Supplementary Material for "Pathways to Substantive Representation: Policy Congruence and Policy Knowledge among Canadian Local Politicians"

October 17, 2024

Contents

1 Survey Questions

Table SM.1 summarizes the issue questions we asked in both the public opinion and politician surveys. Response options for each question were "Support", "Oppose", and "Don't Know". On the survey of municipal politicians, we also asked the following question before asking for politicians' own views: "We would like to know a little about the views of residents in your municipality on each of the following ideas or proposals. For each item, please tell us the percentage of residents in your municipality who would SUPPORT the idea or proposal."

Table SM.1: Overview of Survey Questions: Public Opinion Survey

Question	Responses	Proportion Agree
Do you think the federal government should:		
Ban handguns and assault weapons	10339	0.76
Continue with the carbon tax	10339	0.41
Increase funding for public transit infrastructure	10339	0.68
Raise income taxes on people earning more than $200,000	10339	0.74
Increase trade with China	10339	0.40
Do you think your municipal government should:		
Encourage more immigrants to settle in your municipality	10339	0.34
Give tax breaks to businesses that move to the municipality	10339	0.48
Subsidize public transit for low-income people	10339	0.73
Create stricter rules to limit urban sprawl	10339	0.49

2 Models: Full Table and Detail

To provide additional context for our results in the main text, we summarise the bivariate association for each predictor variable and congruence/knowledge in figure 2.

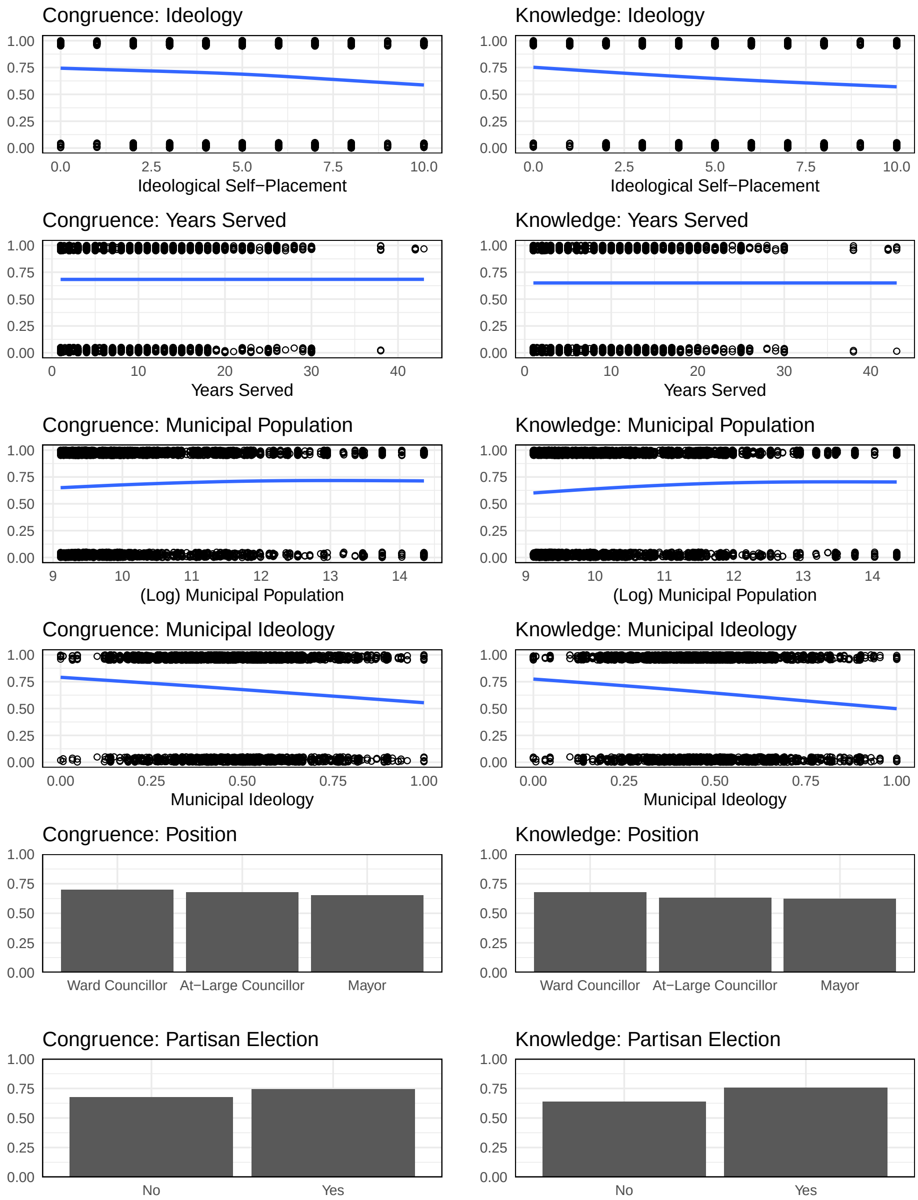

Figure SM.1: Bivariate relationships for each main predictor variable in main text model.

We model congruence and perceptual accuracy as a function of individual predictors and municipal predictors, while allowing intercepts for individual respondents, municipalities, and issues to vary:

$$log\frac{p(congruent_i)}{1-p(congruent_i)} = \theta_0 + \beta_1 years_i + \beta_2 position_i + \beta_3 ideology_i + \alpha^{mun}_{k[i]} + \alpha^{ind}_{m[i]} + \alpha^{issue}_{n[i]}$$

In both cases, we model individual and issue intercepts as drawn from a normal distribution with mean zero:

Table SM.2: Results Table: Congruence and Perceeptual Accuracy

	Congruence					Knowledge				
Variable	Median	SD	Lower CI	Upper CI	1-Pr	Median	SD	Lower CI	Upper CI	1-Pr
Individual										
Years Served	0.26	0.23	-0.18	0.70	0.14	0.16	0.22	-0.28	0.61	0.23
Position: At-Large Council	0.01	0.09	-0.16	0.17	0.46	0.00	0.09	-0.16	0.18	0.48
Position: Mayor	-0.16	0.10	-0.35	0.04	0.05	-0.08	0.10	-0.27	0.11	0.20
Ideology	-0.77	0.20	-1.16	-0.39	0.00	-0.69	0.19	-1.05	-0.33	0.00
Municipal										
Partisan Election	0.19	0.12	-0.04	0.43	0.06	0.41	0.12	0.17	0.64	0.00
Population	0.32	0.17	0.00	0.64	0.02	0.43	0.17	0.10	0.78	0.00
Issues										
Issue Uniformity	2.92	0.24	2.43	3.40	0.00	3.51	0.24	3.04	4.01	0.00
Trade with China	0.30	0.33	-0.34	0.96	0.17	0.47	0.20	0.10	0.90	0.01
Carbon Tax	-0.44	0.32	-1.06	0.20	0.08	0.24	0.18	-0.11	0.62	0.08
Hangun/Assault Ban	0.18	0.34	-0.46	0.85	0.27	-0.14	0.19	-0.53	0.22	0.22
Local Immigration	-1.41	0.33	-2.04	-0.76	0.00	-0.06	0.19	-0.41	0.34	0.37
Income Tax	-0.51	0.33	-1.15	0.13	0.06	-0.43	0.20	-0.85	-0.06	0.01
Transit Subs	0.00	0.33	-0.64	0.66	0.49	-0.66	0.20	-1.08	-0.31	0.00
Business Tax	0.03	0.32	-0.60	0.66	0.46	0.07	0.18	-0.29	0.46	0.33
Federal Transit	1.54	0.35	0.91	2.29	0.00	0.34	0.19	-0.03	0.72	0.03
Urban Sprawl	0.49	0.33	-0.13	1.15	0.06	0.23	0.18	-0.11	0.61	0.09

$$\alpha_m^{ind} \sim \mathcal{N}(0, \sigma^2_{ind})$$
$$\alpha_n^{issue} \sim \mathcal{N}(0, \sigma^2_{issue})$$

We model municipal intercepts as predicted by two municipal variables: logged population density and partisan elections:

$$\alpha_k^{mun} \sim \mathcal{N}(\mu_k^{mun}, \sigma^2_k)$$
$$\mu_k^{mun} \sim \gamma_0 + \gamma_1 density_k + \gamma_2 partisan_k$$

Both are Bayesian multilevel logit models, estimated using rstanarm with default priors. We draw 2,000 samples from each of four chains following a warm-up period of 2,000 iterations. Post-estimation tests provide strong evidence of model convergence; R-hat values are 1.0 for all parameters, and traceplots show clear evidence of mixing. . Traceplots and $\hat{R}$ values show good evidence of convergence.

In the table below, we provide the results of both models summarised in the coefficient plot in the main text.

To test the robustness of these results, we fit alternative models for both knowledge and congruence using continuous rather than dichotomous measures. For congruence, we calculate a continuous agreement measure as the proportion of municipal residents who agree with the politician's stated position. For knowledge, we calculate the absolute error of the politician's estimate and substract this amount from one, such that, for both measures, higher values are equivalent to better performance. While both measures theoretically range from zero to one, our continuous knowledge measure contains less variance than the continuous congruence measure, and for this reason, the coefficients are less directly comparable than those for our dichotomous measure (this is one reason we prefer the dichotomous measure in the main text). We report the results of these models in columns 2 and 5 in table SM.3 (labelled "cont"). While the coefficients are not directly comparable to the main text models (models 1 and 4), the table confirms that the direction and statistical significance of the relationships are consistent regardless of our choice of a dichotomous or continuous measure. Table SM.3 also includes a final model (columns 3 and 6) in which we replace politician's ideological self-placement with their federal party identification.

To assess the relative importance of the issues variable and the other variables in the models, we simply calculate the marginal effects of each variable on the probability of congruence or perceptual accuracy (comparing the maximum to the minimum value in each case, holding other variables at their medians), draw 1,000 of these marginal effects from the model's posterior distribution, and compare the marginal effects. This enables an assessment of the probability that the marginal effect of one variable (policy issues) is larger than other issues. Comparing issues to the other variables in the model, we find that the marginal effect of issues is larger than the marginal effect of the other variables; the probability that this is *not* the case is less than 1/1000 (pr<0.001).

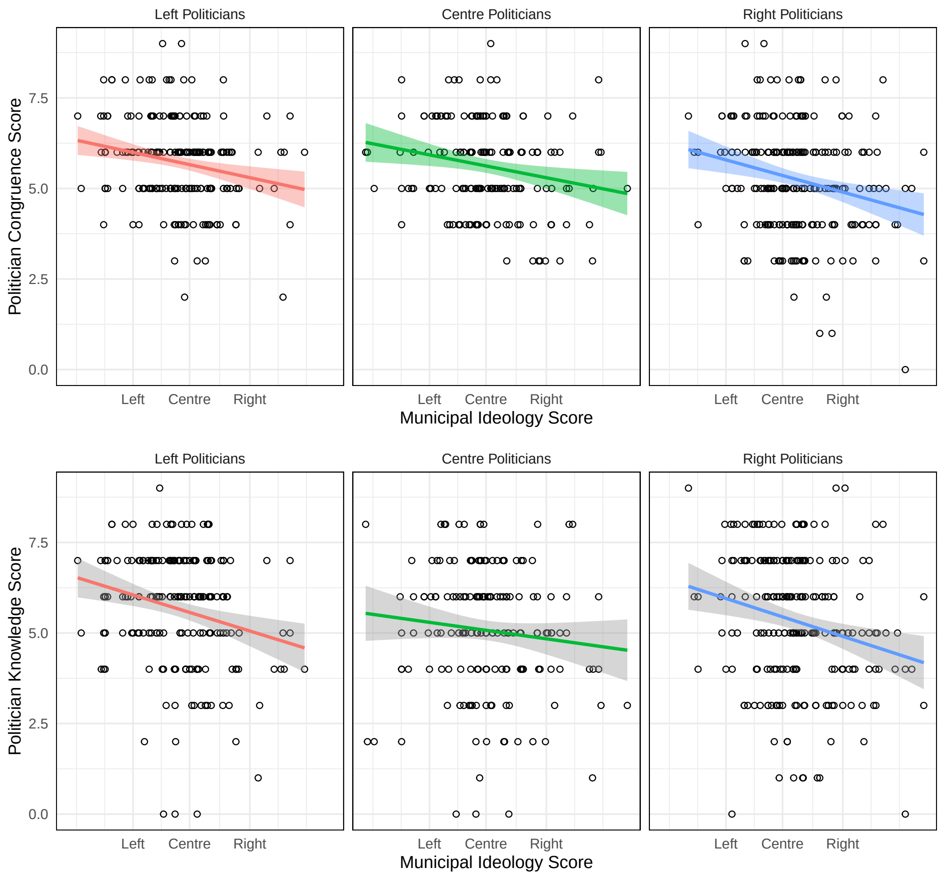

Figure SM.2: Congruence and Knowledge by Municipal Ideology and Politician's Ideological Self-Placement

To more fully understand the ideology results in our model, we carried out an additional analysis, summarized in figure 2 below. The vertical axis describes politicians' congruence scores (top row) and knowledge scores (bottom row). The horizontal axis captures municipal policy ideology scores drawn from Lucas and Armstrong II (2021). We plot the relationship between municipal ideology and performance among politicians who place themselves on the left (the red coefficients in the left column), in the centre (the green coefficients in the centre column) and on the right (the blue coefficients in the right

Table SM.3: Robustness Test: Alternative Models

	Congruence			Knowledge		
	Main	Cont.	Part.	Main	Cont.	Part.
	(1)	(2)	(3)	(4)	(5)	(6)
Years in Office	0.006	0.0003	0.005	0.004	0.001	0.003
	(0.005)	(0.0004)	(0.005)	(0.005)	(0.0005)	(0.005)
Position: At-Large	0.011	−0.003	0.031	0.002	0.005	−0.064
	(0.087)	(0.006)	(0.080)	(0.084)	(0.008)	(0.081)
Position: Mayor	−0.159	−0.017**	−0.172*	−0.084	0.001	−0.169*
	(0.099)	(0.007)	(0.093)	(0.096)	(0.009)	(0.094)
Ideology	−0.077***	−0.012***		−0.069***	−0.012***	
	(0.019)	(0.001)		(0.018)	(0.002)	
PID: Liberal			0.156*			0.066
			(0.090)			(0.088)
PID: Conservative			−0.190**			−0.040
			(0.089)			(0.091)
PID: NDP			0.058			0.250*
			(0.144)			(0.145)
PID: Green			0.155			0.449**
			(0.175)			(0.181)
PID: Bloc			0.356*			0.325
			(0.205)			(0.207)
PID: Other			−0.255			0.379
			(0.540)			(0.584)
Partisan Election	0.191	0.016*	0.163	0.407***	0.030***	0.377***
	(0.119)	(0.009)	(0.110)	(0.117)	(0.010)	(0.115)
Population	0.062*	0.003	0.080***	0.081**	0.012***	0.098***
	(0.032)	(0.002)	(0.029)	(0.032)	(0.003)	(0.031)
Issue Uniformity	2.913***	0.372***	2.721***	3.456***	0.102***	3.494***
	(0.252)	(0.018)	(0.236)	(0.247)	(0.017)	(0.237)
Constant	−0.589	0.480***	−1.099***	−1.336***	0.661***	−1.879***
	(0.466)	(0.033)	(0.425)	(0.401)	(0.038)	(0.376)
Observations	5,116	5,116	5,827	5,213	5,213	5,900
Note:						*p<0.1; **p<0.05; ***p<0.01

column). In each case, the relationship between municipal ideology and performance is negative, indicating that congruence and knowledge scores are lower, on average, in more conservative municipalities. Because right-wing politicians are more likely to be elected in right-wing municipalities, a substantial portion of the performance difference between left-wing and right-wing politicians may originate in this underlying difference between left-leaning and right-leaning municipalities.

3 Multinomial Logit Analysis

Table SM.4 provides the results of a multinomial logit model exploring the predictors of belonging to the four congruence/knowledge classes we identify in the main text.

Table SM.4: Multinomial Logit: Congruence and Knowledge Types

	Congruence (0), Knowledge (1)				Congruence (1), Knowledge (0)				Congruence (1), Knowledge (1)			
Variable	Median	SD	Lower	Upper	Median	SD	Lower	Upper	Median	SD	Lower	Upper
Individual												
Years Served	-0.24	0.42	-1.09	0.52	-0.08	0.44	-0.93	0.80	0.23	0.28	-0.31	0.79
Position: At-Large	0.05	0.15	-0.26	0.36	-0.01	0.17	-0.34	0.33	-0.01	0.11	-0.22	0.22
Position: Mayor	-0.13	0.18	-0.49	0.22	-0.26	0.20	-0.66	0.14	-0.15	0.12	-0.39	0.10
Ideology	-0.12	0.35	-0.81	0.57	0.03	0.39	-0.71	0.80	-0.98	0.24	-1.45	-0.51
Municipal												
Partisan Election	0.26	0.20	-0.11	0.64	-0.26	0.24	-0.72	0.20	0.41	0.15	0.11	0.71
Municipal Population	-0.28	0.28	-0.84	0.28	-0.28	0.31	-0.90	0.32	0.18	0.22	-0.24	0.63
Issues												
Trade with China	-0.27	0.24	-0.77	0.16	-0.46	0.49	-1.45	0.45	-0.78	0.50	-1.77	0.24
Carbon Tax	0.04	0.22	-0.38	0.48	-1.51	0.50	-2.59	-0.56	-0.52	0.50	-1.51	0.47
Gun Control	-0.42	0.29	-1.05	0.06	0.03	0.49	-0.95	1.00	0.78	0.50	-0.19	1.79
Local Immigration	0.29	0.20	-0.08	0.71	-1.84	0.50	-2.85	-0.92	-2.32	0.51	-3.31	-1.31
Income Tax	0.57	0.26	0.11	1.12	0.15	0.49	-0.85	1.08	0.61	0.51	-0.40	1.68
Transit Subsidies	0.10	0.25	-0.40	0.61	1.04	0.48	0.07	1.97	0.67	0.51	-0.30	1.70
Business Tax Breaks	0.12	0.22	-0.31	0.58	0.23	0.47	-0.75	1.18	-0.40	0.50	-1.39	0.60
Federal Transit Funds	-0.25	0.34	-1.02	0.31	1.74	0.50	0.75	2.72	1.98	0.52	0.97	3.05
Stricter Sprawl Limits	-0.19	0.26	-0.74	0.27	0.38	0.48	-0.61	1.31	0.33	0.51	-0.65	1.37

4 MRP Estimates: Additional Detail

Table SM.5: Predictor Variables in MRP Models

Dependent Variable	Predictor Variables (from BMA)
Hangun ban	Municipal ideology, housing (owner), language (French), log(density)
Carbon tax	Municipal ideology, housing (owner), married
Transit funding	Municipal ideology, employment rate, pre-1960 housing stock
Income taxes	Income (top decile), NOC 4 (Education, Law, Government), housing (owner), municipal ideology, commute by transit, commute by car
Trade with China	Proportion Christian, median income, employment rate, median age, married, NOC 7 (trades)
Immigrant settlement	Municipal ideology, Conservative vote share, proportion Christian, university education, language (English), immigrants
Local tax breaks	Immigrants, proportion white, dwellings (single detached)
Transit subsidies	Language (French), housing (owner), commute by car, proportion Christian, proportion white
Urban sprawl	(Log) density, median age, NOC 4 (education, law, government), municipal ideology

To estimate public opinion on each issue in each municipality, we begin with the following model of issue support:

$$log\frac{p(agree_i)}{1-p(agree_i)} = \theta_0 + \alpha^{age.sex.edu}_{j[i]} + \alpha^{mun}_{k[i]} + \alpha^{region}_{l[i]}$$

We model age, gender, and education intercepts as drawn from a normal distribution with mean zero:

$$\alpha^{age.sex.edu}_{j} \sim \mathcal{N}(0, \sigma^2_{age.sex.edu})$$

We model municipal intercepts as predicted by regional intercepts as well as a set of k municipality-level predictors γ_k. To select these predictors, we began by collecting an estimate of Conservative Party votes share by municipality (taken from Lucas (2022)) and a measure of municipal policy conservatism by municipality (taken from Lucas and Armstrong II (2021)), along with a set of twenty-six socio-economic characteristics of each municipality drawn from the Canadian census (these characteristics capture population size, density, income, education levels, housing stock, proportion of immigrants, occupational characteristics, commuting modes, language, and racial diversity). We used Bayesian model averaging (BMA) to select predictors for each model, choosing between three and six predictors per model.[1] We confirmed the results of this test using lasso regularization, which suggested a similar set of variables for each model.

[1]More specifically, we selected all variables with more than a 20% posterior probability of inclusion, with the stipulation that each model would include a minimum of three predictors.

$$\alpha_k^{mun} \sim \mathcal{N}(\mu_k^{mun}, \sigma_k^2)$$
$$\mu_k^{mun} \sim \alpha_{l[i]}^{region} + \gamma_{k1} ... \gamma_{kn} \tag{1}$$

We describe the variables suggested by this procedure in table SM.5. As expected, different policy attitude variables benefit from different sets of predictor variables. This procedure allows us to generate municipal opinion estimates that are more accurate and precise than would be the case with a fixed set of predictors for all models.

Finally, we assume that region intercepts (BC, Prairies, Ontario, Quebec, Atlantic Canada) are drawn from a normal distribution with mean zero:

$$\alpha_l^{region} \sim \mathcal{N}(0, \sigma_{region}^2)$$

We assume diffuse default priors for all γ parameters in study 2, and diffuse normal priors of $\mathcal{N}(0, 2.5)$ for all γ parameters in study 3. We use stan, as implemented in the rstanarm package in R, to generate estimates, drawing 2,000 samples from each of four chains following a warm-up period of 2,000 iterations. Post-estimation tests provide strong evidence of model convergence; $\hat{R}$ values are 1.0 for all parameters, and traceplots show clear evidence of mixing.

4.1 MRP Estimates and Local Weights

To further validate our MRP estimates, we compare the MRP estimates to weighted local estimates for 237 municipality-issue pairs in which available data allows us to construct weighted estimates using respondents' age, sex, and education level using nothing but local data. These are, of course, only a subset of the full data; in addition to its several other advantages, the MRP estimate allows us to incorporate estimates from many more issues in many more municipalities than the simple local weighted means. When both *are* available, however, the two estimates are strongly correlated (r=0.96), providing further reassurance that the MRP estimates are performing well.

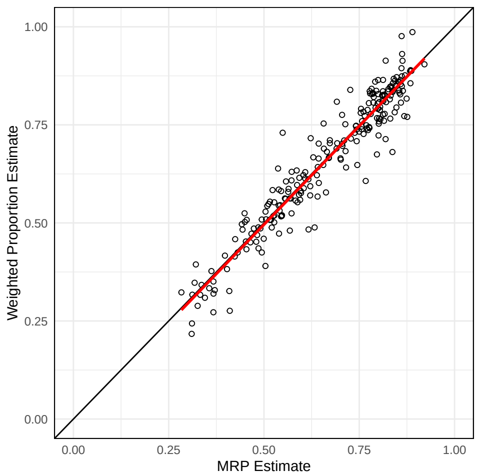

Figure SM.3: Comparison: MRP Estimates and Local Weighted Estimates

5 MRP Estimates: Propagating Uncertainty

A major advantage of fully Bayesian multilevel regression and poststratification models is that they enable researchers to inspect the *uncertainty* of local public opinion estimates, and to incorporate this uncertainty in subsequent analysis. To explain how we do this in our paper, and to provide more detail on why this is valuable, we begin with a single example: public opinion on the issue of property tax incentives for business in the Town of Conception Bay in Newfoundland (population 26,000). Our MRP estimate is that a strong majority of Conception Bay residents (67%) favour this policy proposal. When we inspect the posterior distribution of this estimate across the 4,000 posterior draws, we find the following distribution:

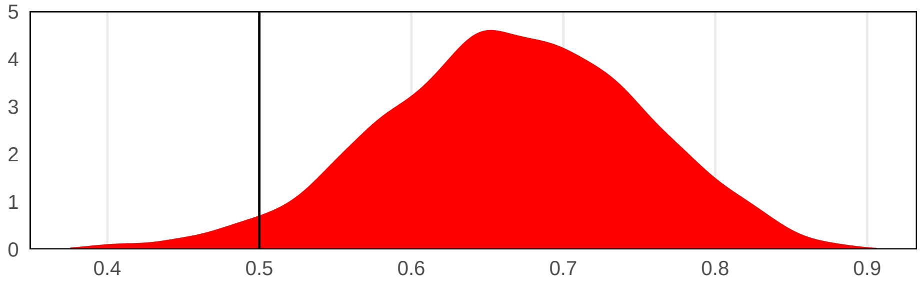

Figure SM.4: Illustrative Example: Distribution of MRP Estimates for Property Tax Issue in Conception Bay, Newfoundland

Given this distribution, we can be quite confident that a majority of Conception Bay residents favour the policy. But it is also clear that a small portion of the probabiilty distribution (3.2%) is on the left side of 50%. Thus, if a politician in Conception Bay had said that less than 50% of residents opposed the policy, it is *possible*, given these data, that the politician is correct. Similarly, if the politician had said that he or she opposes the policy, it is *possible* that they are in fact congruent with their constituents. Put simply, we should not pretend that our MRP estimates in each municipality are estimated without error. We should instead propagate our own uncertainty in the estimates through the scores that we give municipal councillors for their responses.

In the case of our analysis in this paper, incorporating this underlying uncertainty is relatively simple. The Bayesian multilevel regression model provides 4,000 posterior draws for the parameters in the model. We can use these to calculate 4,000 MRP estimates of public opinion in each municipality for each issue. These provide a distribution of 4,000 plausible values for public opinion in each municipality for each issue – 4,000 distributions like the one for Conception Bay that we visualize above. We can then calculate congruence and knowledge scores for each politician for each of these draws. In the case of the property tax issue in Conception Bay, for example, this will mean that politicians who guessed that a majority supports the issue in their district will be recorded as "correct knowledge" for most but not all draws. By summarizing these congruence and knowledge scores for each posterior draw, and then describing the 2.5%, 50%, and 97.5% percentiles of those summaries, we can express, for example, the overall probability that politicians are congruent on the property tax issue as well as the 95% credible intervals for that probability estimate.

As is clear in the main text, these credible intervals are generally small, which reflects the fact that we are estimating public opinion in relatively large communities using a very large (N>10,000) sample, and also that our municipal-level predictors in the multilevel model perform well.

6 Congruence and Knowledge Relationship: Continuous Measures

In the figure below, we replicate the figure from the main text using politicians' performance on the continuous knowledge and congruence measures, rather than the dichotomous measures. The results reinforce the findings in the main text. See table SM.3 above and associated text for more detail on the calculation of the continuous measures.

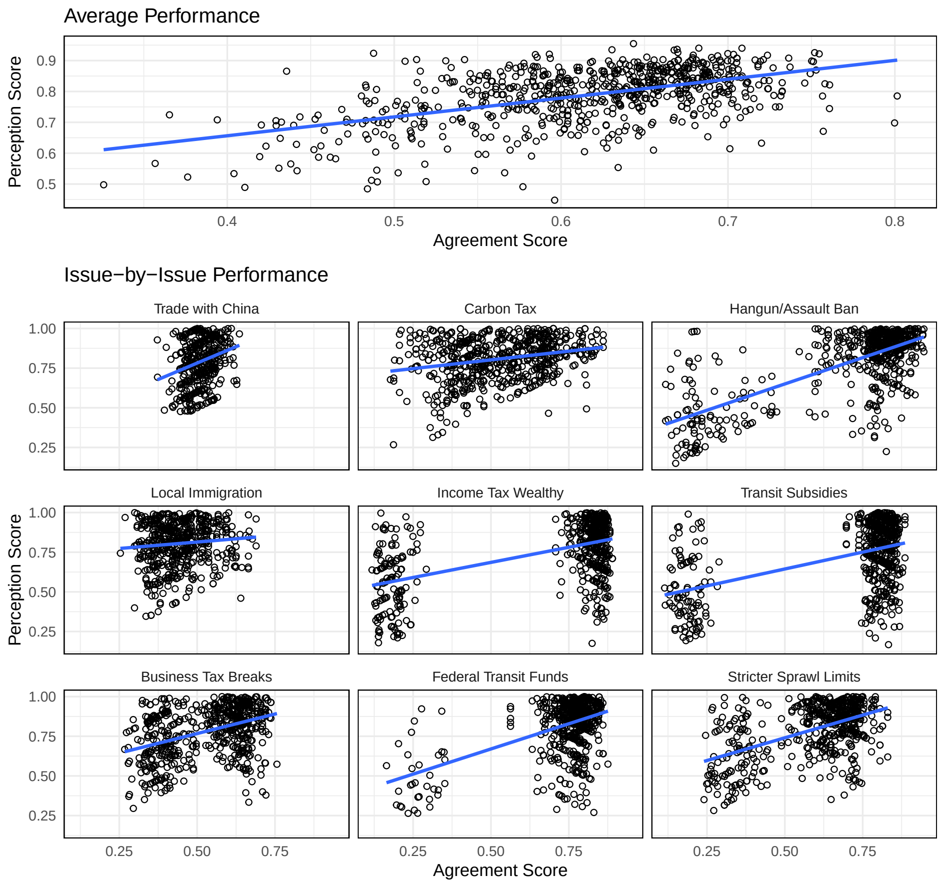

Figure SM.5: Relationship between Congruence and Knowledge, Continuous Measures

7 Ward and At-Large Politicians

Figure 7 and Table SM.6 replicate the main results from the main text when ward councillors are removed. The results demonstrate that the substantive findings do not depend on the inclusion of ward councillors in the analysis.

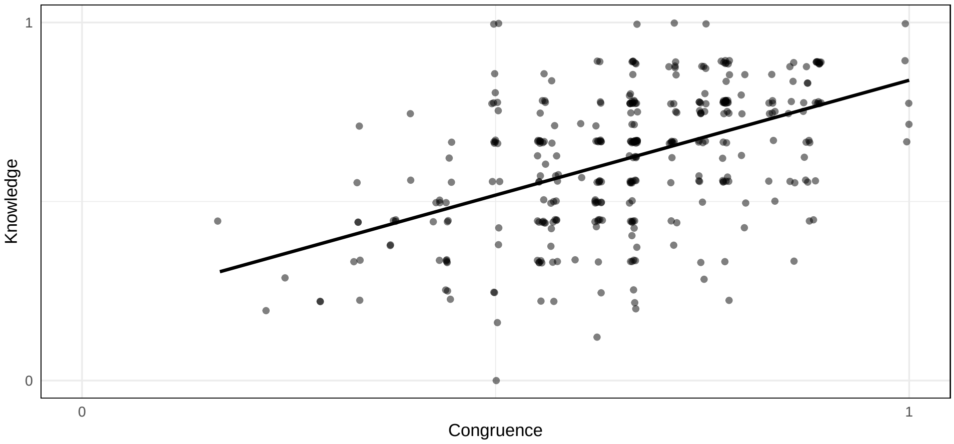

Figure SM.6: Relationship between Congruence and Knowledge, No Ward Councillors

Table SM.6: Robustness Test: Excluding Ward Councillors

	Congruence	Perception
	(1)	(2)
Years in Office	0.537*	0.215
	(0.318)	(0.314)
Ideology	−1.083***	−0.768***
	(0.267)	(0.267)
Position: Mayor	−0.172	−0.072
	(0.106)	(0.106)
Partisan Election	0.020	0.159
	(0.196)	(0.197)
Population	0.404	0.539*
	(0.285)	(0.289)
Issue Uniformity	2.616***	3.245***
	(0.340)	(0.343)
Constant	0.216	−0.476*
	(0.322)	(0.244)
Observations	2,544	2,608

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

References

Lucas, Jack. 2022. "Do 'Non-Partisan' Politicians Match the Partisanship of their Constituents?" *Urban Affairs Review* 58(1):103–128.

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