The impact of war in Ukraine on the spread of anti-EU political parties' attitudes in Poland

Anna Lewczuk, PhD, Chair of Political Economy
Kateryna Zabarina, PhD, Chair of Statistics and Econometrics

GUS

UNIVERSITY OF WARSAW | Faculty of Economic Sciences

SPATIAL WARSAW TEAM

Outline

1. Introduction and motivation
2. Threefold theoretical outline:

➔ The concept of Euroscepticism and how it is related to war
➔ War and support for anti-EU parties in Central & Eastern Europe
➔ Polish 2019 and 2023 parliamentary elections and voters' tolerance for anti-EU attitude

1. Database
2. Methodology
3. Results
4. Conclusions, challenges and future directions
5. *additional slide* (if needed)

Introduction

- Our initial idea was to analyse influence of war on both populistic and anti-EU behaviour of Polish parties, however, finally stopped only on EU scepticism
- According to the report published by the Public Opinion Research Center (CBOS) 20 years after Poland became a member of the European Union (EU), the Poles attitude towards EU membership is the lowest in a decade, with 77% of respondents in favour of Poland's presence in this organisation and 17% against (CBOS 2024).
- A variety of studies from the fields of public choice or political science focused on the relationship between the parties' populist attitudes and their declared support for Ukraine (e.g. Hooghe et al., 2024; Stoica, 2023)
- To assess the correlation of the war in Ukraine with the spread of voters' tolerance for anti-EU attitudes of political parties in Poland, we **propose a spatial empirical model forecasted on a municipality-level data in Poland**.
- Based on the municipality-level lower chamber election results and the Chapel Hill Expert Survey data (Bakker *et al.* 2020), we **propose an index capturing the change in the intensity of voters' tolerance for parties' anti-EU position between the elections of 2019 and 2023**
- We aim to verify the following research hypothesis: ***The greater exposure to war in Ukraine measured by the municipality's proximity to Polish-Ukrainian border could trigger voters' support for Eurosceptic parties***

Euroscepticism

- The concept of Euroscepticism is very broad as it may at the same time include an opposition to European integration together with critique of its performance, as well as citizens' or parties' doubts regarding only particular elements or policies pursued in the European Union
- The interaction between individual voters' characteristics and local economic characteristics reveal a pattern reflecting a "*geography of discontent*" (Los et al. 2017, Dijkstra et al. 2020, Koeppen et al. 2021, Rodríguez-Pose 2018). This concept explains the **vote share on populist and/or anti-systemic parties by the level of the aggregate discontent at the regional level**, i.e. the regions characterised by lower economic development, higher unemployment are characterised by a collective feeling of "places that do not matter" (Koeppen et al. 2021)
- Another factor playing a role in shaping Eurosceptic attitudes is the **fear of immigration** (Lubbers & Scheepers 2007, McLaren 2002, Luedtke 2005, Stockemer et al. 2020, Dunin-Wąsowicz & Gartzou-Katsouyanni 2023). In line with the "ethnic threat theory" people with anti-immigrant attitudes often see immigrants as members of an out-group that poses a threat to the group which they identify themselves with (Azrout et al. 2011).

War and support for anti-EU parties in Central & Eastern Europe

- The outbreak of war in Ukraine is perceived as **one of the triggers of support for Eurosceptic views in Central and Eastern Europe**. Russia's military invasion on Ukraine in February 2022 destroyed the European security order established post-cold war (Börzel 2023).
- Fagerholm (2025) based on the outcomes of content analysis of political parties' standpoints argues that **Euroscepticism constitutes a factor explaining the party's sympathy towards Russia** (Fagerholm 2025, Snegovaya 2021). The pro-Russian attitude in Eastern Europe may be also explained by **communist nostalgia**, i.e. a collective attitude associated with a feeling of loss experienced during the period of post-communist transition and dissatisfaction with the present (Koleva 2011, Ramonaitė 2023).
- In particular it is related to the perception that the EU did not ensure the promised levels of prosperity and security and that the communist period was characterised by economic stability and social cohesion (Stoica & Voina 2023). Ramonaitė (2023) claims that post-communist nostalgia is one of the predictors of conspiratorial thinking, understood as antipathy to official or mainstream accounts, in Central and Eastern Europe.

Polish 2019 and 2023 parliamentary elections and voters' tolerance for anti-EU attitude

Party	Family	% of votes in 2019 elections	Support for EU in 2019	% of votes in 2023 elections	Support for EU in 2023
PiS	TAN/Radical Right	43.59%	3.0	35.38%	2.6
KO	Christian-Democratic	27.40%	6.7	30.70%	6.9
Polska 2050	Liberal			14.40%	5.9
PSL	Agrarian	8.55%	5.1		
SLD/ Nowa Lewica	Socialist/Social-Democratic	12.56%	6.6	8.61%	6.5
Konfederacja	TAN/Radical Right	6.81%	1.4	7.16%	1.2

Database

- We use Polish municipality (*gmina*) data, 2477 observations in total
- Dependent variable - **change in EU tolerance from 2019 to 2023** (source: Chapel Hill Expert Survey 2019 and 2023 + election results from the National Electoral Commission in Poland)
- To calculate the dependent variable value for each municipality we apply the following formulas

(for 1 - applying the similar approach as in Di Matteo & Mariotti, 2021 and Albanese et al. 2022 with minor changes)

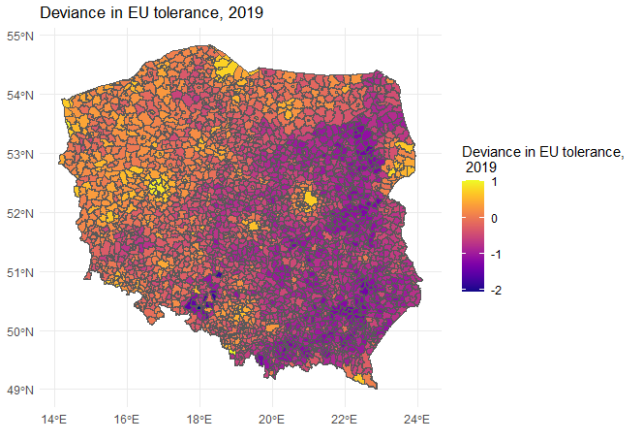
$$EUtolerance\ in\ Poland_t = \sum_{j=1}^{n}(\%\ of\ votes\ for\ a\ party\ j\ in\ Poland_t * EUtolerance\ of\ party j_t)\ (1)$$

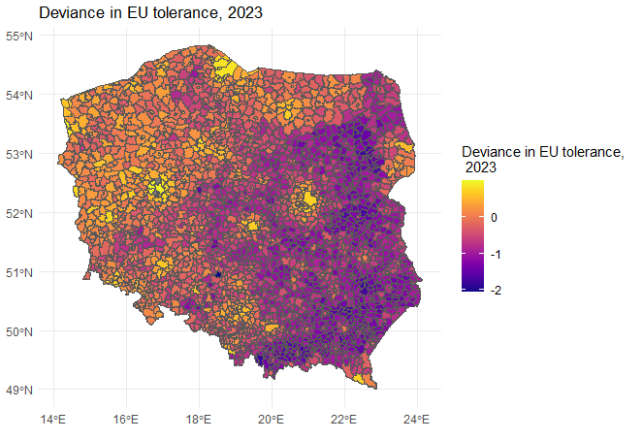
$$EUtolerance\ in\ municipality_{ti} = \sum_{j=1}^{n}(\%\ of\ votes\ for\ a\ party\ j\ in\ municipality_{ti} * EUtolerance\ of\ party\ j_t)\ (2)$$

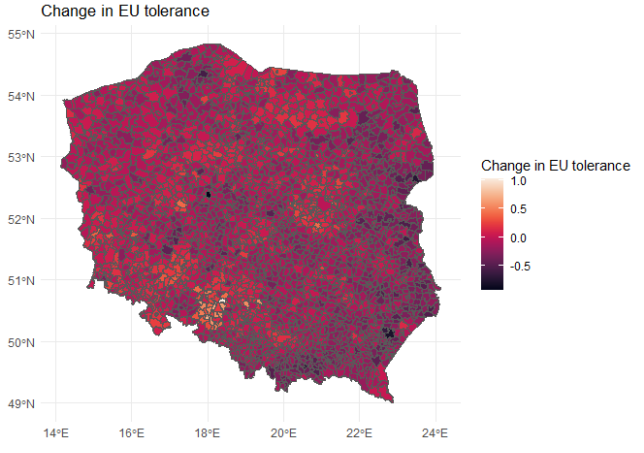
$$deviation\ in\ EUtolerance_{ti} = EUtolerance\ in\ municipality_{ti} - EUtolerance\ in\ Poland_t\ (3)$$

$$change\ in\ EUtolerance_i = deviance\ in\ EUtolerance_{2023i} - deviance\ in\ EUtolerance_{2019i}\ (4)$$

Dependent variable - change in EU tolerance





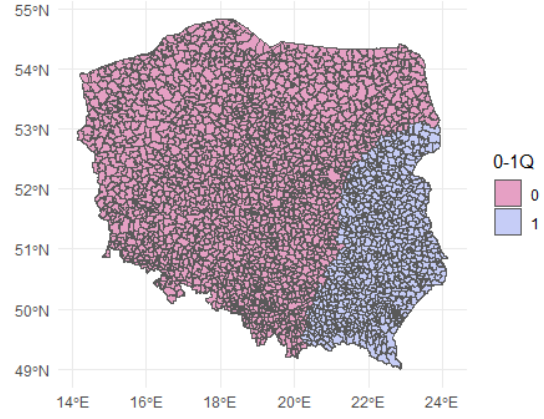


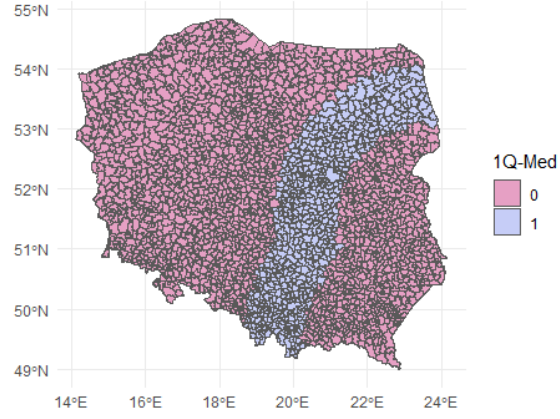
Source: own calculations in R

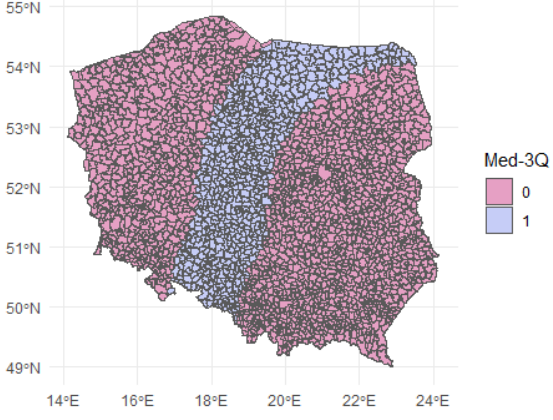
Database

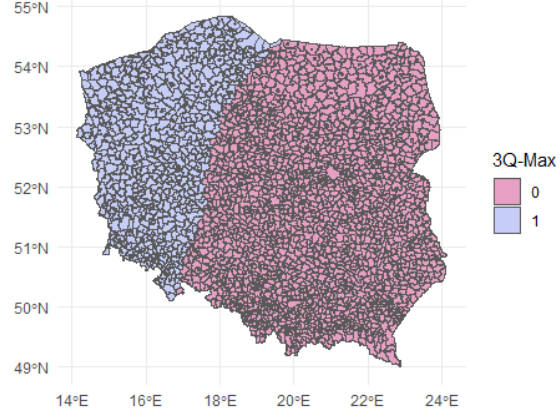
- We use municipality (*gmina*) data, 2477 observations in total
- Dependent variable - **change in EU tolerance from 2019 to 2023** (source: Chapel Hill Expert Survey 2019 and 2023 + election results from the National Electoral Commission in Poland)
- Explanatory variables: % of female population in municipality, unemployment rate, total income, total expenditures (all for 2022, from Local Data Bank, Polish Statistics); municipality type (TERYT register); Polish borders - country and municipalities (National Register of Boundaries); Ukrainian border (Amerigeoss); distances (various measures calculated based on centroids, common borders, data from Polish Statistics)
- 4 distance measures in total: distance from border (continuous vs categorical - based on quartiles), being in a border zone, being in a direct neighbourhood
- Distance measures (which are of our great interest) are presented on the following 2 slides

Distance measures - quartiles



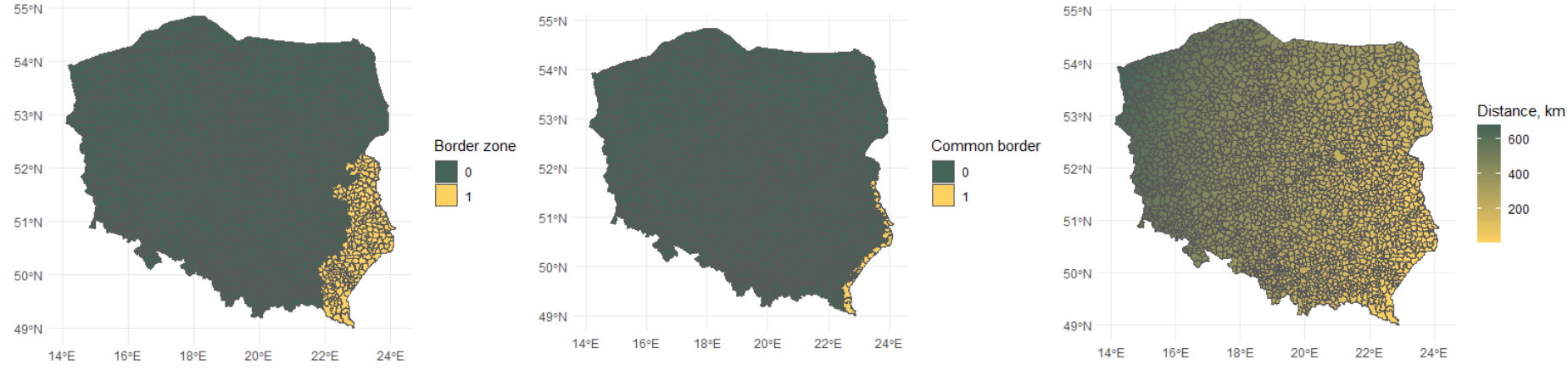






Source: own calculations in R

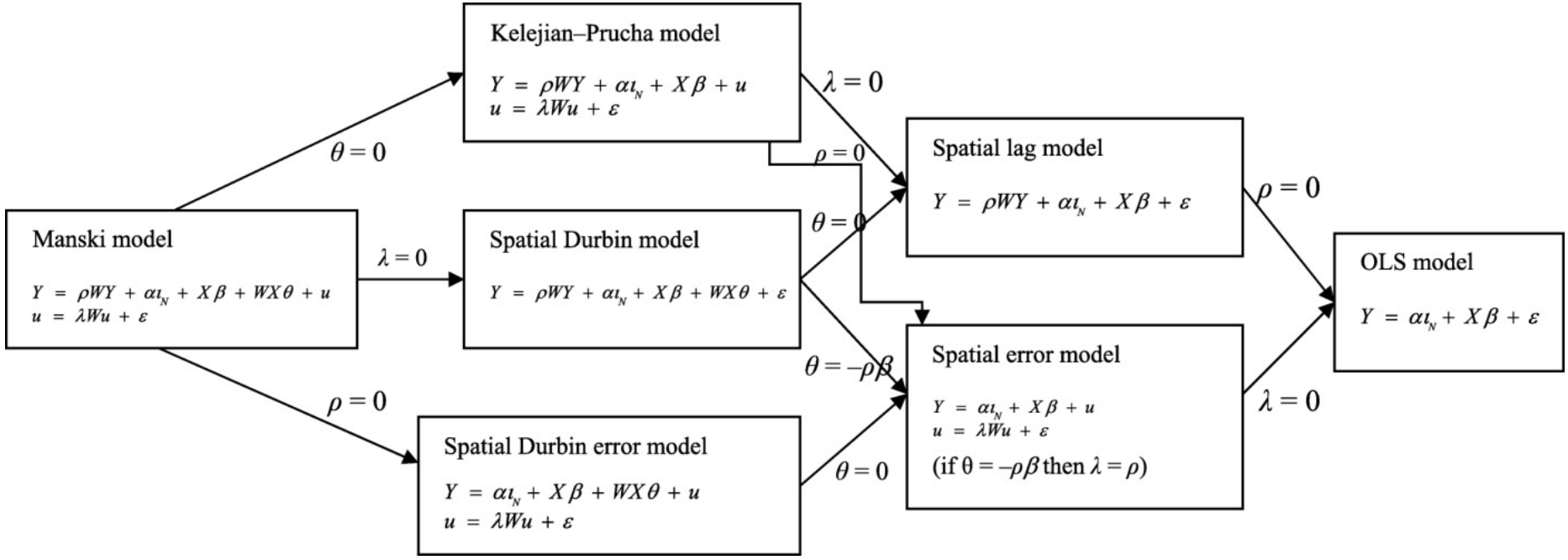
Distance measures



Source: own calculations in R

Methodology

- We apply here standard spatial regressions from the most general (Manski model) to the simplest ones (as Spatial Error Model), as mentioned by Elhorst (2010) (see Fig. on the next slide)



Source: Elhorst (2010)

Note 1: here, rho, lambda and theta are coefficients for spatial lag (=value in a neighbouring region) for Y, epsilon and X respectively

Note 2: Kelejian-Prucha model is also usually denoted as SAC model and will be referred to as SAC hereafter; Spatial Lag model is usually referred to as SAR model; SLX model (spatial lag of X) is not presented on a diagram above, but will be estimated to see whether theta in Manski, Spatial Durbin or Spatial Durbin error model is statistically significant

Methodology

- We apply here standard spatial regressions from the most general (Manski model) to the simplest ones (as Spatial Error Model), as mentioned by Elhorst (2010)
- In total, we estimate 4 specifications * 8 kinds = 32 models
- Specifications are as follows:

$$change\ in\ EUtolerance = \beta_0 + fperc2022 + income2022 + expend2022 + brob2022 + gmina\ type + common\ border + \epsilon \quad (5)$$

$$change\ in\ EUtolerance = \beta_0 + fperc2022 + income2022 + expend2022 + brob2022 + gmina\ type + distances + \epsilon \quad (6)$$

$$change\ in\ EUtolerance = \beta_0 + fperc2022 + income2022 + expend2022 + brob2022 + gmina\ type + border\ zone + \epsilon \quad (7)$$

$$change\ in\ EUtolerance = \beta_0 + fperc2022 + income2022 + expend2022 + brob2022 + gmina\ type + distance\ med + distance\ 3q + distance\ max + \epsilon \quad (8)$$

Methodology

- We apply here standard spatial regressions from the most general (Manski model) to the simplest ones (as Spatial Error Model), as mentioned by Elhorst (2010)
- In total, we estimate 4 specifications * 8 kinds = 32 models
- Before estimation - Moran I, to check for spatial autocorrelation

Methodology

- We apply here standard spatial regressions from the most general (Manski model) to the simplest ones (as Spatial Error Model), as mentioned by Elhorst (2010)
- In total, we estimate 4 specifications * 8 kinds = 32 models
- Before estimation - Moran I, to check for spatial autocorrelation

Model	**(1)**	**(2)**	**(3)**	**(4)**
Moran's I	0.484384	0.420936	0.450344	0.390167
p-value	0	0	0	0

Source: own calculations in R

Methodology

- We apply here standard spatial regressions from the most general (Manski model) to the simplest ones (as Spatial Error Model), as mentioned by Elhorst (2010)
- In total, we estimate 4 specifications * 8 kinds = 32 models
- Before estimation - Moran I, to check for spatial autocorrelation
- Then, Anselin’s algorithm (briefly - to see whether we need to include spatial lag of Y and/or epsilon) - it turns out, we need rather spatial lag of Y than of epsilon

Methodology

- We apply here standard spatial regressions from the most general (Manski model) to the simplest ones (as Spatial Error Model), as mentioned by Elhorst (2010)
- In total, we estimate 4 specifications * 8 kinds = 32 models
- Before estimation - Moran I, to check for spatial autocorrelation
- Then, Anselin's algorithm (briefly - to see whether we need to include spatial lag of Y and/or epsilon)
- Final model choice was made based on information criteria and LR tests of significance (also, we checked whether a given spatial model is better than OLS - and it was true in all cases)

Results

- Postestimation analysis detected Manski model as the best one in majority cases
- Due to the fact that the Manski model is usually not recommended to use because of overspecification (Kopczewska, 2020), we decided to switch to the second best, **SAC model**. ANOVA confirmed that this model cannot be reduced to SAR and SEM model.
- Spatial specification of SAC model is presented as follows:

$$change\ in\ EUtolerance = \beta_0 + \rho W * change\ in\ EUtolerance + X\beta + u, u = \lambda W u + e$$

- In a given specification, both rho and lambda were **significant**
- Next slide shows which variables were significant

Variable	Dependent variable			
	change_in_pro_EU_attitude			
Model	1	2	3	4
(Intercept)	***	***	***	***
f_perc2022	***	***	***	***
income2022	**	***	**	***
expend2022				
brob2022				
gmina_type_country	***	**	***	**
gmina_type_mixed	*			
common_border_UA				
distance		***		
border_zone			***	
distance_med				***
distance_3q				***
distance_max				***
rho	+, ***	+, ***	+, ***	+, ***
lambda	-, ***	-, ***	-, ***	-, ***
LR test	1298***	1027***	1153***	908***
spatial autocorrelation in the residuals	No	No	No	No
heteroscedasticity in OLS specification	Yes	Yes	Yes	Yes
heteroscedasticity in the residuals from spatial model	No, for all alfas	No, for 5% and 1%	No, for 5% and 1%	Yes

P-value is denoted by *, ** or *** for 10%, 5% and 1%, respectively

Source: own calculations in R

Conclusions

Significant rho and lambda parameters suggest that spatial lags of both dependent variable and error term shall be included in the model. The proposed interpretation is as follows:

- negative value of *rho* demonstrates the dissimilarity between municipalities,
- positive *lambda* reflects the short-term spillovers' fluctuations, similar in neighboring locations (interpretation follows the one proposed by Kopczewska et al. (2017)).

Results

- Postestimation analysis detected Manski model as the best one in majority cases
- Due to the fact that the Manski model is usually not recommended to use because of overspecification (Kopczewska, 2020), we decided to switch to the second best, **SAC model**. ANOVA confirmed that this model cannot be reduced to SAR and SEM model.
- Spatial specification of SAC model is presented as follows:

$$change\ in\ EUtolerance = \beta_0 + \rho W * change\ in\ EUtolerance + X\beta + u, u = \lambda W u + e$$

- In a given specification, both rho and lambda were **significant**
- Significance of coefficients was discussed - some coefficients were surprisingly having no impact on change in euroscepticism measure
- Since there is spatial lag of Y, we have to estimate impacts

Results

- Since there is spatial lag of Y, we have to estimate impacts
- (no formula to be provided for impacts calculation but logic)

Results

- Since there is spatial lag of Y, we have to estimate impacts
- (no formula to be provided for impacts calculation but logic)
- It is possible to calculate total impact of X on Y, and then split on direct and indirect effects

Results

- Since there is spatial lag of Y, we have to estimate impacts
- (no formula to be provided for impacts calculation but logic)
- It is possible to calculate total impact of X on Y, and then split on direct and indirect effects
- If direction of effects is the same, one calculates ratio direct over total to see how big is the proportion of direct effects
- Otherwise, one takes abs(direct)/abs(indirect)

Results

- Since there is spatial lag of Y, we have to estimate impacts
- (no formula to be provided for impacts calculation but logic)
- It is possible to calculate total impact of X on Y, and then split on direct and indirect effects
- If direction of effects is the same, one calculates ratio direct over total to see how big is the proportion of direct effects
- Otherwise, one takes abs(direct)/abs(indirect)
- We will be focusing first on distance measures, and then on another variables which were significant

Results

- Since there is spatial lag of Y, we have to estimate impacts
- (no formula to be provided for impacts calculation but logic)
- It is possible to calculate total impact of X on Y, and then split on direct and indirect effects
- If direction of effects is the same, one calculates ratio direct over total to see how big is the proportion of direct effects
- Otherwise, one takes abs(direct)/abs(indirect)
- We will be focusing first on distance measures, and then on another variables which were significant
- What's important to remember - our dependent variable took **negative** values, if the **pro-EU attitude in a given municipality has decreased** from 2019 to 2023, and **positive** values otherwise

Variable	Model	Direct	Indirect	Total	Ratio^	Interpretation
distance	2	+, ***	+, ***	+, ***	0.208	strengthening of effect (increase of X_i and X_j result in increase in Y_i)
border_zone	3	-, ***	-, ***	-, ***	0.194	weakening of effect (increase of X_i and X_j result in decrease in Y_i)
distance_med	4	+, ***	+, ***	+, ***	0.228	strengthening of effect
distance_3q	4	+, ***	+, ***	+, ***	0.228	strengthening of effect
distance_max	4	+, ***	+, ***	+, ***	0.228	strengthening of effect

P-value is denoted by *, ** or *** for 10%, 5% and 1%, respectively

Source: own calculations in R

- Concerning the results of model (1), **sharing border with Ukraine appeared to be only one statistically insignificant distance measure among four adopted**.
- Models (2) and (4) show that **increase of the municipality's distance from Ukrainian border in locations *i* and *j* positively affect pro-EU attitude in location *i***. This is consistent with the map of the dependent variable - **pro-EU attitude decrease was clearly visible close to the Ukrainian border and increase with the increase of the distance.**
- Surprisingly, in model (3) impacts showed weakening of the effect.

Variable	Model	Direct	Indirect	Total	Ratio^	Interpretation
f_perc2022	1	+, ***	+, ***	+, ***	0.178	strengthening of the effect
income2022		-, **	-, **	-, **	0.178	weakening of the effect
gmina_type_country		-, ***	-, ***	-, ***	0.178	weakening of the effect
gmina_type_mixed		+, *	+	+, *	0.178	strengthening of the effect
f_perc2022	2	+, ***	+, ***	+, ***	0.208	strengthening of the effect
income2022		-, ***	-, ***	-, ***	0.208	weakening of the effect
gmina_type_country		-, **	-, **	-, **	0.208	weakening of the effect
f_perc2022	3	+, ***	+, ***	+, ***	0.194	strengthening of the effect
income2022		-, **	-, **	-, **	0.194	weakening of the effect
gmina_type_country		-, ***	-, ***	-, **	0.194	weakening of the effect
f_perc2022	4	+, ***	+, ***	+, ***	0.228	strengthening of the effect
income2022		-, ***	-, ***	-, ***	0.228	weakening of the effect
gmina_type_country		-, **	-, **	-, **	0.228	weakening of the effect

Increase of **females' proportion** in a given and neighbouring counties leads to increase of pro-EU attitude. This result is in line with the outcomes of empirical studies highlighting that, as compared to other political parties, populist radical right parties have more male supporters than female (see *inter alia* Spierings & Zaslove (2017), Harteveld et al. (2015), Immerzeel et al. (2015)).

P-value is denoted by *, ** or *** for 10%, 5% and 1%, respectively

Source: own calculations in R

Variable	Model	Direct	Indirect	Total	Ratio^	Interpretation
f_perc2022	1	+, ***	+, ***	+, ***	0.178	strengthening of the effect
income2022		-, **	-, **	-, **	0.178	weakening of the effect
gmina_type_country		-, ***	-, ***	-, ***	0.178	weakening of the effect
gmina_type_mixed		+, *	+	+, *	0.178	strengthening of the effect
f_perc2022	2	+, ***	+, ***	+, ***	0.208	strengthening of the effect
income2022		-, ***	-, ***	-, ***	0.208	weakening of the effect
gmina_type_country		-, **	-, **	-, **	0.208	weakening of the effect
f_perc2022	3	+, ***	+, ***	+, ***	0.194	strengthening of the effect
income2022		-, **	-, **	-, **	0.194	weakening of the effect
gmina_type_country		-, ***	-, ***	-, **	0.194	weakening of the effect
f_perc2022	4	+, ***	+, ***	+, ***	0.228	strengthening of the effect
income2022		-, ***	-, ***	-, ***	0.228	weakening of the effect
gmina_type_country		-, **	-, **	-, **	0.228	weakening of the effect

On the other hand, growth of **income** in a given and neighbouring municipalities decreases EU tolerance. This result goes in line with the outcomes of studies highlighting that voters characterised by higher socio-economic status may oppose the EU due to the reluctance in for financing perceived financial burdens of EU (Eick 2024). At the same time poorer municipalities may view the EU as a chance for development and solutions for economic problems (Ritzen et al. 2016).

P-value is denoted by *, ** or *** for 10%, 5% and 1%, respectively

Source: own calculations in R

Variable	Model	Direct	Indirect	Total	Ratio^	Interpretation
f_perc2022	1	+, ***	+, ***	+, ***	0.178	strengthening of the effect
income2022		-, **	-, **	-, **	0.178	weakening of the effect
gmina_type_country		-, ***	-, ***	-, ***	0.178	weakening of the effect
gmina_type_mixed		+, *	+	+, *	0.178	strengthening of the effect
f_perc2022	2	+, ***	+, ***	+, ***	0.208	strengthening of the effect
income2022		-, ***	-, ***	-, ***	0.208	weakening of the effect
gmina_type_country		-, **	-, **	-, **	0.208	weakening of the effect
f_perc2022	3	+, ***	+, ***	+, ***	0.194	strengthening of the effect
income2022		-, **	-, **	-, **	0.194	weakening of the effect
gmina_type_country		-, ***	-, ***	-, **	0.194	weakening of the effect
f_perc2022	4	+, ***	+, ***	+, ***	0.228	strengthening of the effect
income2022		-, ***	-, ***	-, ***	0.228	weakening of the effect
gmina_type_country		-, **	-, **	-, **	0.228	weakening of the effect

Finally, for **municipalities of type 'country'** the effect is positive - for countryside, Euroscepticism is higher than for cities. The lower support for the EU among residents of rural areas is related to the ideological underpinnings such as nativism and reluctance towards migrants, satisfaction with democracy and trust in European institutions (Crulli 2024, Luca & Kenny 2024).

P-value is denoted by *, ** or *** for 10%, 5% and 1%, respectively

Source: own calculations in R

Conclusions

- Our results highlight the importance of exposure to war in Ukraine as one of the factors correlated with the increase in Eurosceptic views in Polish municipalities.
- The result is robust across the variety of distance measures between a given municipality and Polish-Ukrainian border.
- Other municipality characteristics such as female % in population, income level, and classification as a countryside were identified as significant for explanation of the level of tolerance for the EU. Whereas female % in population and countryside municipality showed positive effect on EU tolerance, influence of income was negative.

Challenges and future research

- Possible endogeneity
- Lack of data on municipality level
- Extension of our study to other EU countries

Challenges and **future research**

- Except for the inclusion of the alternative distance measure we consider other independent variables (depending on the availability of data) such as the age structure in a municipality (in particular the share of people 65+), the amount of EU funds received by a municipality in several last years, cultural change proxied by the change in percentage of municipality inhabitants with tertiary education in last 10-15 year and immigration level.
- We also consider the use of different *W* matrices for different spatial lags (adopting for example the approach proposed in Kubara and Kopczewska (2024)).
- Lastly, we consider use of another tools - incorporating instrumental approach, causal inference and propensity score matching in spatial modelling

Thank you for your attention!

All your comments and suggestions are very welcome :)

X	Spatial Warsaw	https://spatial.wne.uw.edu.pl/
X	PolEconUW	https://ekonomiapolityczna.wne.uw.edu.pl/en
X	k_zabarina	