Supplementary Material

Indicators and Federal Electoral Districts: Additional Detail

As noted in the main text, our measurement model incorporates six indicators of urbanity. Here we provide additional detail on our sources for each indicator.

- Dynamic threshold. For the 1871–1951 period, we retrieved population counts and incorporation status for census subdivisions from aggregate tables digitized by the Canadian Century Research Infrastructure. To compute the proportion of these municipalities' populations in each electoral district, we used district population breakdown tables in each decennial census volume. For later years we assembled data from decennial census data products available through the University of Toronto's Canadian Census Analyzer facility and Map and Data Library.
- Population density: FED populations were manually from paper census records for 1871-1976. To calculate each district's land area, the contemporary inland and coastal water features as defined in 2016 Census cartographic hydrologic boundary files was subtracted from the federal electoral district shapes, which contain generalized coastlines and omit lakes and rivers, after which the net land area was calculated using ArcGIS software.
- Apartments as a proportion of total dwellings. This variable is available in census records from 1961 onward. However, while the census included a housing type variable in 1971, the raw source data file required for our analysis could not be processed due to the absence of the required record layout file.
- Racial diversity. This variable is calculated from census data (see below for more detail) using the following racial fractionalization index: $1 - \sum_{i=1}^{N} s_i^2$, where s represents each census racial group and i is each electoral district.
- Religious diversity. This variable is calculated from the Blake dataset for the 1951 census and from official census records for subsequent censuses (see below for more detail). We calculate religious diversity as a religious fractionalization index in the same manner as racial diversity above.

More generally, our sources for census-based indicators are as follows: data on religion and occupation for RO 1947 (Census 1951) are from Blake (1984). Data for religion, occupation, and housing stock for RO 1952 (Census 1961), RO 1966 (Census 1971), RO 1976 (Census 1981) are aggregated from the basic summary tabulation files available from the University of Toronto's Map and Data Library (https://mdl.library.utoronto.ca/collections/numeric-data/census-canada). All subsequent data are downloaded from the University of Toronto's Canadian Census Analyzer facility: RO 1987 (Census 1991), RO 1996 (Census 1996), RO 2003 (2006), and RO 2013 (Census 2016).

As we discussed in the main text, we have also created a uniform system of identification codes for each federal electoral district from 1867-2019. This ID code follows the logic of Statistics Canada's federal electoral district code, which is available starting in RO 1987 – a two digit province code, followed by a three-digit district code – to which we appended the four-digit RO year as a prefix. We constructed similar codes for the 1867–1976 ROs. From RO 1933 to RO 1976, we adopted standard numbering systems for electoral districts found in the redistribution statute or official atlases. In RO 1924 and earlier, we numbered districts based on their alphabetical order. We also corrected the inconsistent coding of the territories in different ROs and accounted for the creation of new provinces.

Table 1 and figure 1 provide quantitative and visual summaries of each of the indicator variables in the district urbanity measurement model.

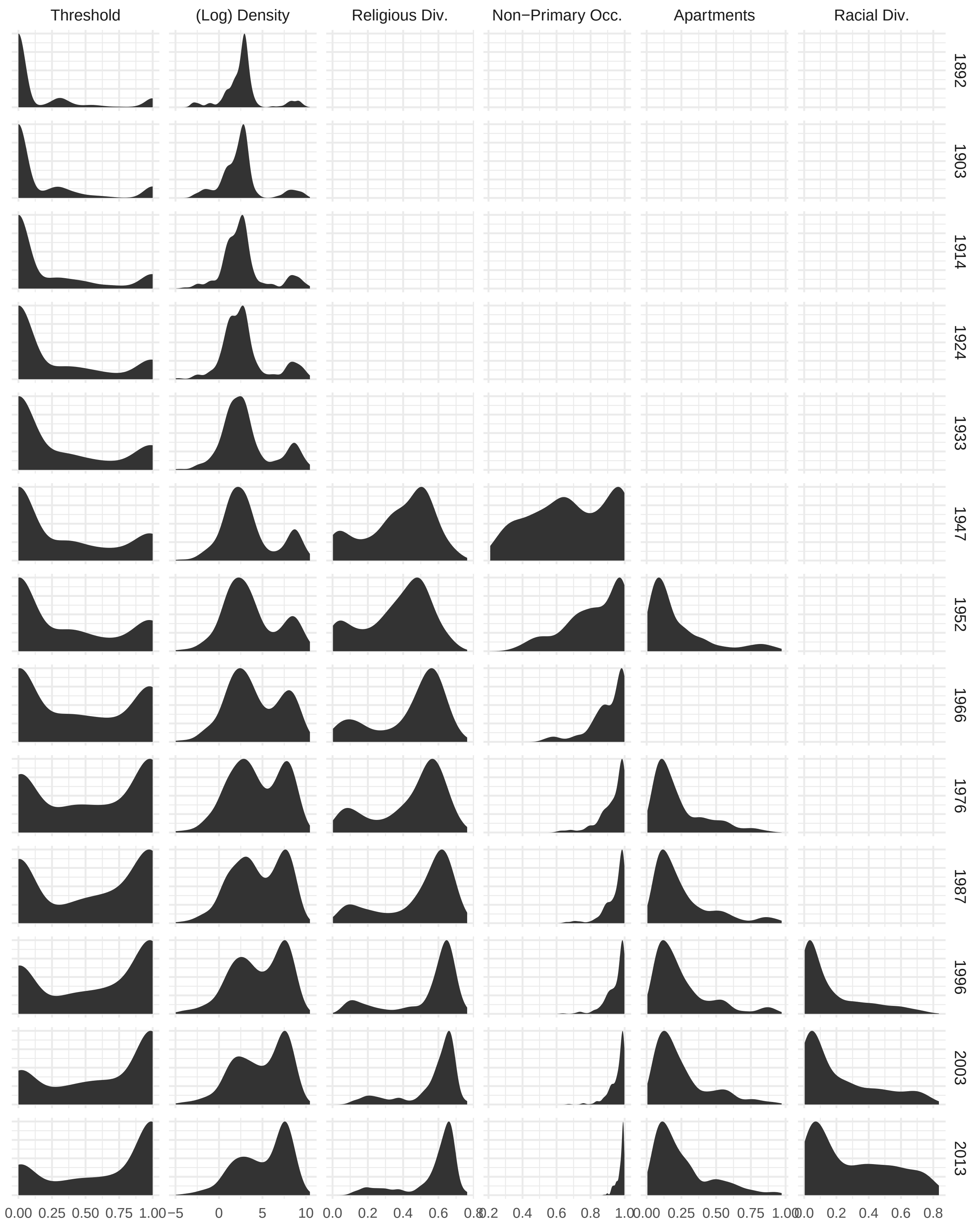

Figure 1: Distribution of Indicator Variables, by Representation Order

Table 1: Summary Statistics for Indicator Variables

id	N	mean	sd	min	max
Apartment Dwellers 1952	263	0.22	0.23	0.01	0.96
Apartment Dwellers 1976	282	0.23	0.19	0.01	0.88
Apartment Dwellers 1987	295	0.25	0.21	0.01	0.96
Apartment Dwellers 1996	302	0.25	0.20	0.02	0.95
Apartment Dwellers 2003	309	0.25	0.20	0.02	0.96
Apartment Dwellers 2013	338	0.26	0.21	0.02	0.97
Density 1892	207	602.78	2295.70	0.04	18343.37
Density 1903	228	703.18	2697.63	0.06	20245.23
Density 1914	230	989.93	3506.05	0.02	28865.48
Density 1924	241	1204.72	3962.18	0.01	34696.80
Density 1933	243	1356.72	3979.21	0.01	32608.70
Density 1947	260	1486.41	3960.42	0.01	28896.67
Density 1952	263	1478.96	3721.67	0.01	27173.35
Density 1966	264	1482.73	3201.40	0.01	22732.69
Density 1976	282	1254.99	2389.96	0.01	16336.32
Density 1987	295	1094.88	1875.80	0.01	10351.94
Density 1996	303	1138.21	1896.61	0.01	11371.77
Density 2003	309	1203.24	1906.08	0.01	10987.92
Density 2013	338	1389.31	2186.14	0.02	16941.81
Dynamic Threshold 1892	207	0.16	0.31	0.00	1.00
Dynamic Threshold 1903	228	0.18	0.32	0.00	1.00
Dynamic Threshold 1914	230	0.22	0.35	0.00	1.00
Dynamic Threshold 1924	241	0.26	0.38	0.00	1.00
Dynamic Threshold 1933	243	0.29	0.40	0.00	1.00
Dynamic Threshold 1947	260	0.32	0.40	0.00	1.00
Dynamic Threshold 1952	263	0.34	0.40	0.00	1.00
Dynamic Threshold 1966	264	0.44	0.42	0.00	1.00
Dynamic Threshold 1976	282	0.54	0.42	0.00	1.00
Dynamic Threshold 1987	295	0.54	0.43	0.00	1.00
Dynamic Threshold 1996	303	0.59	0.42	0.00	1.00
Dynamic Threshold 2003	309	0.63	0.40	0.00	1.00
Dynamic Threshold 2013	338	0.66	0.40	0.00	1.00
Non-Primary Occupation 1947	232	0.69	0.24	0.21	1.00
Non-Primary Occupation 1952	263	0.82	0.17	0.35	1.00
Non-Primary Occupation 1966	264	0.90	0.11	0.52	1.00
Non-Primary Occupation 1976	282	0.93	0.08	0.61	1.00
Non-Primary Occupation 1987	295	0.94	0.06	0.65	1.00
Non-Primary Occupation 1996	302	0.95	0.06	0.64	1.00
Non-Primary Occupation 2003	309	0.96	0.05	0.67	1.00
Non-Primary Occupation 2013	338	0.98	0.02	0.88	1.00
Racial Diversity 1996	302	0.16	0.19	0.00	0.78
Racial Diversity 2003	309	0.22	0.23	0.01	0.81
Racial Diversity 2013	338	0.30	0.25	0.01	0.83
Religious Diversity 1947	259	0.37	0.19	0.00	0.70
Religious Diversity 1952	263	0.36	0.18	0.00	0.68
Religious Diversity 1966	264	0.44	0.20	0.01	0.72
Religious Diversity 1976	282	0.44	0.20	0.03	0.73
Religious Diversity 1987	295	0.49	0.20	0.05	0.76
Religious Diversity 1996	302	0.53	0.19	0.06	0.76
Religious Diversity 2003	309	0.56	0.16	0.10	0.76
Religious Diversity 2013	338	0.57	0.15	0.11	0.76

Measurement Model and Analysis

We use a Bayesian factor analysis model to measure district urbanity. To improve model fit, we use the log of racial diversity and apartment dwellings, and transform non-primary occupation using a Box-Cox transformation. Figure 2 summarizes the correlations among these six indicators.

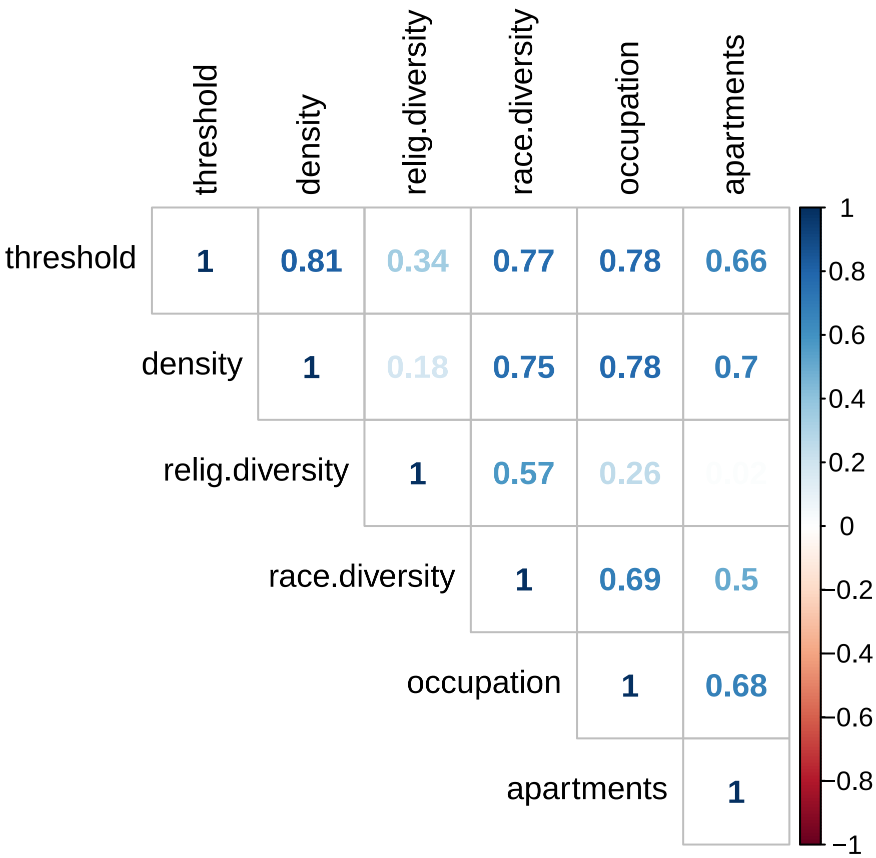

Figure 2: Correlations Among Urbanity Indicator Variables

We implement our model in JAGS, drawing 5,000 posterior samples from each of two chains following a burn-in period of 10,000 iterations. Post-estimation quantities (such as r-hat values and effective number of samples) provide good evidence of convergence.

Figure 3 summarizes the relationship between each indicator and the latent variable at each Representation Order.

We use Monte Carlo integration to propagate uncertainty in the urbanity measure through our subsequent party vote share analyses. We first select a random subset of 1,000 posterior draws from the measurement model; each of these draws captures a vector of plausible district urbanity scores. We then regress party vote share on district urbanity (with region fixed effects) 1,000 times, using a distinct vector of urbanity values in each iteration. We take a random draw from the posterior distribution of $\beta_{urbanity}$ for each of the 1,000 models; more specifically, we draw from the multivariate normal distribution of the model and record our draw for $\beta urbanity$ in each iteration. Summarizing the median and 95% probability bounds of this distribution of 1,000 draws provides our estimate of the relationship between urbanity and party vote share, incorporating uncertainty in the latent variable.

We repeat this procedure for each party in the analysis (Conservative, Liberal, CCF/NDP, and Reform/Alliance) at each election to produce the results summarized in Figure 1 in the main text. We then repeat the procedure within each of the five regions to produce the results in Figure 2.

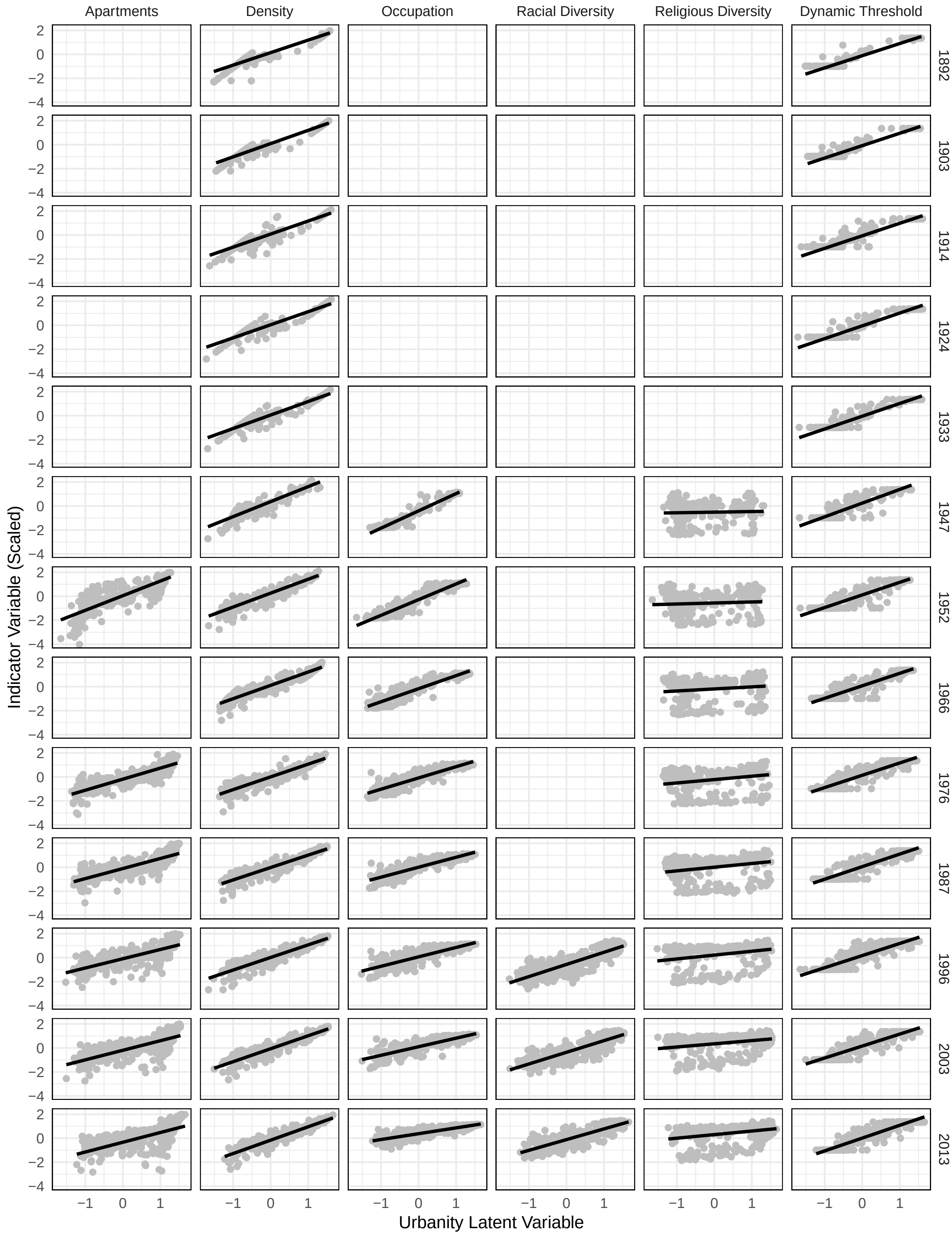

Figure 3: Relationship Between Indicators and Urbanity Measure

Table 2: Summary Statistics for Urbanity Measure

ro	N	mean	sd	min	max
1892	207	-0.49	0.67	-1.52	1.58
1903	223	-0.47	0.69	-1.46	1.55
1914	230	-0.38	0.74	-1.63	1.61
1924	241	-0.31	0.80	-1.71	1.61
1933	243	-0.23	0.83	-1.68	1.59
1947	259	-0.41	0.75	-1.67	1.32
1952	263	-0.28	0.82	-1.65	1.28
1966	264	-0.01	0.88	-1.36	1.37
1976	282	0.15	0.90	-1.36	1.46
1987	295	0.21	0.90	-1.31	1.51
1996	302	0.22	0.89	-1.66	1.53
2003	308	0.35	0.86	-1.51	1.54
2013	338	0.51	0.82	-1.23	1.66

Urbanity Measure: Summary Statistics

Table 2 and figure 4 provide quantitative and visual summaries of our district urbanity measure at each Representation Order.

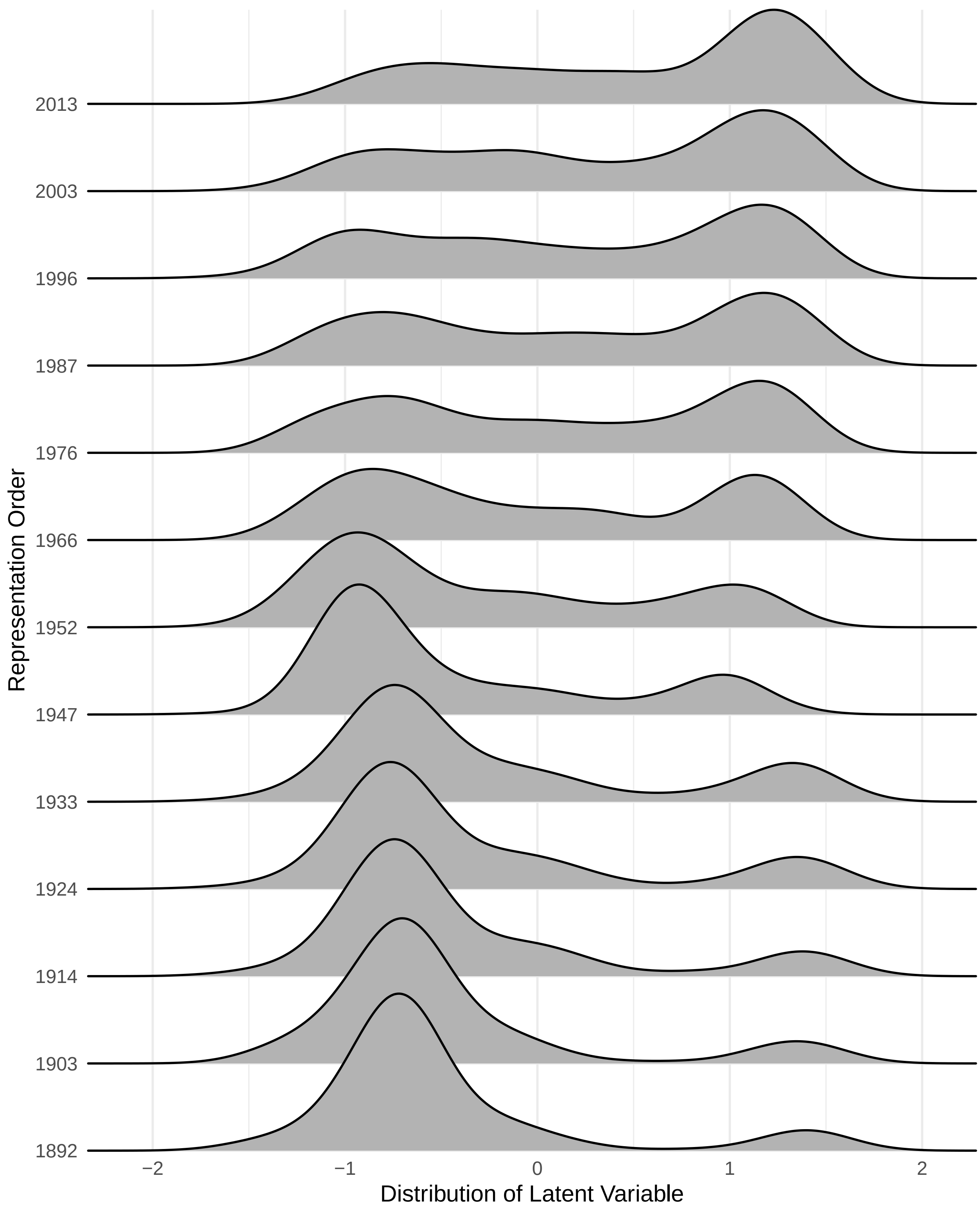

Figure 4: Distribution of Latent Variable, by Representation Order

Robustness: Density Indicator

To demonstrate that our results are not driven by the varying presence of particular indicators in the measurement model, figure 5 summarizes our vote share models in the main text using population density rather than our latent measure as the independent variable of interest. The results are substantively identical to those reported in the main text.

While our overall results are substantively identical using the density indicator, we re-emphasize our argument in the main text that there are several advantages to our latent urbanity approach. For example, when we compare multinomial logit models using log density versus our latent measure, AIC comparisons strongly favour the urban latent measure 9 times out of 36 and favour the log density model zero times out of 36. A Clarke Test on the two models suggests that the latent urbanity model is statistically better than the log density model for 15 of 36 general elections and the log density model is better in just 4 of 36 years. Thus, while the overall trends look similar, we have good reason to believe that our latent measure leads to a reduction in measurement error and an improvement in model fit over a more basic population density measure.

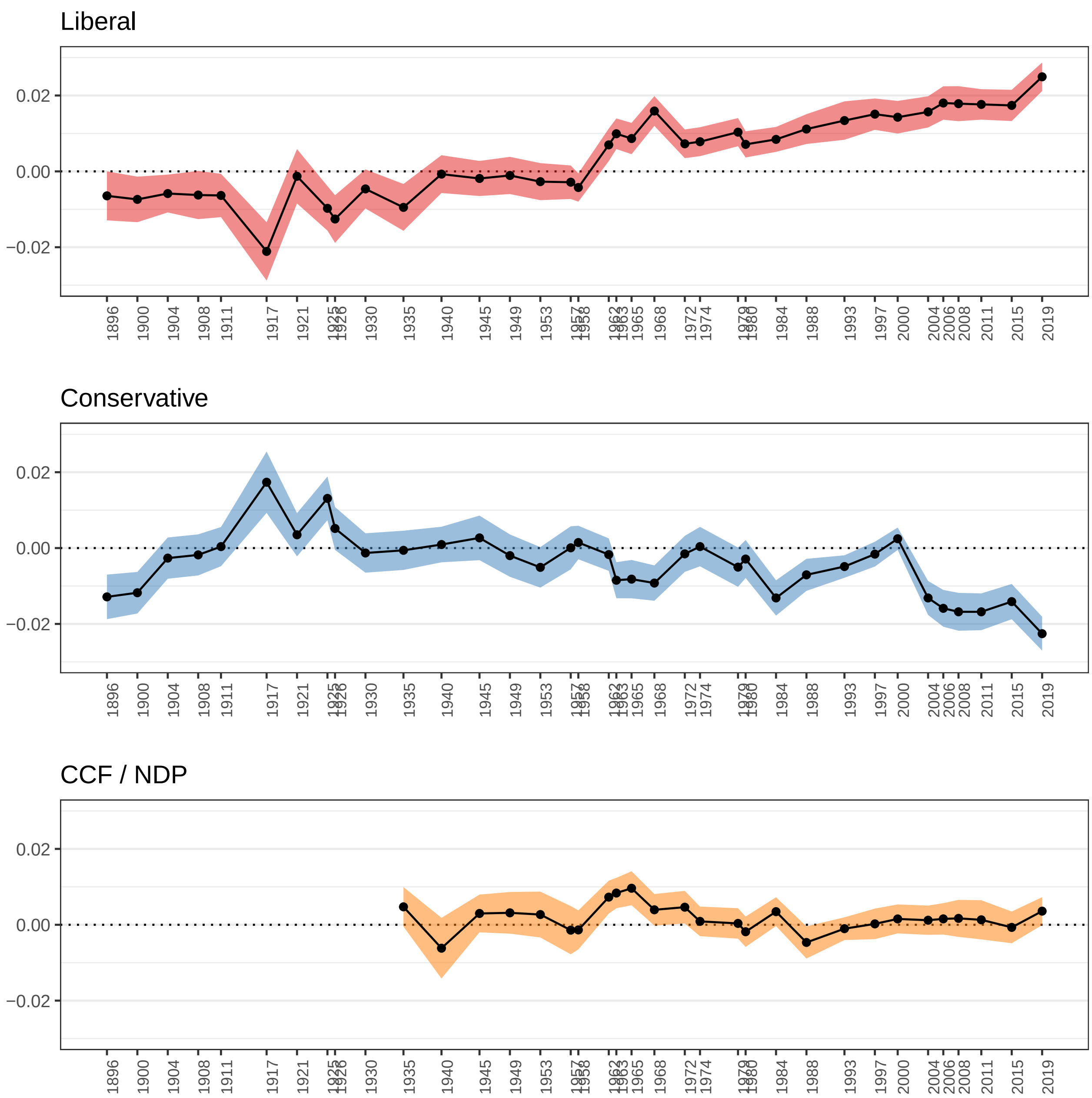

Figure 5: Party Vote Share Analysis with District Population Density