

IN GOVERNMENT WE TRUST?:

Spatializing Public Support for Government Spending

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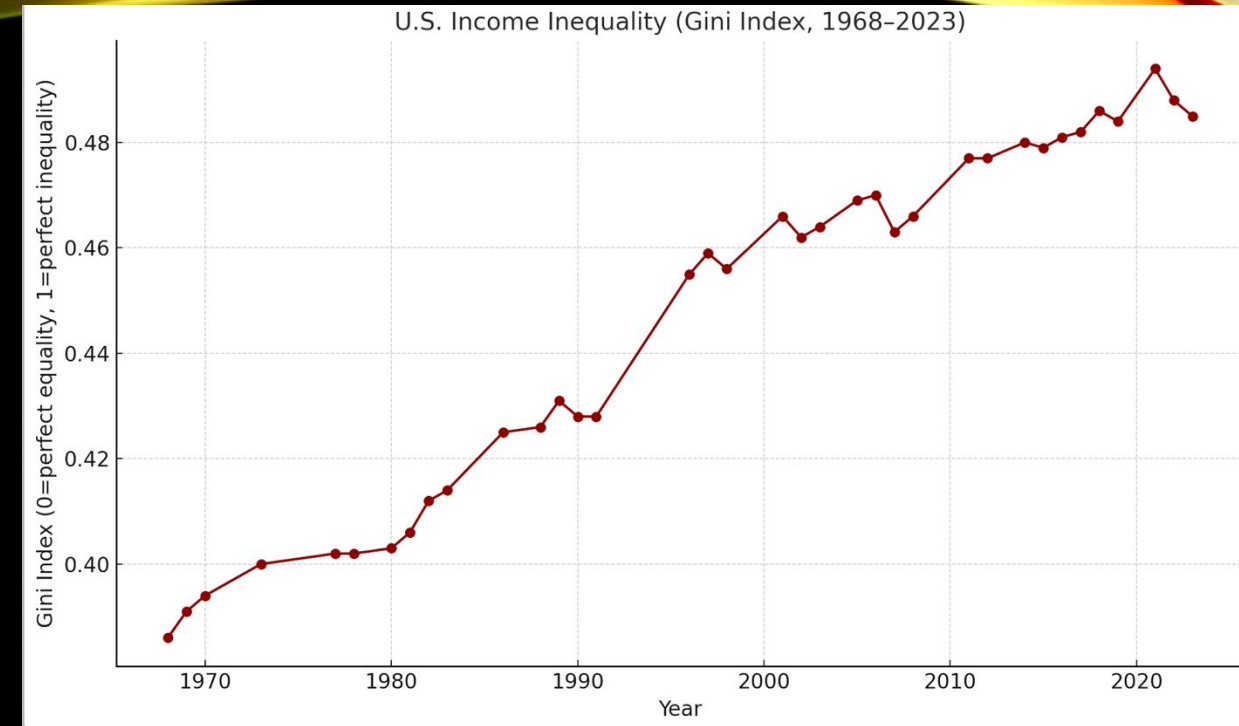
RESEARCH QUESTION

To what extent does Geographically Weighted Regression (GWR) increase sensitivity to local context and explanatory power compared to Ordinary Least Squares Regression (OLS), and how does incorporating a geographic reference advance political science research and policymaking?



IMPORTANCE

- Why does geography matter in prediction?
 - It shows where the variables are strong and where the relationships between variables are strong. Important for scholars and policymakers.
- Geographically Weighted Regression (GWR) provides greater sensitivity to local context, essential to better understanding political behavior.
- Specific to the variable relationships: Inequity rising, trust declining, but redistribution often blocked, which is important for democracy and equity.



Data Source: U.S. Census Bureau

- OLS tables generalize and can hide patterns across entire countries, but attitudes can differ across regions/states. Spatializing local data and analysis through tools such as GWR can help uncover them.
- Spatial begins to approach the individual level and greater sensitivity to local variation.
- Spatial heterogeneity can provide additional theoretical significance (why certain attitudes differ across space/institutions and methodological innovation (using R and ArcGIS Pro)).



CONTRIBUTIONS

- **Gaps in the Literature**

- **Trust & Redistribution** → Focused on individuals, not spatial variation.
- **Neoliberalism / Housing** → Emphasizes institutions, neglects spatial attitudes.
- **Methods** → Lack tools for local variation (GWR).
 - Data restrictions, modeling challenges.
 - OLS conceals geographic differences until mapped.
- This study bridges theory and method by integrating spatial analysis (via GWR) with debates on redistribution that also considers the role of trust and neoliberal housing policy, revealing variation hidden by OLS and national averages.
- **Contributions**
 - **Substantive:** spatial analysis of redistribution attitudes.
 - **Methodological:** combining R OLS + ArcGIS OLS + GWR.
- Each has a strength and contribution that is necessary to increase local sensitivity to produce data that is more democratic and impactful.

THEORETICAL FRAMEWORK

- Housing as political economy (Harvey, Ansell)
- Trust mediates redistribution (Macdonald 2020)
- Neoliberalism & data politicization (Stiglitz; Fishkin & Forbath)
- Measurement bias and better indicator need: (Jones & Klenow)
- Elite-driven inequities via “us vs. them” moral divides: (Morone 2003)
- Spatial heterogeneity:
 - Ties into trust, neoliberalism, redistribution
 - Ignoring = misleading conclusions
- Contribution: integrate comparative political economy + spatial political analysis
- “Why”:
 - ability to spatialize prediction to make policymaking and implementation more targeted and sophisticated.
 - democratic expansion via greater balance between economic and political power, while addressing concerns related to data politicization and bias.



DATA

- ANES (U.S.), CES (Canada), and in the future Sweden as well.
- Unit of analysis: U.S., states, Canada, Provinces and Territories and census districts and MSAs later with special permission following IRB approval from ICPSR, Canada, and Sweden.
- DV: public support for government spending; and IVs (political attitudes and demographics)
 - Moran's I and econometrics.
- Methodological Innovation: integration of spatial regression and visualization as well as democratizing effects of visual pedagogies for policymaking and public communication to respond to mistrust, bias, and data manipulation.

State	Trust	GovSpending	PartyID	Ideology	N
01	2.43	4.05	3.67	4.63	501
06	2.34	4.12	3.65	4.02	2804
12	2.35	4.01	3.84	4.30	1370
36	2.33	4.29	3.53	4.05	1503
48	2.40	3.98	3.67	4.38	2224

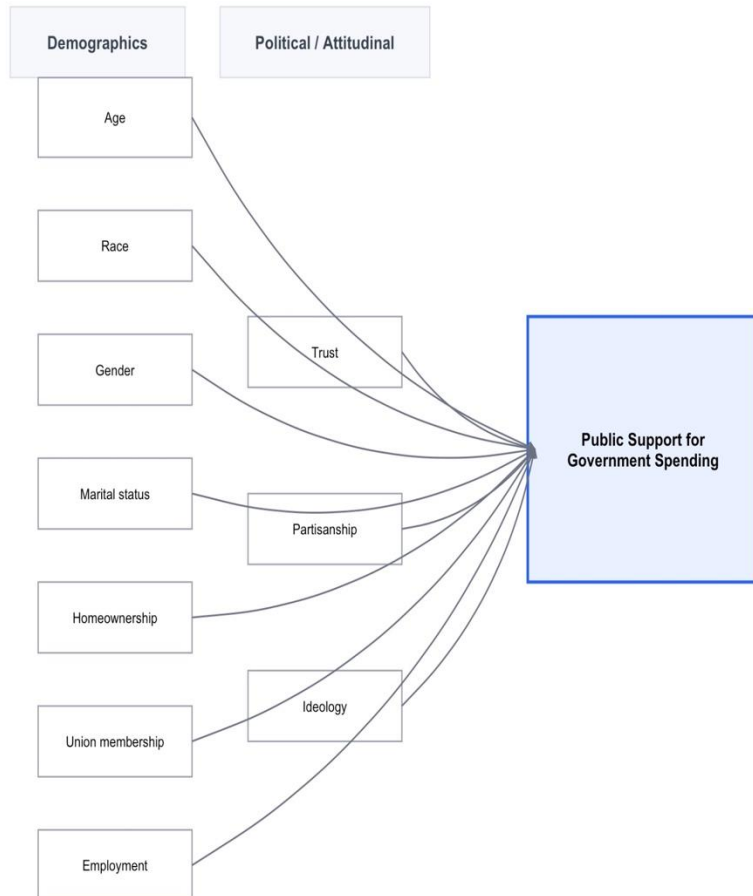
R Formula:

redistribution= β_0 + β_1 ×trust+ β_2 ×age
+ β_3 ×education+ β_4 ×gender+ β_5 ×race
+ β_6 ×marital status+ β_7 ×home ownership
+ β_8 ×union membership+ β_9 ×partisanship
+ β_{10} ×ideology+ ϵ

Where:

- redistribution is the dependent variable
- trust, age, education, gender, race, marital status, home ownership, union membership, partisanship, and ideology are the independent variables.
- β_0 is the intercept coefficient
- $\beta_1, \beta_2, \dots, \beta_{10}$ are the coefficients for each independent variable.
- ϵ represents the error term.





Formulas

Global OLS (R or ArcGIS, multiple Ivs)

$$\text{GovSpending}_i = \beta_0 + \beta_1(\text{Trust}_i) + \beta_2(\text{Age}_i) + \dots + \beta_{10}(\text{Ideology}_i) + \epsilon_i$$

One set of coefficients for all states. Slope does not change across space.

Global OLS (ArcGIS, one IV: Partisanship)

$$\text{GovSpending}_i = \beta_0 + \beta_1(\text{Partisanship}_i) + \epsilon_i$$

Simple bivariate linear model. One slope for the entire U.S.

Local GWR(ArcGIS, one IV: Partisanship)

$$\text{GovSpending}_i = \beta_0(u_i, v_i) + \beta_1(u_i, v_i)(\text{Partisanship}_i) + \epsilon_i$$

Coefficients vary by location. (u,v)=geographic coordinates. **Maps reveal spatial heterogeneity.**

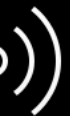
Survey Data

R OLS

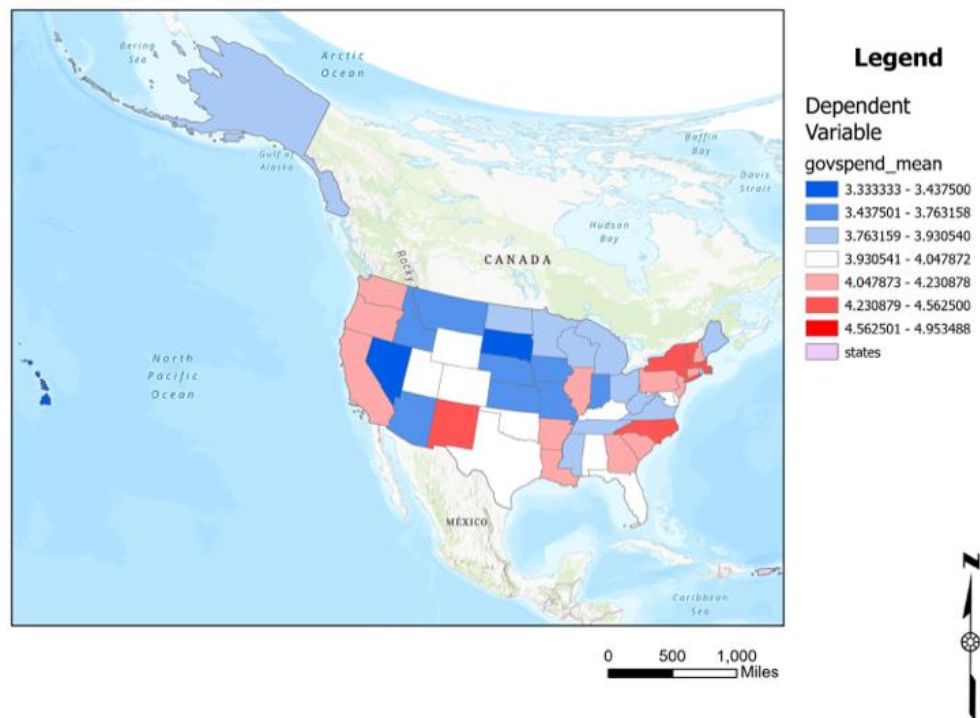
ArcGIS OLS

GWR

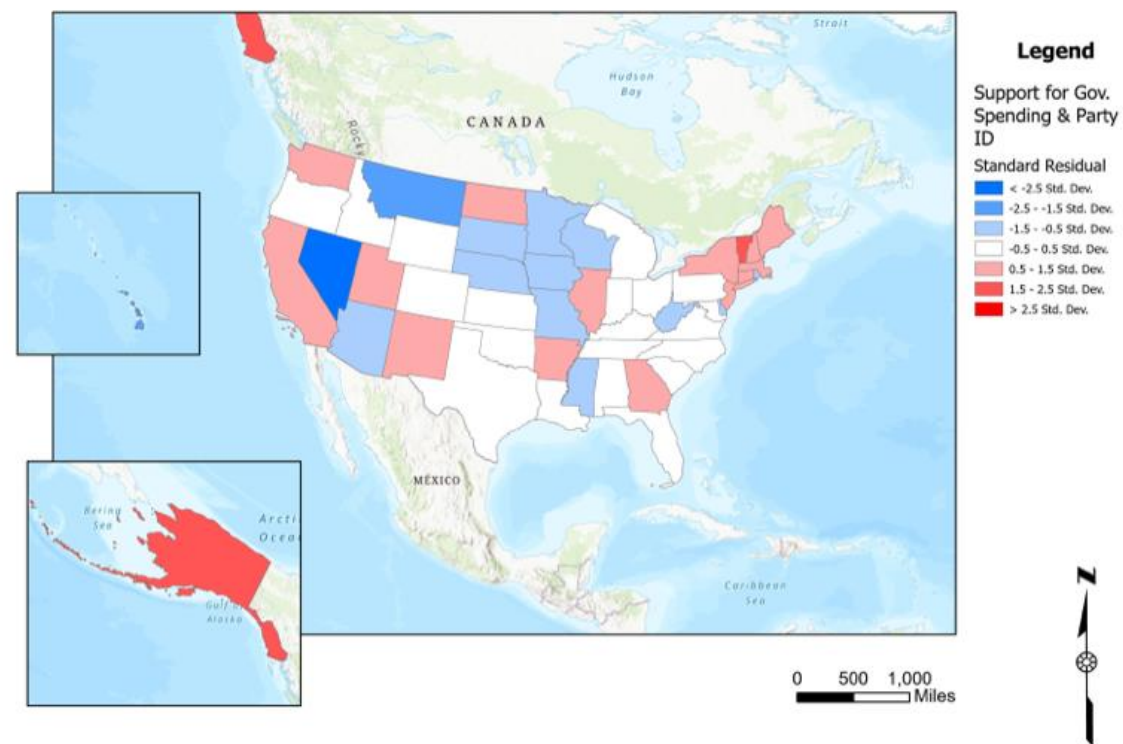
Analysis and Recommendations



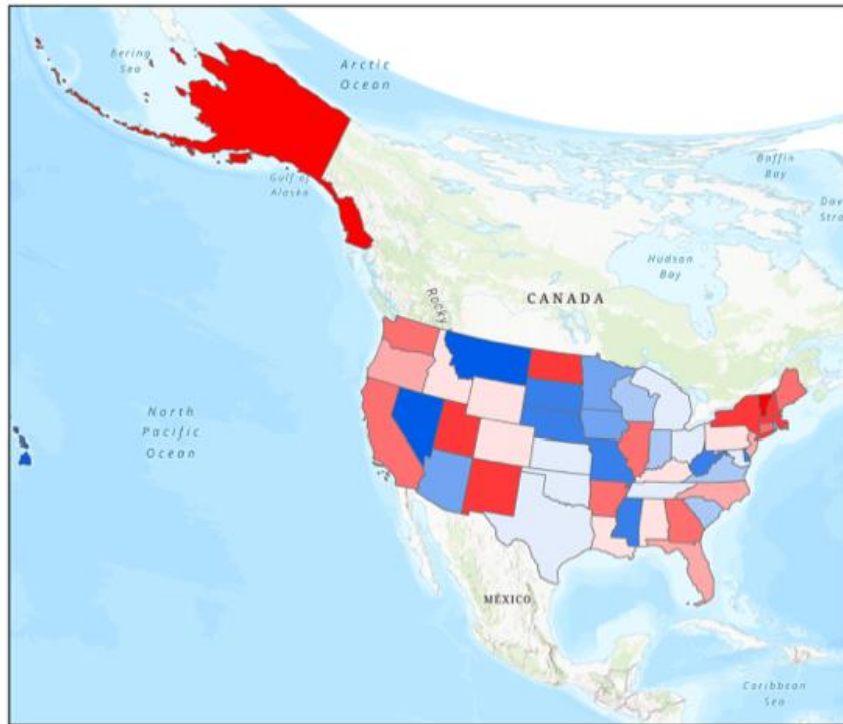
U.S. OLS Map of the Dependent Variable: Government Spending



U.S. OLS Support for Government Spending and Party ID



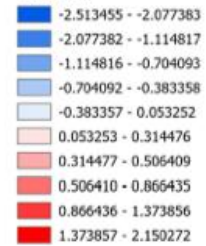
U.S. OLS Map: Standard Residuals for Model Fit



Legend

Standard Residual-
Model Fit

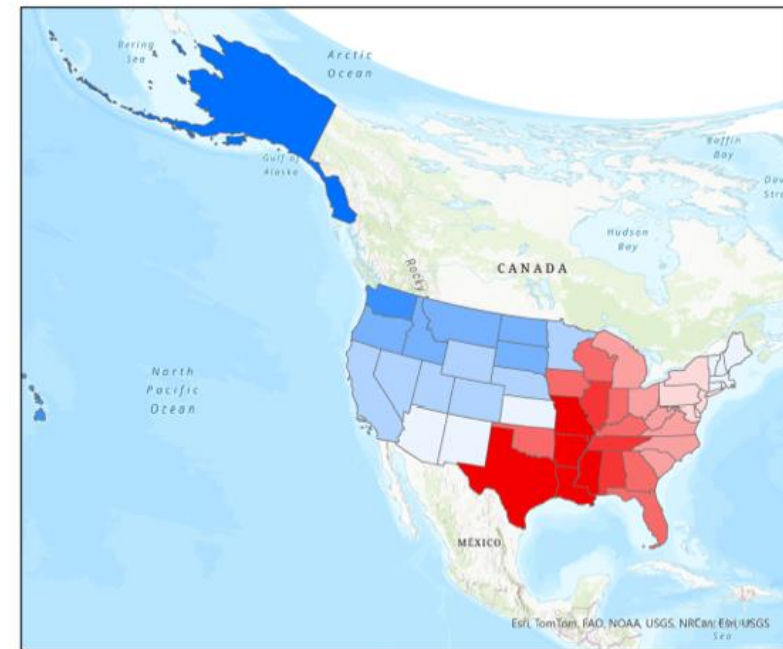
StdResid



0 230460 920
Miles



U.S. GWR Map: Partisanship and Government Spending



Legend

GWR-US-
Partisanship &
Government
Spending

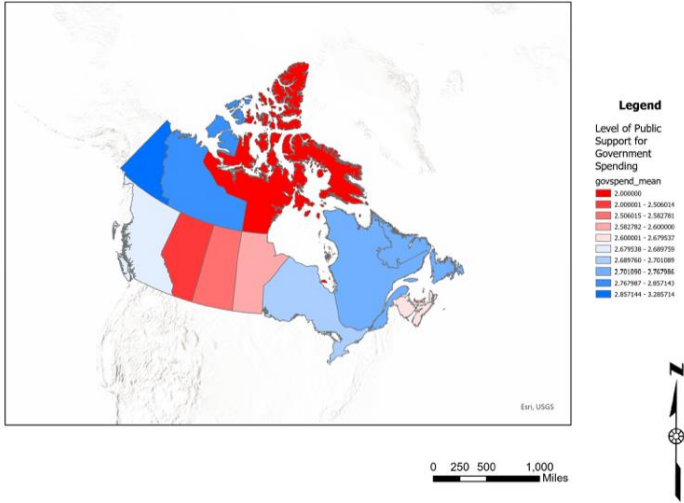
Coefficient Values



0 500 1,000
Miles



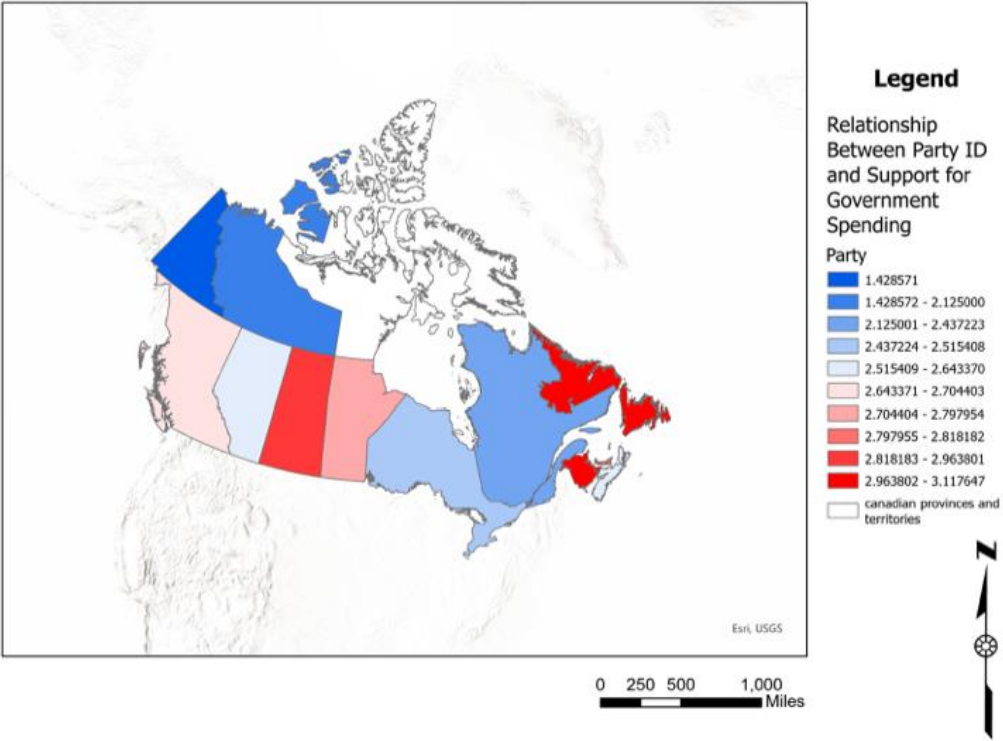
Canadian Choropleth Map: Levels of Public Support for Government



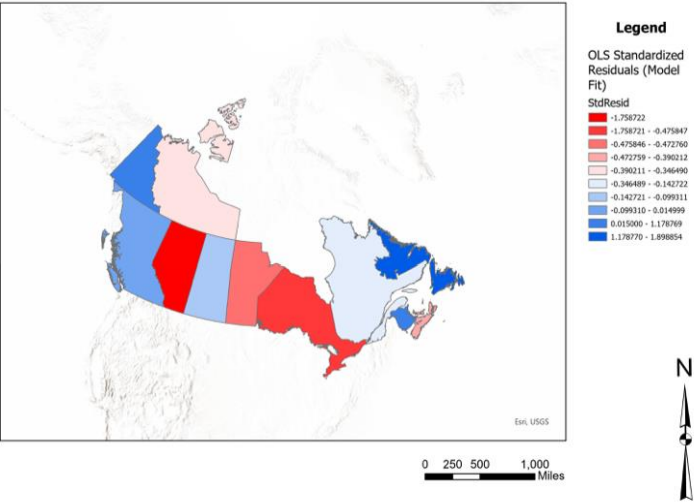
CANADIAN CHOROPLETH DV MAP

CANADIAN OLS BIVARIATE MAP

Canadian OLS Bivariate Map: Partisanship and Public Support for Government Spending



Canadian OLS Standardized Residuals (Model Fit)



CANADIAN MODEL FIT MAP



FINDINGS & CONTRIBUTIONS

- Partisanship is one of the strongest, most consistent predictors of support for redistribution. Trust is weaker, on average, but still shows meaningful local variation. OLS masks these differences; GWR reveals them.

Substantive Contributions

- Support for redistribution varies spatially, not just individually
- GWR Shows **where** political and policy reform is most feasible by mapping spatial heterogeneity.
- Bridges debates on redistribution, neoliberalism, housing as political economy, and the politicization of data.

Methodological Contributions

- Expands the political science toolkit: OLS + GWR + ArcGIS Pro.
- Democratizes regression: maps make coefficients and data more interpretable and publicly accessible.
- Advances visual pedagogy: combining regression tables and maps is a best practice for communicating spatial variance and inequality.



BROADER IMPACTS

- **Regression tables**→ **spatial data**: Provide critical inputs for ArcGIS Pro mapping and policy analysis.
- **Localized sensitivity**: spatialized data + visual communication improve responsiveness of measurement.
- **Housing as political economy**: goes beyond GDP/per capita GDP by revealing heterogeneity and obstacles masked by averages and outliers.
- **Equity and democracy**: local variation in housing and redistribution policy matters for fair outcomes.
- **Methodological advancement**: R + ArcGIS Pro expands data creation, sharing, interpretation in political science.
- **Democratizing access**: maps and visual pedagogy increase public understanding of data.



CONCLUSION

Next steps

- Secure IRB approval and data permissions for MSA-level analyses (Jacksonville, Montreal, & Stockholm).

Key Takeaways

- Support for government spending is driven most by partisanship and ideology, but **local variation** reveals where reform is more probable.
- Combining OLS with GWR in ArcGIS Pro highlights not just **if** relationships exist, but **where** they matter.



*SPATIALIZING REDISTRIBUTION REVEALS WHAT OLS TABLES
ALONE MAY CONCEAL.*

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THANK YOU!
[APSA IPOSTER LINK](#)

