is higher in the neighbouring areas, it could influence their voting preferences and potentially increase the party's vote share.

The indirect effect of other significant variables, the share of skilled workers, the share of productive people and the share of the Roma population are also significant; they display the same sign and magnitude as the direct effect of variables. In the case of the model from 2016, the average wage in the surrounding counties is insignificant, and the only significant indirect effect is the share of skilled workers.

Interpretation of SMER - municipalities

As explained in the previous chapter, we present two models display in the table 8.11 when interpreting the results on the municipality level, SAC and SDM. We start describing the coefficients and statistics in the SAC model. The output highlights variables and their corresponding lag versions, which consider the influence of the neighbouring values of the independent variables on the dependent variable. ρ and λ terms can be observed in the SAC model, whereas in SDM, we observe λ.

The coefficient ρ measures the spatial lag effect. ρ in the model is 0.98, which suggests strong spatial autocorrelation in the vote share. On the other hand, λ represents the spatial error term. λ in the model is 0.98 indicating strong spatial spillovers in the error term, meaning that if some event impacts one municipality, it could also, lead to changes in the number of people voting for the SMER party in nearby municipalities.

The LR test is a statistical method used to compare the goodness-of-fit of two nested models. In the context of a SAC, the LR test compares the model with the OLS. A lower p-value suggests that the SAC model better fits the data than the OLS model.

Table 8.11: Estimating SAC and SDM on the municipality level - SMER

	SMER - municipalities	
	SAC	*SDM*
unemployment	0.083*	0.038
	(0.050)	(0.054)
university_degree	−0.326***	−0.264***
	(0.029)	(0.032)
share_productive	−0.161***	−0.140***
	(0.037)	(0.038)
share_preproductive	−0.410***	−0.332***
	(0.032)	(0.034)
unskilled_workers	0.029	0.059
	(0.045)	(0.046)
roman_catholic	−0.508***	−0.052***
	(0.005)	(0.007)
hungarian	−0.2545***	−0.259***
	(0.008)	(0.009)
lag.unemployment	-	2.657***
	-	(0.662)
lag.university_degree	-	−0.835*
	-	(0.435)
lag.share_productive	-	1.350
	-	(0.904)
lag.share_preproductive	-	−2.093***
	-	(0.424)
lag.unskilled_workers	-	−5.079***
	-	(0.990)
lag.roman_catholic	-	0.156**
	-	(0.075)
lag.hungarian	-	−0.003
	-	(0.052)
Constant	23.729	−14.507
	(22.52)	(60.914)
ρ	0.985***	0.984***
λ	0.982***	-
Nagelkarke R^2	0.57	0.57
Log Likelihood	-9,808.972	−9,812.036
LR Test	489.33***	144.495***
Note:	*p<0.1; **p<0.05; ***p<0.01	

Interpreting the coefficients, we notice that all variables are statistically significant except for the share of unskilled workers, and only unemployment is significant at the 10% level; otherwise, there is significance at the 1% level. The SDM on the municipality level shows strongly significant ρ with a value of 0.98, confirming the spatial spillovers in the dependent variable, the vote share of the party SMER. Nagelkarke is almost identical to the SAC model, explaining 57% of the model's variation. Explaining the coefficient of the SDM, the unemployment variable is insignificant. Nonetheless, its lagged value is. The model analysis reveals that the unemployment rate in the local area does not exhibit a significant relationship with the dependent variable. However, the unemployment rate in neighbouring spatial units demonstrates a positive and statistically significant correlation with the dependent variable. Results suggest that unemployment influences the vote share more in the surrounding municipalities than the local unemployment rate. These findings emphasise the importance of spatial relationships when analysing data with a geographical component.

Another issue is the contrasting relationship between the Roman Catholic direct and indirect effects. The direct effect of the share of Roman Catholics is negative and significant, whereas the indirect effect of the variable is positive and significant. The differential relationship between the Roman Catholic population and the dependent variable in local and neighbourhood areas can be interpreted in several ways. Results indicate that the local Roman Catholic population significantly influences the vote share of the party SMER compared to the Roman Catholic population in the neighbouring counties. The contrast may be caused by differences in cultural, social, or other factors that are not captured by the direct effect of the roman_catholic variable but are captured by the lag.roman_catholic variable. Alternately, there may be a spillover effect whereby the influence of the Roman Catholic population in neighbouring areas is more vital than the effect of the local Roman Catholic population. It can also result from various factors such as social networks, communication or regional policies beyond local borders. These findings suggest that the Roman Catholic population in neighbouring areas has a negative impact on voting for the SMER party, and a higher Roman Catholic population in the local area is associated with a higher vote share for the SMER party.

The share of productive and pre-productive display significant and negative both effects, direct and indirect. Significance suggests that an increase in the share of productive and pre-productive workers in surrounding areas negatively influences the vote share of the party SMER. The share of people with a university degree negatively affects the support for the party SMER with its direct effect. The coefficients of the SAC model display the significance of all variables except the share of unskilled workers.

Interpretation of ĽSNS - counties

The column 1 and 2 in the table 8.12 displays the results of the SDM Specification 1 estimated with the ĽSNS vote share as the dependent variable. The Nagelkerke pseudo-R2 is, in both cases, relatively high, explaining around 80% variation. However, ρ spatial lag term is insignificant in the model explaining the vote share in 2020. Therefore we cannot confirm the spatial autocorrelation of the dependent variable. On the other hand, the ρ is statistically significant at a 1% level in 2016, showing a remarkable difference between the two examined years.

In 2020, we can see multiple statistically significant variables. The only insignificant variables are the share of unskilled workers and the lagged variable explaining the indirect effect of unemployment and the share of unskilled workers. On the other hand, in the model describing the vote share in 2016, we notice a lower amount of significant variables. The only significant variable describing the indirect effect is the share of Hungarians.

The output in the column 3 and 4 in the table 8.12 shows the significance of ρ, spatial lag term, resulting in spatial spillovers in the vote share of the party ĽSNS. It means that the vote share of neighbouring counties influences the vote share of the particular county. The Nagelkerke pseudo-R2 is 0.73 and 0.72, respectively, suggesting the overall goodness fit of the model.

Regarding the coefficients in 2020, we can see significant effects of the share of the Roman Catholics, Roma population and Hungarian minority. Whereas the share of Hungarians in the county negatively impacts the vote share, the counties with higher shares of Roma people and Roman Catholics are more likely to vote for the party. As we can see, their direct effect is influential, whereas the lagged version and their indirect effect are insignificant. However, it is not the case with the model in 2016. Results display more significant variables, such as the negative significance of the share of skilled workers and those in productive age. On the other hand, positive signs can be seen in the share of unskilled workers. We are aware of the indirect effect, specifically in

Table 8.12: Estimated SDM model - ĽSNS

	SDM - ĽSNS			
	Specification 1		*Specification 2*	
	(2020)	(2016)	(2020)	(2016)
unemployment	0.506***	0.257***	-	-
	(0.075)	(0.056)		
university_degree	−0.144***	−0.035	-	-
	(0.042)	(0.061)		
average_wage	-	-	0.0003	−0.003
			(0.002)	(0.002)
share_productive	−0.267*	0.373**	0.008	0.101
	(0.157)	(0.148)	(0.215)	(0.174)
share_preproductive	−0.421***	0.132	−0.272*	0.011
	(0.109)	(0.110)	(0.154)	(0.140)
skilled_workers	-	-	−0.088**	0.001
			(0.036)	(0.030)
unskilled_workers	0.109	0.018	0.286***	−0.051
	(0.071)	(0.078)	(0.099)	(0.106)
roman_catholic	0.059***	0.028**	0.035**	0.038***
	(0.013)	(0.012)	(0.015)	(0.014)
share_roma	-	-	0.537***	0.141***
			(0.173)	(0.046)
hungarian	−0.136***	−0.140***	−0.111***	−0.111***
	(0.014)	(0.015)	(0.019)	(0.016)
lag.unemployment	0.551	−0.191	-	-
	(0.504)	(0.296)		
lag.university_degree	0.828***	0.326	-	-
	(0.207)	(0.315)		
lag.average_wage	-	-	0.026*	−0.022
			(0.013)	(0.015)
lag.share_productive	−1.189*	1.034	0.301	−1.154
	(0.697)	(0.801)	(0.916)	(1.167)
lag.share_preproductive	−1.508**	−0.218	−0.443	−1.264*
	(0.666)	(0.676)	(0.718)	(0.676)
lag.skilled_workers	-	-	0.094	0.336*
			(0.189)	(0.174)
lag.unskilled_workers	1.141	1.174	3.560***	−0.760
	(0.915)	(0.941)	(1.054)	(1.404)
lag.roman_catholic	0.419***	0.013	−0.060	0.217
	(0.132)	(0.082)	(0.124)	(0.164)
lag.share_roma	-	-	−0.147	−0.061
			(1.046)	(0.301)
lag.hungarian	0.416***	0.283**	0.290	0.164
	(0.139)	(0.116)	(0.178)	(0.132)
Constant	76.588	−111.949	−65.810	96.617
	(58.912)	(73.573)	(84.925)	(106.482)
ρ	0.487	0.726**	0.731**	0.740**
Nagelkarke R^2	0.80	0.80	0.73	0.73
Akaike Inf. Crit.	290.155	291.077	335.378	312.054
Wald Test (df = 1)	3.551*	19.348***	20.290***	21.735***
LR Test (df = 1)	2.047	6.089**	4.336**	6.032**

Note: *p<0.1; **p<0.05; ***p<0.01

the lagged variable average wage and unskilled workers. It is evident that the average wage has a neighbouring effect more significant than the local one.

Interpretation of ĽSNS - municipalities

The table 8.13 displays the results of SAC (column 1) and SDM (column 2) models estimation. Firstly, we describe the SAC model on the municipality level. ρ and λ are statistically significant with values above 0.98, explaining spatial spillovers of the party's vote share ĽSNS and error terms. However, Nagelkerke explains that the model represents only 41% variation. As the results show, unemployment is the only insignificant variable; otherwise, all variables are statistically significant.

The SDM shows significant spatial autocorrelation in the dependent variable with ρ 0.98. Similarly, Nagelkerke is slightly above 40%, and coefficients display the same signs and significance as in the SAC, except for the Roman Catholics. In the SDM, the direct effect of the variable is not significant; however, its indirect effect is. Neighbouring effects of unemployment, the share of people with a university degree, the share of people in productive age and the share of Hungarians are significant and influential on the ĽSNS vote share.

8.5 Discussion

Location matters. The analysis of the SMER model reveals spatial spillovers in vote share as well as in some variables in both specifications and both years examined. Our findings underscore the importance of assessing spatial relationships when analysing data with a geographic dimension. The models show the importance of the share of university-educated people, which confirms our first hypothesis. Also, the share of people in pre-productive age as well as the importance of minorities - the share of Roma and Hungarians.

As for the second hypothesis, we discover that the spillovers in vote share are significant in all cases, except for Specification 1 of ĽSNS for the year 2020 on the county level. It may suggest that people across regions strongly affect each other's political opinions. Furthermore, the indirect effects of the observed variables are essential. The spillover effects of unemployment and the share of unskilled workers and minorities also explain electoral support. Analysis at the level of municipalities further confirms our findings. This renders the third hypothesis confirmed. Interestingly, even though we have a strongly statisti-

Table 8.13: Estimating SAC and SDM on the municipality level - ĽSNS

	ĽSNS - municipalities	
	SAC	*SDM*
unemployment	0.031	−0.006
	(0.030)	(0.034)
university_degree	−0.210***	−0.163***
	(0.018)	(0.020)
share_productive	0.122***	0.120***
	(0.023)	(0.024)
share_preproductive	−0.116***	−0.109***
	(0.019)	(0.021)
unskilled_workers	0.050*	0.060**
	(0.028)	(0.028)
roman_catholic	0.011***	0.003
	(0.003)	(0.004)
hungarian	−0.118***	−0.146***
	(0.005)	(0.006)
lag.unemployment	-	0.920**
	-	(0.410)
lag.university_degree	-	−0.871***
	-	(0.269)
lag.share_productive	-	1.263**
	-	(0.560)
lag.share_preproductive	-	−0.001
	-	(0.262)
lag.unskilled_workers	-	−0.358
	-	(0.612)
lag.roman_catholic	-	0.177***
	-	(0.046)
lag.hungarian	-	0.139***
	-	(0.032)
Constant	−4.929	−91.602**
	(18.655)	(37.690)
ρ	0.985***	0.984***
λ	0.987***	-
Nagelkarke R^2	0.41	0.40
Log Likelihood	-8,406.741	−8,406.964
LR Test	504.36***	151.211***
Note:	*p<0.1; **p<0.05; ***p<0.01	

cally significant average wage in the OLS analysis of the SMER vote share, the spatial analysis reveals that the direct effect of the variable is not significant, while the indirect effect is.

Similarly, in Specification 1, the proportion of unskilled workers is not statistically significant in OLS, while spatial analysis reveals strong significance in both direct and indirect effects. When interpreting the ĽSNS vote share, the OLS results are quite similar to those obtained from the spatial analysis. Nevertheless, spatial analysis is important as we find spillover effects. The SAC model on the municipality exhibits the spillovers in the error term are present in our data, which confirms the fourth hypothesis.

Regarding the fifth hypothesis, we can confirm the stability over time for the results of the party SMER. However, there are discrepancies for the party ĽSNS. The reasoning behind the difference might be that SMER is well-established party, participating in many various elections hence we expect they have consistent voter base. Also, the party has a higher vote share. On the other hand, ĽSNS is younger party with smaller voter base. Further inaccuracy can be caused by the fact that some of the data used for the 2016 dataset were from the year 2011.

Chapter 9

Conclusion

The system of factors influencing the election outcome is complex, and it is difficult to capture its essence in numbers and mathematical models. Researchers point towards several socio-demographic characteristics that help uncover why people in some regions gravitate towards populist parties. It appears that it is insufficient only to study individuals and predict their decisions based on the metrics we know about them and the place they live in. However, it is also beneficial to examine the regions' influence on each other. This thesis aimed to apply the econometric tools in Slovakia and try to comprehend the factors and interactions that dictated the parliamentary election outcomes in 2016 and 2020. We used the data from the 2021 census plus a set of regional statistics as input to OLS models to determine which factors determine the populist parties' success. Then we used a variety of spatial models to refine the results. We expanded the work of Dusková (2021) by using an updated dataset and adding another variable, education structure, which was not available in the data of that time.

We estimated an OLS and six spatial models and chose two multi-factor models, namely SAC and SDM, as our preferred estimation approaches. The results of the models confirmed the hypotheses, since we discovered the spillover effects of vote share, variables and errors. Based on the AIC metric, we found that the most robust models incorporate spillover of the outcome. Regarding the first hypothesis and the investigation of the influence of education on vote share, we found that the variable appears to be a critical correlate of vote share; the variable was negative and significant for both years and both parties at both levels. The fifth hypothesis can be confirmed only for the party SMER, since there is greater variance in ĽSNS results.

The limitation of this work is in the missing average wage values for the municipality level and, therefore, the impossibility of estimating the model at the municipalities level for specification 2.

Our research could be extended by comparing more than two parliamentary elections or different types of elections, such as presidential or municipal. Municipal elections have already taken place since the last parliamentary elections in 2020, and at the end of that year another parliamentary election awaits Slovakia. There is an opportunity to explore other populist or non populist political parties, as the political situation is constantly changing.

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Appendix A

Descriptive statistics

Table A.1: Descriptive statistics of variables on the county level

	2016			2020		
variable	mean	median	st. dev	mean	median	st. dev
SMER_voteshare	30,32	30,27	8,67	19,75	19,9	6.23
LSNS_voteshare	8,63	8,79	2,7	8,78	8,85	3,02
unemployment	14,07	12,53	6,59	6,71	5,2	4,18
average_wage	924,86	885	169,63	1138,5	1101	193,4
share_productive	70,21	70,42	1,71	67,68	67,79	1,46
share_preproductive	15,25	14,41	2,43	15,62	14,91	2,44
unskilled_workers	7,34	7,27	2,47	7,51	7,02	2.64
skilled_workers	33,35	32,62	7,38	31,5	30,97	6.81
roman_catholic	60,81	63,93	16,92	55,2	57,08	16,47
share_roma	5,58	2,21	6,85	1,28	0,4	2,02
hungarian	6,24	0,16	13,96	5,75	0,17	13,14
university_degree	13,24	11,16	5,53	17,34	14,95	7,1

Appendix B

Correlation table

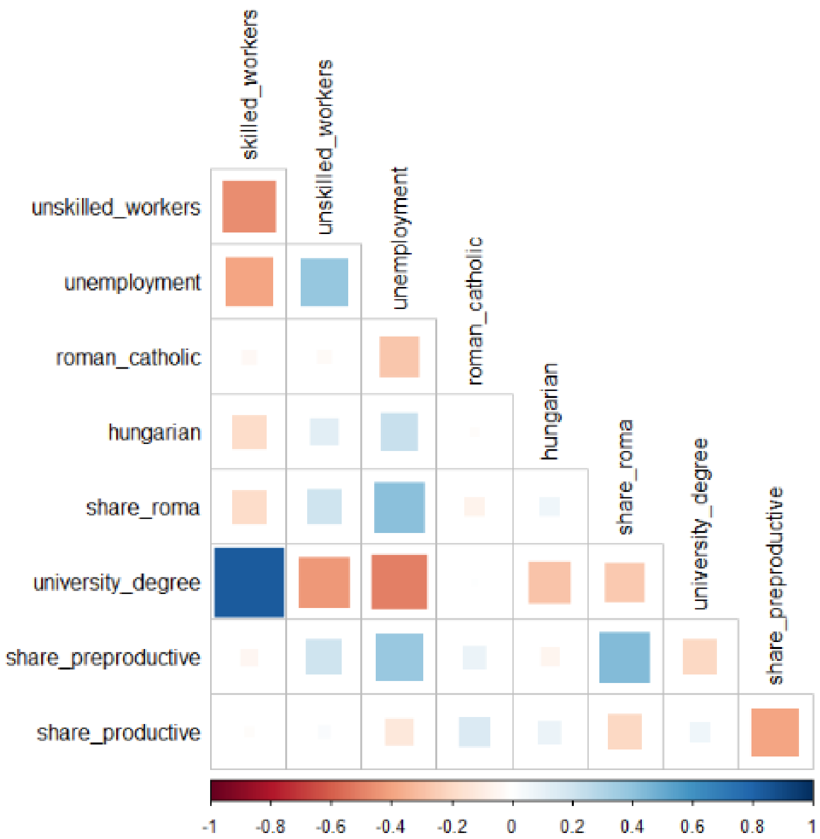

Figure B.1: Correlation table of municipalities

Appendix C

OLS assumptions

- MLR. 1 - Linearity in parameters:

  The model is as follows:

  $$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_k x_k + u,$$

  where β_0,β_1,...,β_k represents the parameters and u is the error term.

- MLR. 2 - Random sampling

  An observation sample of n, (x_{i1}, x_{i2},...,x_{ik},y): $i = 1, 2, ..., n$, is randomly drawn, which follows the MLR. model.

- MLR. 3 - No perfect collinearity

  Each independent variable in the sample is constant, and there is no exact relationship between them.

- MLR. 4 - Zero conditional mean

  There is a zero correlation between explanatory variables and the error term.

  $E(u/x_1, x_2, ..., x_k) = 0$

- MLR. 5 - Homoskedasticity

  The error term has the same variance given any value of the independent variables.

  $Var(u/x_1, x_2, ..., x_k) = \sigma^2$

Appendix D

LISA maps - 2016

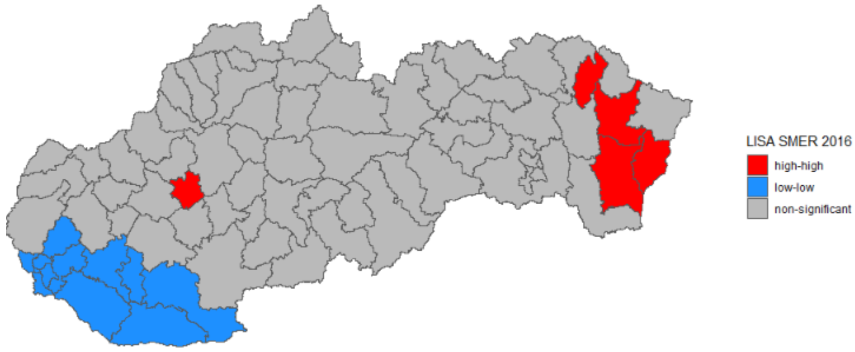

Figure D.1: LISA SMER Contiguity 2016

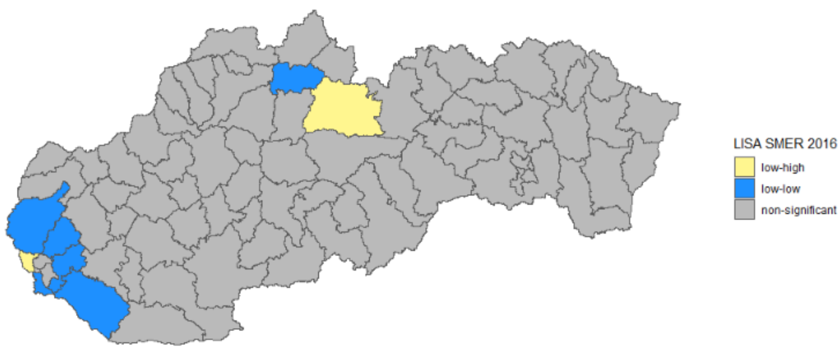

Figure D.2: LISA SMER Inverse 2016

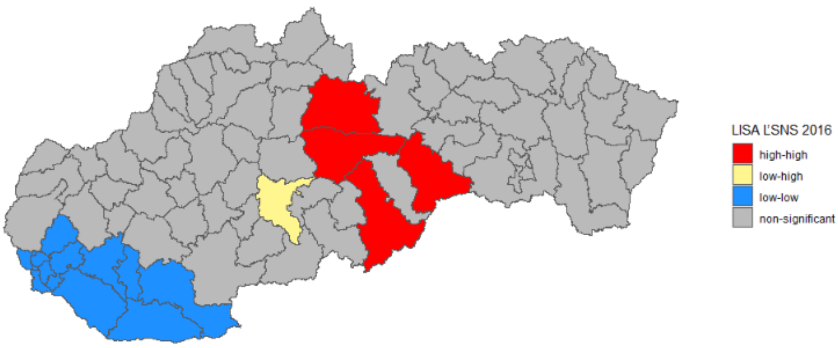

Figure D.3: LISA ĽSNS Contiguity 2016

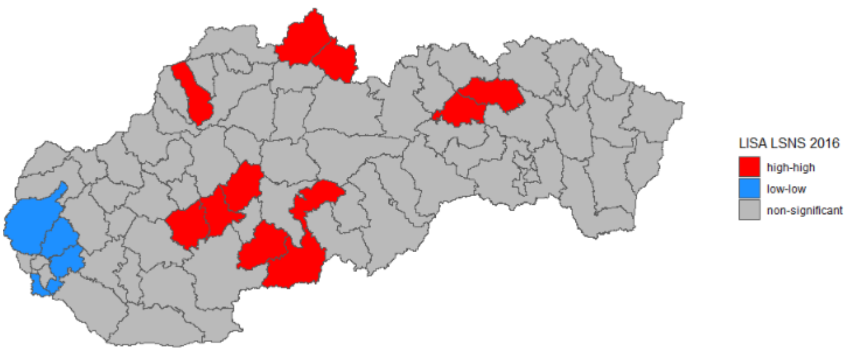

Figure D.4: LISA ĽSNS Inverse 2016

Appendix E

SAC models results

Table E.1: Estimating SAC Specification 1

	SMER		*ĽSNS*	
	2020	*2016*	*2020*	*2016*
unemployment	0.395***	0.260**	0.358***	0.189***
	(0.143)	(0.117)	(0.075)	(0.042)
university_degree	−0.278***	−0.643***	−0.164***	−0.094*
	(0.082)	(0.140)	(0.042)	(0.048)
share_productive	−0.049	−0.044	−0.293*	0.146
	(0.289)	(0.281)	(0.153)	(0.100)
share_preproductive	−0.975***	−0.817***	−0.379***	−0.036
	(0.209)	(0.260)	(0.106)	(0.094)
unskilled_workers	0.012	0.266	0.036	−0.027
	(0.140)	(0.186)	(0.073)	(0.067)
roman_catholic	−0.001	−0.033***	0.055***	0.043***
	(0.027)	(0.032)	(0.014)	(0.011)
hungarian	−0.294***	−0.426***	−0.113***	−0.114***
	(0.029)	(0.036)	(0.014)	(0.012)
Constant	28.233	35.543	29.359***	−7.915
	(20.703)	(21.384)	(10.711)	(7.688)
ρ	0.729**	0.620**	0.320	0.407
λ	0.799***	0.841***	0.827***	0.809***
Log Likelihood	−194.262	−214.955	−142.321	−134.152
LR Test	20.598***	22.767***	13.891***	14.921***
Note:	*p<0.1; **p<0.05; ***p<0.01			

Table E.2: Estimating SAC Specification 2

	SMER		*ĽSNS*	
	2020	*2016*	*2020*	*2016*
average_wage	-0.007^{***}	-0.010^{**}	-0.002	-0.002
	(0.003)	(0.004)	(0.001)	(0.001)
share_productive	0.119	-0.267	-0.151	0.132
	(0.287)	(0.304)	(0.181)	(0.121)
share_preproductive	-1.062^{***}	-1.180^{***}	-0.294^{**}	-0.070
	(0.222)	(0.264)	(0.132)	(0.104)
skilled_workers	-0.161^{***}	-0.259^{***}	-0.097^{***}	-0.045^{*}
	(0.054)	(0.067)	(0.033)	(0.026)
unskilled_workers	0.004	0.298	0.110	-0.013
	(0.143)	(0.193)	(0.089)	(0.077)
roman_catholic	-0.013	-0.014	0.036^{**}	0.039^{***}
	(0.023)	(0.030)	(0.014)	(0.012)
share_roma	0.860^{***}	0.322^{***}	0.460^{***}	0.124^{***}
	(0.255)	(0.100)	(0.154)	(0.040)
hungarian	-0.289^{***}	-0.393^{***}	-0.099^{***}	-0.100^{***}
	(0.028)	(0.033)	(0.017)	(0.013)
Constant	27.792	60.417	19.823	-7.915
	(21.376)	(26.612)	(13.117)	(7.688)
ρ	0.775^{**}	0.823^{**}	0.7295^{*}	0.709^{**}
λ	0.753^{**}	0.772^{**}	0.677	0.707^{*}
Log Likelihood	-192.811	-214.368	-154.67	-140.690
LR Test	23.827^{***}	30.448^{***}	22.174^{***}	22.477^{***}
Note:	*p<0.1; **p<0.05; ***p<0.01			