Online Appendix for "City Limits to Partisan Polarization in the American Public"

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A Surveys

The surveys were conducted for bgC3 by YouGov in January and February of 2018 in eight Metropolitan Statistical Areas (MSAs): Charlotte, Cleveland, Houston, Indianapolis, Memphis, Rochester, St. Louis, and Seattle. The surveys are representative samples of the adult population of each MSA. YouGov employs matched sampling in which interviews are conducted from participants in YouGov's online panel and then matched to sampling frames for each MSA on gender, age, race, and education. The sampling frames are constructed from the full 2016 American Community Survey. All matched respondents were then assigned weights stratified on 2016 presidential vote, age, sex, race, and education to correct for remaining imbalances. The final number of observations was 1,000 in each of the MSAs except Rochester for which the total was 800.

Charlotte

Means	*Raw*	*Weighted*
Age	45.66	45.25
Female	0.59	0.53
White	0.71	0.65
Black	0.18	0.23
Latino	0.03	0.07
College Degree	0.55	0.41
Some College	0.78	0.64
In the Labor Force	0.66	0.64
Democrat	0.36	0.36
Republican	0.31	0.32
Voted Clinton 2016	0.47	0.47
Voted Trump 2016	0.45	0.50
Observations	1,000	1,000

Cleveland

Means	*Raw*	*Weighted*
Age	48.64	48.98
Female	0.59	0.53
White	0.79	0.73
Black	0.15	0.19
Latino	0.02	0.05
College Degree	0.51	0.39
Some College	0.72	0.61
In the Labor Force	0.60	0.57
Democrat	0.41	0.42
Republican	0.25	0.24
Voted Clinton 2016	0.51	0.56
Voted Trump 2016	0.40	0.40
Observations	1,000	1,000

Houston

Means	*Raw*	*Weighted*
Age	44.66	44.51
Female	0.55	0.51
White	0.51	0.41
Black	0.17	0.17
Latino	0.23	0.33
College Degree	0.47	0.40
Some College	0.70	0.60
In the Labor Force	0.65	0.66
Democrat	0.34	0.36
Republican	0.29	0.28
Voted Clinton 2016	0.47	0.49
Voted Trump 2016	0.44	0.47
Observations	1,000	1,000

Indianapolis

Means	*Raw*	*Weighted*
Age	46.50	46.53
Female	0.62	0.52
White	0.82	0.76
Black	0.12	0.14
Latino	0.02	0.05
College Degree	0.54	0.42
Some College	0.76	0.62
In the Labor Force	0.63	0.63
Democrat	0.32	0.31
Republican	0.34	0.36
Voted Clinton 2016	0.45	0.44
Voted Trump 2016	0.44	0.51
Observations	1,000	1,000

Memphis

Means	*Raw*	*Weighted*
Age	45.65	45.03
Female	0.63	0.53
White	0.61	0.48
Black	0.33	0.45
Latino	0.01	0.03
College Degree	0.51	0.36
Some College	0.80	0.60
In the Labor Force	0.65	0.63
Democrat	0.37	0.42
Republican	0.31	0.27
Voted Clinton 2016	0.47	0.55
Voted Trump 2016	0.45	0.42
Observations	1,000	1,000

Rochester

Means	*Raw*	*Weighted*
Age	48.44	48.12
Female	0.61	0.53
White	0.84	0.81
Black	0.06	0.09
Latino	0.04	0.06
College Degree	0.58	0.47
Some College	0.76	0.64
In the Labor Force	0.59	0.57
Democrat	0.36	0.34
Republican	0.29	0.29
Voted Clinton 2016	0.48	0.49
Voted Trump 2016	0.42	0.46
Number of Observations	800	800

St. Louis

Means	*Raw*	*Weighted*
Age	48.13	48.25
Female	0.57	0.52
White	0.81	0.77
Black	0.13	0.16
Latino	0.01	0.03
College Degree	0.53	0.42
Some College	0.77	0.63
In the Labor Force	0.62	0.60
Democrat	0.38	0.37
Republican	0.26	0.28
Voted Clinton 2016	0.50	0.48
Voted Trump 2016	0.39	0.48
Observations	1,000	1,000

Seattle

Means	*Raw*	*Weighted*
Age	45.99	46.15
Female	0.55	0.51
White	0.73	0.69
Black	0.04	0.05
Latino	0.05	0.08
College Degree	0.58	0.52
Some College	0.78	0.72
In the Labor Force	0.64	0.63
Democrat	0.44	0.44
Republican	0.17	0.19
Voted Clinton 2016	0.61	0.63
Voted Trump 2016	0.27	0.30
Observations	1,000	1,000

Table A-1: *Summary Statistics.*

B Local Problems

Word category	Share
Economy and employment	33.3
Crime	30.3
Government and politics	25.3
Poverty and social issues	20.2
Housing	13.4
Education	10.2
Traffic and transport	10.1
Race	7.8
Observations	7,800

Table A-2: *Major Issues Facing People Across MSAs: Word Categories.* The table reports the percentage of respondents across all eight MSAs who answered the question: "What do you think are the major issues facing people in the [MSA Name] area these days?" with a response that included a given category. The open-ended responses could include more than one category and therefore do not sum to 100%.

Word	Share
crime	21.0
job	15.3
housing	9.5
education	8.6
lack	8.0
homeless	7.7
people	7.2
poverty	6.6
drug	5.4
transport	4.7
tax	4.7
violence	4.5
issue	4.4
government	4.2
public	4.2
unemployment	4.2
traffic	4.1
cost	3.9
city	3.8
living	3.5
Observations	7,800

Table A-3: *Major Issues Facing People Across MSAs: Single Words.*

Charlotte

Word category	*Share*
Economy and employment	29.7
Government and politics	25.5
Crime	24.1
Housing	16.6
Traffic and transport	14.8
Poverty and social issues	11.9
Education	9.7
Race	9.6
Observations	1,000

Cleveland

Word category	*Share*
Economy and employment	43.8
Crime	32.0
Government and politics	23.8
Poverty and social issues	19.9
Education	12.8
Housing	10.4
Race	6.5
Traffic and transport	4.1
Observations	1,000

Houston

Word category	*Share*
Economy and employment	26.5
Government and politics	22.4
Poverty and social issues	15.9
Crime	15.0
Traffic and transport	14.9
Housing	7.7
Education	4.6
Race	2.5
Observations	1,000

Indianapolis

Word category	*Share*
Crime	39.3
Economy and employment	35.2
Government and politics	25.6
Poverty and social issues	17.3
Traffic and transport	11.1
Education	11.0
Housing	9.1
Race	5.2
Observations	1,000

Memphis

Word category	*Share*
Crime	48.3
Economy and employment	31.8
Government and politics	20.6
Poverty and social issues	19.6
Education	15.1
Race	13.4
Housing	4.9
Traffic and transport	2.4
Observations	1,000

Rochester

Word category	*Share*
Economy and employment	47.8
Government and politics	29.5
Poverty and social issues	25.6
Crime	25.5
Education	15.6
Housing	10.9
Race	4.3
Traffic and transport	2.8
Observations	800

St. Louis

Word category	*Share*
Crime	44.1
Economy and employment	34.6
Government and politics	26.6
Race	18.9
Poverty and social issues	17.4
Education	9.8
Housing	5.3
Traffic and transport	5.0
Observations	1,000

Seattle

Word category	*Share*
Housing	42.2
Poverty and social issues	35.3
Government and politics	29.6
Traffic and transport	24.0
Economy and employment	19.8
Crime	13.5
Education	4.4
Race	1.6
Observations	1,000

Table A-4: *Major Issues Facing People by MSA: Word Categories.*

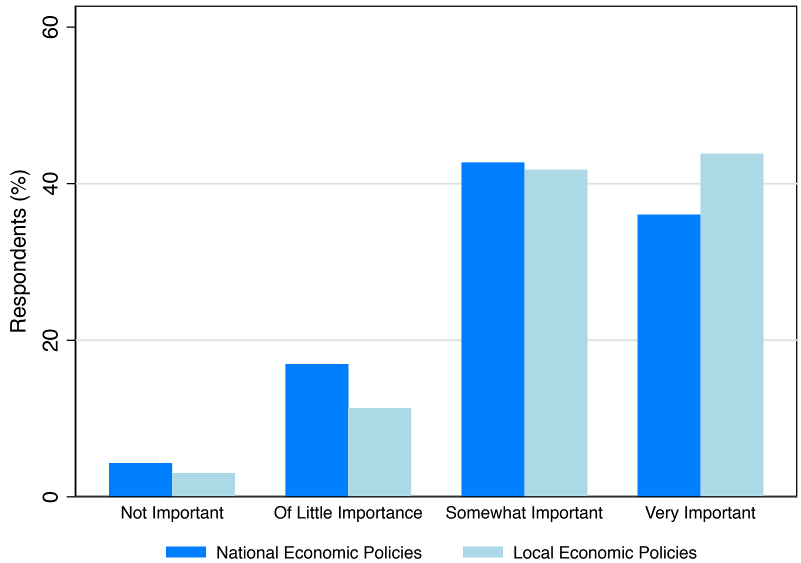


Figure A-1: *Importance of National and Local Policies for MSA Performance.* This graph shows respondents' assessment of the importance of national and local policies, respectively, for changes in the economy in their MSA over the last 20 years.

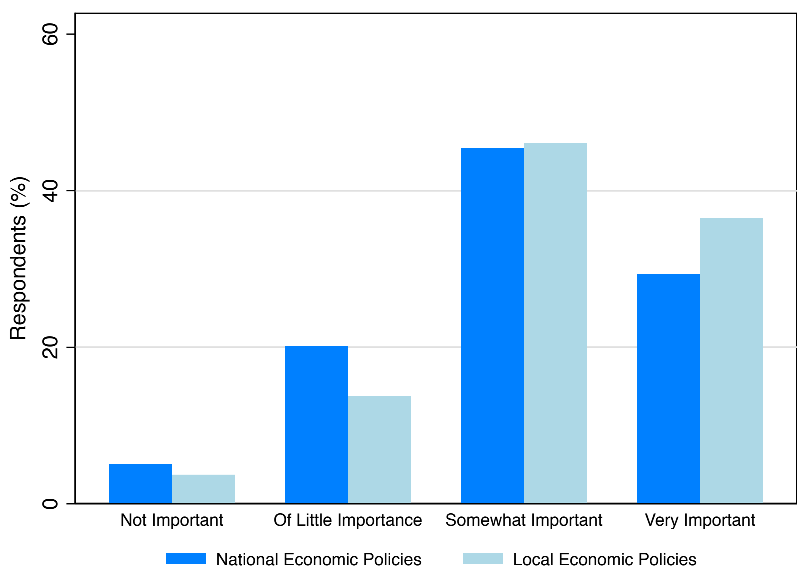


Figure A-2: *Importance of National and Local Policies for MSA Performance - Economy Improved.* This graph shows respondents' assessment of the importance of national and local policies, respectively, for changes in the economy in their MSA over the last 20 years. The graph is based on a subsample of respondents who think that the MSA economy improved over the period.

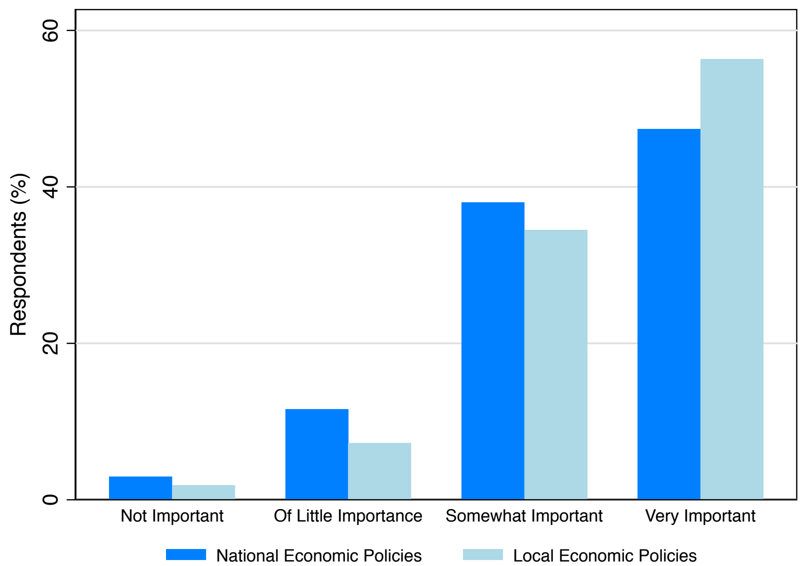


Figure A-3: *Importance of National and Local Policies for MSA Performance - Economy Got Worse.* This graph shows respondents' assessment of the importance of national and local policies, respectively, for changes in the economy in their MSA over the last 20 years. The graph is based on a subsample of respondents who think that the MSA economy got worse over the period.

C Conjoint Introduction Text

Now we'd like to ask you some questions about [MSA Name].

Given the impact of globalization and technological change on the [MSA Name] economy in the past and their potential impact in the future, there are lots of different ideas about the policies that [MSA Name] should adopt to generate economic growth and good jobs for its citizens. We want to know what you think.

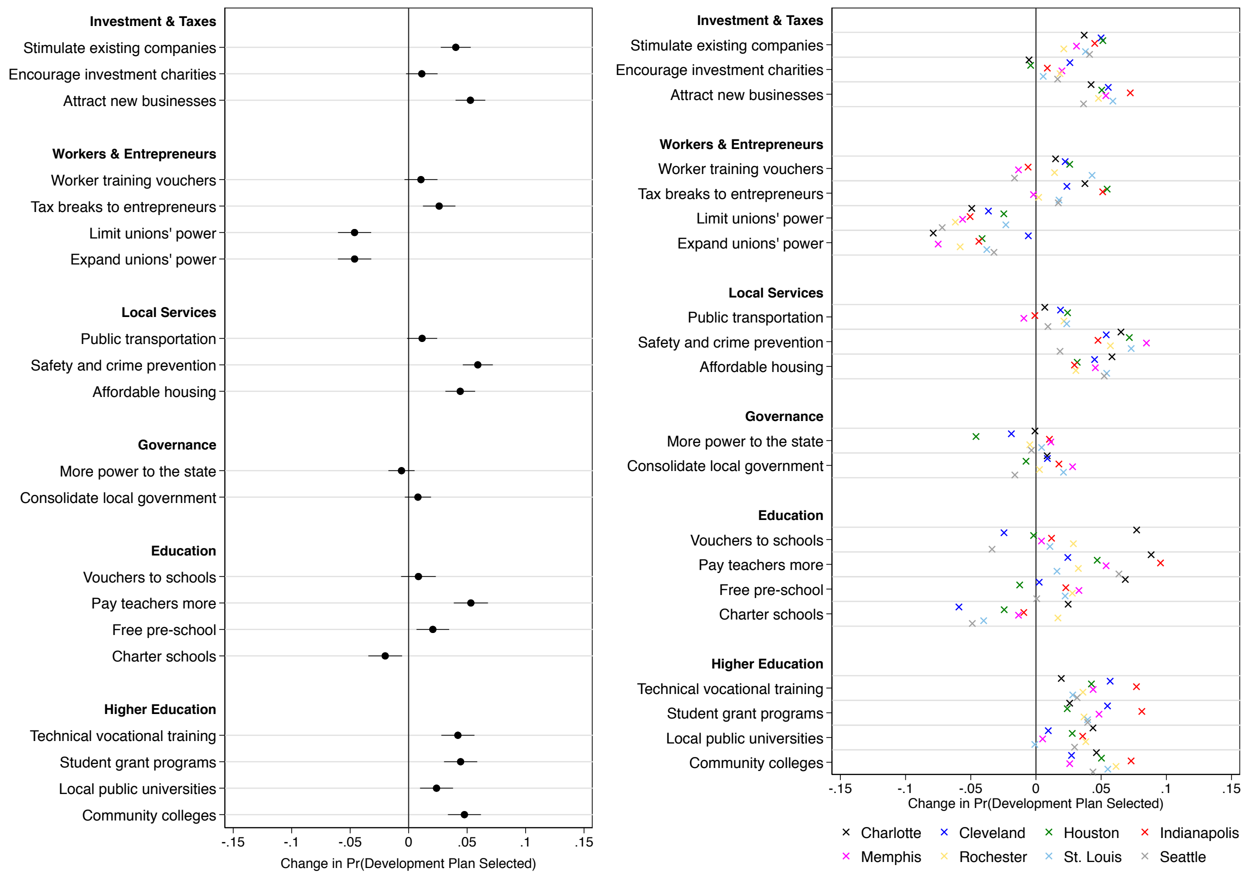
We will provide you with several possible development plans to help [MSA Name] adapt to technology and globalization. Please remember that any new spending programs will require higher taxes or spending cuts to existing programs. Similarly, any tax cuts will require offsetting tax increases or spending cuts. We will always show you two possible proposals in comparison. For each comparison, please indicate which of the two plans you prefer. Please just tell us which one you like best. You may like both or not like either one. In any case, choose the one you prefer the most. In total, we will show you five comparisons.

People have different opinions about these issues, and there are no right or wrong answers. Please take your time when reading the potential plans.

D Experimental Conjoint: Additional Results

Figure A-4a presents the conjoint estimates for all the MSAs pooled together. Table A-5 presents the same results in tabular form. As an example of how to interpret the results, consider the *Higher Education* dimension and the estimate for *Community Colleges*. The dot is the point estimate, and the bars indicate the 95% confidence interval for this estimate. The point estimate of *Community Colleges* is 0.048, which indicates that respondents had a 4.8 percentage point higher probability of choosing a local development plan that invested more in community colleges compared to plans that had the *Keep Current Policies* option for the *Higher Education* dimension. This is the average marginal component-specific effect, and it has a causal interpretation. Figure A-4b shows these same estimates for each MSA individually.

Three general patterns from these estimates should be noted. First, on average, citizens support active policies to support businesses in their communities. “Attract new businesses,” “Stimulate existing companies,” and “Tax breaks to entrepreneurs” all have positive and significant effects on the probability that a respondent chooses a plan. Second, citizens are also supportive of greater investments in human capital. “Pay teachers more,” “Community colleges,” “Local public universities,” “Technical vocational training,” and “Student grant programs” also have substantively and statistically significant positive effects on support for local development plans. Third, the evidence in Figure A-4b suggests that although there is some variation across MSAs, the general pattern of estimates is quite similar across communities.



(a) Pooled Across MSAs

(b) Within MSAs

Figure A-4: *Conjoint Estimates of Local Development Policy Preferences Across and Within MSAs.* This plot shows estimates of the effect of randomly assigned attribute values for local development plan dimensions on the probability of supporting a development plan relative to the status quo policy for that dimension. The left-hand side pools all MSAs together, while the right-hand side disaggregates by MSA. Estimates are based on the regression of *Local Development Plan Support* on dummy variables for the values of the plan dimensions with SEs clustered by respondent. The status quo for each dimension is always the omitted category (not pictured). The bars indicate 95% confidence intervals on the left. Confidence intervals are omitted for clarity on the right.

Policies	(1) Estimate	(2) SE
Investment and Taxes		
Stimulate existing companies	0.040***	(0.007)
Encourage investment by charities	0.011	(0.007)
Attract new businesses	0.053***	(0.006)
Workers and Entrepreneurs		
Worker training vouchers	0.011	(0.007)
Tax breaks to entrepreneurs	0.026***	(0.007)
Limit unions' power	−0.046***	(0.007)
Expand unions' power	−0.046***	(0.007)
Local Services		
Public transportation	0.012*	(0.007)
Public safety and crime prevention	0.059***	(0.007)
Affordable housing	0.044***	(0.006)
Governance		
More power to the state	−0.006	(0.006)
Consolidate local government	0.008	(0.006)
Education		
Vouchers to schools	0.008	(0.008)
Pay teachers more	0.053***	(0.007)
Free pre-school	0.021***	(0.007)
Charter schools	−0.020***	(0.007)
Higher Education		
Technical vocational training	0.042***	(0.007)
Student grant programs	0.044***	(0.007)
Local public universities	0.024***	(0.007)
Community colleges	0.048***	(0.007)
Observations	78,000	
Respondents	7,800	
Root MSE	0.497	

Table A-5: *Conjoint Estimates for Local Development Policy Preferences.* Standard errors clustered at the individual level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Plan Dimension	Level	Coefficient	SE	p-value	95% CI
Investment & Taxes	Attract new businesses	0.028	(0.020)	0.173	$[-0.01, 0.08]$
	Stimulate existing companies	0.034	(0.022)	0.113	$[-0.01, 0.08]$
	Encourage investment charities	-0.016	(0.021)	0.455	$[-0.06, 0.03]$
Workers & Entrepreneurs	Limit unions' power	0.052^*	(0.025)	0.035	$[0.00, 0.10]$
	Expand unions' power	-0.142^*	(0.024)	0.000	$[-0.19, -0.09]$
	Worker training vouchers	-0.048^*	(0.024)	0.046	$[-0.09, -0.00]$
	Tax breaks to entrepreneurs	-0.018	(0.023)	0.449	$[-0.06, 0.03]$
Local Services	Affordable housing	-0.051^*	(0.022)	0.023	$[-0.09, -0.01]$
	Public transportation	-0.036	(0.022)	0.103	$[-0.08, 0.01]$
	Safety and crime prevention	0.058^*	(0.021)	0.005	$[0.02, 0.10]$
Governance	Consolidate local government	-0.005	(0.020)	0.815	$[-0.04, 0.03]$
	More power to the state	0.004	(0.019)	0.832	$[-0.03, 0.04]$
Education	Charter schools	0.091^*	(0.026)	0.001	$[0.04, 0.14]$
	Vouchers to schools	0.093^*	(0.025)	0.000	$[0.04, 0.14]$
	Free pre-school	-0.072^*	(0.024)	0.002	$[-0.12, -0.03]$
	Pay teachers more	-0.039	(0.024)	0.095	$[-0.09, 0.01]$
Higher Education	Community colleges	0.008	(0.024)	0.726	$[-0.04, 0.06]$
	Local public universities	-0.011	(0.024)	0.647	$[-0.06, 0.04]$
	Technical vocational training	-0.006	(0.024)	0.793	$[-0.05, 0.04]$
	Student grant programs	-0.056^*	(0.025)	0.023	$[-0.10, -0.01]$
Intercept	Strong Rep. - Strong Dem.	0.026	(0.035)	0.460	$[-0.04, 0.09]$

Table A-6: *OLS Interaction Coefficients.* This table shows the interaction coefficients of an OLS regression using data from strong partisans of the outcome variable on the conjoint levels plus indicators for being a Strong Republican. The coefficients show the differences in CAMCE between Strong Republicans compared to Strong Democrats. Standard errors are clustered at the respondent level. $^*p < 0.05$

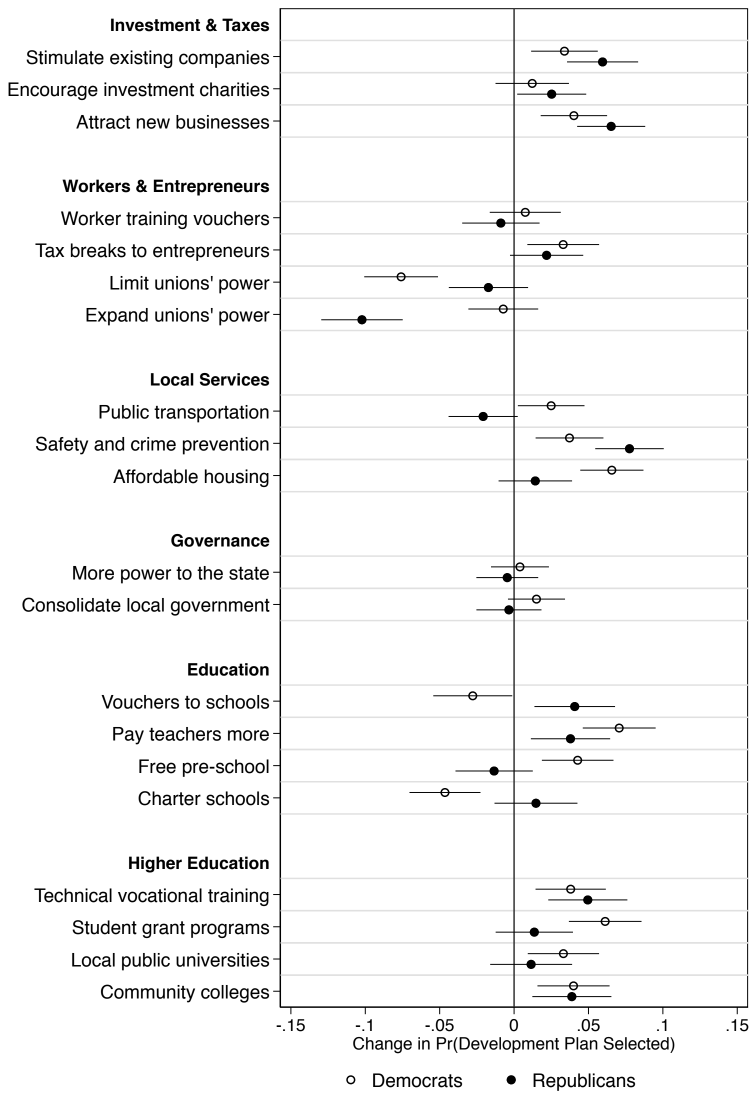


Figure A-5: *Conjoint Estimates of Local Development Policy Preferences by Party Identification.* Party identification is measured in a single question: "Generally speaking, do you usually think of yourself as a Democrat, a Republican, an independent, or what?" The estimates reported here are for "Democrat" and "Republican" only.

E Hierarchical Model Details

In this Appendix, we first provide more details on the model. We then provide some guidance for other researchers interested in adapting the model for their own applications.

E.1 Model Details

Our proposed method is to estimate a random-slopes hierarchical model that admits heterogeneity in the individual-level marginal component effects. To recap from the main text, the experimental setup is such that each individual, indexed by $i \in \{1, \ldots, N\}$, sees several conjoint profiles, indexed by $j \in \{1, \ldots, J\}$. In our survey, there are $N = 7,800$ respondents who each complete 5 conjoint tasks in which they see 2 conjoint profiles, so $J = 10$. Let $y_{ij} = 1$ if respondent i indicates that she prefers profile j to its alternative, and $y_{ij} = 0$ otherwise. Let X_{ij} denote a vector of dummy variables that describes the conjoint profile, and denote the dimension of X_{ij} by K.

We model the probability of choosing a profile as a linear function of the attributes, as is standard in the conjoint literature. However, in contrast to the standard analysis, we also allow the coefficients to vary by respondent. We specify the first-level equation

$$y_{ij} = \alpha_i + X'_{ij}\beta_i + \epsilon_{ij}, \tag{A-1}$$

where α_i is the probability that respondent i chooses a conjoint profile in which all the levels are set to their baseline category, β_i is the individual-level coefficient vector (which has length K), and ϵ_{ij} is a mean-zero error term.

Next, we model α_i the β_i's to be a linear function of respondent-level covariate vector Z_i

(which may include an intercept).[1] For α_i and element k of the β_i vector, we specify

$$\alpha_i = Z_i'\gamma_\alpha + \eta_i^\alpha \tag{A-2}$$

$$\beta_i^k = Z_i'\gamma_k + \eta_i^k, \tag{A-3}$$

where γ_α and γ_k are vectors of second-level regression coefficients and η_i^α and η_{ij} are mean-zero error terms.

We specify that $\epsilon_{ij} \overset{iid}{\sim} \text{Normal}(0, \sigma_\epsilon^2)$, $\eta_i^\alpha \overset{iid}{\sim} \text{Normal}(0, \sigma_{\eta^\alpha})$, $\eta_i^k \overset{iid}{\sim} \text{Normal}(0, \sigma_{\eta^k}^2)$, where the variances are terms to be estimated and independence is across both respondents i and conjoint levels k. The distributions on the η terms induce a hierarchical random-effects structure on the α and β coefficients, which enables partial pooling across similar observations (Gelman and Hill, 2007).

We specify the following diffuse independent priors on the second-level coefficients:

$$\gamma_\alpha \sim \text{Normal}(0, 10^2 \cdot I) \tag{A-4}$$

$$\gamma_k \sim \text{Normal}(0, 10^2 \cdot I) \tag{A-5}$$

where I is the identity matrix of dimension equal to $\dim(Z_i)$, so each element of the γ vectors has an independent $\text{Normal}(0, 10^2)$ prior. The standard deviations are given the following half-Cauchy priors:

$$\sigma_\epsilon \sim \text{Half-Cauchy}(0, 2) \tag{A-6}$$

$$\sigma_{\eta^\alpha} \sim \text{Half-Cauchy}(0, 2) \tag{A-7}$$

$$\sigma_{\eta^k} \sim \text{Half-Cauchy}(0, 2). \tag{A-8}$$

[1] Z_i in our estimates includes age, race, sex, education, income, employment status, homeownership, length of time living in the region, MSA indicators, and an intercept. Age is broken into the following bins: under 30 years, 31-50 years, 51-65 years, and over 65 years. Race is broken into the following categories: white, black, Latino, and other. Income is measured as an indicator for the respondent's income quartile within survey respondents from the same MSA. Employment status is defined as either "looking for work" or not (which includes those who are currently employed, retired, and not in the labor force).

E.2 Estimation

We estimate the model by Markov chain Monte Carlo implemented in Stan (Carpenter et al., 2017). We run 8 chains each for 1200 iterations, discarding the first 600 from each chain as a warm-up period. Thus, our final analysis includes 4,800 samples from the posterior distribution.

We take several steps to ensure that the posterior is well-approximated by the sampler. First, we examined traceplots of various parameters (both coefficients and variance parameters). Visual inspection indicated that the chains mixed well and had each converged to a stationary distribution. Next, we examined the Gelman-Rubin $\hat{R}$ statistic (Gelman and Rubin, 1992). If the chains have converged, we should expect $\hat{R} \approx 1$, with values larger than unity indicating poor convergence. Across all parameters (of which there are tens of thousands, counting the individual-level IMCE parameters), the $\hat{R} \leq 1$. Finally, we examine the Bayesian fraction of missing information to assess convergence (Betancourt, 2016). The BFMI is a diagnostic tool for Hamiltonian Monte Carlo samplers like the one that Stan uses. The BFMI did not indicate any pathological behavior, providing further reassurance that the posterior is well-approximated.

E.3 Further Discussion of the Hierarchical Model

The main advantages of the hierarchical modeling approach are: (1) to enable estimates of individual-level marginal component effects; (2) to explore how individual-level marginal component effects differ according to theoretically interesting covariates. Here we provide some recommendations and discussion of the model.

As we detail in the main text, it is theoretically possible to obtain IMCEs nonparametrically if each respondent rates a large number of profiles and is shown each possible level at least once. In that case, individual-level estimates could be obtained by simply running the standard conjoint regression separately for each respondent. This is not the case for most surveys, which motivates our hierarchical model, which partially pools information across respondents. Nonetheless, if the goal is to obtain good estimates of IMCEs, it will help to have respondents complete a reasonably large number of conjoint tasks. Precision can be further improved if second-level covariates are included in the model, especially if they are good predictors of opinions. In that case, the covariates contain a lot of information that the model uses to predict IMCEs even for levels that any given respondent might not see.

As noted above in discussing priors, we make several conditional independence assumptions. Perhaps the one most likely to be violated is the assumption that there is no correlation between individual-level marginal component effects within the same factor. This implies that a priori, we expect there to be no correlation between IMCEs for different levels within the same factor (after conditioning on covariates). Without covariates, this assumption would be especially untenable; for example, we should expect there to be a strong correlation between respondents' views towards limiting unions' power and expanding unions' power. When a rich set of covariates is included, as in our application, this concern is mitigated because the assumption only applies to any individual-level variation that is not explained by the covariates. A more general model might specify a block-diagonal structure for the η_i terms, to allow correlations within factor i. However, this approach is more computationally intensive because it requires estimating the elements of the covariance matrices, so we did not implement it.

Another question relates to power: how powerful is the estimator in detecting differences across groups? While we do not have formal results on this question, there are several features of our application that lead us to believe that we have sufficient power to detect meaningful differences. Our sample size is large, with 7,800 respondents each rating 10 different development plans. Informally, with such a large sample size, we would expect that if partisan differences are large enough to be politically important, we expect that we will be able to detect them. Further, the uncertainty estimates obtained from the hierarchical model on the second-level coefficients (e.g., the posterior standard deviations reported in Table 2) are relatively small — on the order of 2 percentage points — and generally smaller than the corresponding uncertainty estimates from the split-sample approach (Table A-6). This fact should not be surprising, given that hierarchical models and Bayesian estimation in general typically trades off some bias for lower variance. Nonetheless, a more formal investigation into the power of this estimator would be worthwhile.

Finally, a note on implementation. To aid computation, we estimate a re-parameterized version of this model. MCMC methods will not perform well when the model written here is implemented directly, due to a high degree of correlation in the parameters that is induced in the sampling process. Instead, we implement a "non-centered parameterization" that avoids these sampling problems but is numerically equivalent to the model written here. For details, see Stan Development Team (2019), section 21.7. Stan code to implement the model is available in the replication archive.

E.4 Limitations of the Method

In the main text, we outlined several limitations of our method. We provide more discussion of these limitations here.

First, and most importantly, we can only control for observable individual-level characteristics: standard caveats about omitted variables bias apply here. In order to interpret the second-level coefficients as causal, we need to make the strong assumption that the second-level error term is uncorrelated with the regressors. That is, we should not interpret differences in estimated parameters as being *caused* by partisanship.[2]

Second, our approach requires some parametric assumptions that may be violated, unlike the standard AMCE estimator which is fully nonparametric (Hainmueller, Hopkins and Yamamoto, 2014). We place parametric distributions on the random effects (e.g., assuming that the β_i^k terms are drawn from a normal distribution with a mean that depends on

[2] If there were some experimental treatment applied before the conjoint section of the survey, we could include that treatment and interpret differences in CAMCEs as causal, since by design the treatment is uncorrelated with other variables. See Bansak (2018) for a thorough discussion of the assumptions needed to identify causal moderation effects. Our estimation approach is analogous to the estimator he proposes in section IVb.

covariates). If the distributions are misspecified, the estimates may be inconsistent. That said, we think this probably is not a large concern. The structure we place on the model is fairly flexible — with the inclusion of covariates, separate variance terms for each level, etc. — rendering the distributional assumptions less restrictive than they initially appear. Even if the functional form is not correctly specified, the estimates will still converge (as the sample size increases) to a well-defined estimand; namely, the parameters that most closely approximate the true model under the maintained functional form (e.g., White, 1982). While this is not the same as the target marginal component effect estimand, the discussion above suggests that it is likely to be a close approximation.

Third, we follow standard practice in specifying a linear probability model for the first-level regression. Because we model the IMCEs as a function of covariates, it is theoretically possible to obtain predicted IMCEs that are outside of the $[-1, 1]$ interval — which is inconsistent with the interpretation of the marginal component effect as being the change in probability of selecting a given conjoint profile. In contrast, the standard AMCE regression estimator without covariates always yields estimates in this interval. While we could theoretically fix this problem by specifying a probit or logit link for the first-level regression, we eschew this choice because it sacrifices the simple interpretability of the coefficients. Additionally, in practice, all of the IMCEs we estimate are well within the $[-1, 1]$ interval, leading us to conclude that at least for our application this problem is not very important.

F Hierarchical Regression Tables

Here we report the full set of hierarchical regression results. In terms of the notation used in Section 4.1, these are γ coefficients. There are separate coefficients on each individual-level variable for every level in the conjoint. In all tables that follow, the coefficients are posterior means, and posterior standard deviations are presented in parentheses. Coefficients have stars next to them if $|\bar{\theta}/sd(\theta)| \geq 1.96$, i.e., p-value less than 0.05 using a normal approximation to the posterior distribution.

Table A-7: Partisanship – Factor: Education

	Charter schools	Vouchers to schools	Free pre-school	Pay teachers more
Party: Weak Dem.	0.010	0.030	−0.035	−0.030
	(0.019)	(0.020)	(0.019)	(0.020)
Party: Lean Dem.	0.013	0.014	−0.025	−0.012
	(0.022)	(0.022)	(0.022)	(0.022)
Party: Independent	0.044*	0.063*	−0.011	−0.026
	(0.020)	(0.020)	(0.019)	(0.020)
Party: Lean Rep.	0.092*	0.082*	−0.090*	−0.048*
	(0.024)	(0.025)	(0.025)	(0.024)
Party: Weak Rep.	0.036	0.075*	−0.060*	−0.046*
	(0.021)	(0.021)	(0.021)	(0.021)
Party: Strong Rep.	0.103*	0.105*	−0.090*	−0.062*
	(0.020)	(0.020)	(0.020)	(0.020)
Age: 31-50	0.011	−0.022	−0.026	−0.028
	(0.017)	(0.017)	(0.017)	(0.017)
Age: 51-65	0.023	−0.009	−0.018	−0.016
	(0.018)	(0.018)	(0.018)	(0.018)
Age: 65+	0.017	−0.021	−0.015	−0.019
	(0.021)	(0.021)	(0.021)	(0.021)
Race: Black	0.019	0.028	−0.004	−0.038*
	(0.018)	(0.018)	(0.018)	(0.018)
Race: Latino	−0.014	0.017	−0.042	−0.008
	(0.028)	(0.028)	(0.027)	(0.028)
Race: Other	0.047*	−0.017	−0.014	−0.005
	(0.024)	(0.025)	(0.025)	(0.024)
Female	−0.007	−0.000	0.007	0.032*
	(0.012)	(0.012)	(0.012)	(0.012)
College	0.010	0.015	−0.002	0.031*
	(0.013)	(0.013)	(0.013)	(0.013)
Income: Second Quartile	0.024	−0.009	0.016	0.029
	(0.017)	(0.017)	(0.017)	(0.017)
Income: Third Quartile	0.019	−0.010	0.041*	0.057*
	(0.018)	(0.018)	(0.018)	(0.018)
Income: Fourth Quartile	0.005	−0.008	0.012	0.024
	(0.019)	(0.019)	(0.019)	(0.019)
Looking for Work	0.014	−0.017	−0.031	−0.034
	(0.020)	(0.020)	(0.020)	(0.020)
Homeowner	−0.005	−0.015	−0.021	−0.017
	(0.014)	(0.015)	(0.015)	(0.014)
Years in MSA: 1-5	−0.049	−0.015	−0.037	−0.058
	(0.033)	(0.033)	(0.033)	(0.033)
Years in MSA: 6-10	−0.032	0.007	−0.003	−0.007
	(0.035)	(0.034)	(0.035)	(0.034)
Years in MSA: 11-15	−0.081*	−0.039	−0.028	−0.063
	(0.037)	(0.037)	(0.037)	(0.036)
Years in MSA: 16+	−0.048	−0.012	−0.015	−0.048
	(0.028)	(0.028)	(0.028)	(0.027)
Intercept	−0.021	0.031	0.128*	0.157*
	(0.037)	(0.037)	(0.037)	(0.036)

Table A-8: Partisanship – Factor: Higher Education

	Community colleges	Local public universities	Technical vocational training	Student grant programs
Party: Weak Dem.	0.004	0.021	−0.005	−0.010
	(0.020)	(0.020)	(0.019)	(0.020)
Party: Lean Dem.	0.038	0.030	−0.002	0.018
	(0.022)	(0.023)	(0.022)	(0.023)
Party: Independent	0.029	−0.011	0.014	−0.020
	(0.020)	(0.020)	(0.019)	(0.020)
Party: Lean Rep.	0.005	−0.030	−0.006	−0.041
	(0.025)	(0.024)	(0.024)	(0.025)
Party: Weak Rep.	−0.011	−0.019	0.002	−0.056*
	(0.022)	(0.021)	(0.021)	(0.022)
Party: Strong Rep.	0.005	−0.041*	−0.025	−0.048*
	(0.020)	(0.020)	(0.020)	(0.020)
Age: 31-50	0.001	−0.009	0.012	−0.018
	(0.017)	(0.017)	(0.016)	(0.017)
Age: 51-65	0.008	−0.036*	0.012	−0.010
	(0.018)	(0.018)	(0.018)	(0.018)
Age: 65+	−0.018	−0.033	0.007	−0.029
	(0.021)	(0.021)	(0.021)	(0.021)
Race: Black	0.009	−0.007	0.010	0.004
	(0.018)	(0.018)	(0.019)	(0.018)
Race: Latino	0.027	0.014	−0.040	−0.026
	(0.027)	(0.028)	(0.027)	(0.028)
Race: Other	−0.048*	−0.029	−0.055*	−0.039
	(0.024)	(0.024)	(0.024)	(0.025)
Female	0.018	−0.002	0.023	0.038*
	(0.012)	(0.012)	(0.012)	(0.012)
College	0.006	0.001	0.000	0.002
	(0.013)	(0.013)	(0.012)	(0.013)
Income: Second Quartile	0.024	0.004	−0.016	0.010
	(0.017)	(0.017)	(0.017)	(0.017)
Income: Third Quartile	−0.015	−0.012	−0.025	−0.018
	(0.018)	(0.018)	(0.018)	(0.018)
Income: Fourth Quartile	−0.013	−0.016	−0.020	−0.006
	(0.019)	(0.019)	(0.019)	(0.019)
Looking for Work	−0.011	−0.023	−0.001	−0.007
	(0.020)	(0.020)	(0.020)	(0.020)
Homeowner	0.024	0.019	0.020	0.005
	(0.015)	(0.015)	(0.015)	(0.015)
Years in MSA: 1-5	0.041	0.017	−0.008	0.011
	(0.033)	(0.033)	(0.033)	(0.034)
Years in MSA: 6-10	0.027	0.017	0.004	0.064
	(0.034)	(0.034)	(0.034)	(0.035)
Years in MSA: 11-15	−0.019	−0.004	−0.030	0.018
	(0.036)	(0.036)	(0.036)	(0.037)
Years in MSA: 16+	0.017	−0.010	−0.031	0.005
	(0.027)	(0.027)	(0.028)	(0.028)
Intercept	−0.006	0.082*	0.048	0.033
	(0.037)	(0.037)	(0.037)	(0.038)

Table A-9: Partisanship – Factor: Investment and Taxes

	Attract new businesses	Stimulate existing companies	Encourage investment by charities
Party: Weak Dem.	0.019	0.016	−0.008
	(0.017)	(0.018)	(0.018)
Party: Lean Dem.	0.017	−0.007	−0.001
	(0.020)	(0.020)	(0.020)
Party: Independent	0.018	0.011	0.004
	(0.018)	(0.017)	(0.018)
Party: Lean Rep.	0.028	0.035	−0.021
	(0.022)	(0.022)	(0.022)
Party: Weak Rep.	0.021	0.019	0.007
	(0.019)	(0.019)	(0.019)
Party: Strong Rep.	0.013	0.018	−0.010
	(0.018)	(0.018)	(0.018)
Age: 31-50	0.025	0.026	0.012
	(0.015)	(0.015)	(0.015)
Age: 51-65	0.017	0.020	−0.012
	(0.016)	(0.016)	(0.016)
Age: 65+	0.032	0.006	−0.005
	(0.019)	(0.019)	(0.019)
Race: Black	−0.017	−0.007	−0.001
	(0.017)	(0.016)	(0.017)
Race: Latino	−0.012	−0.010	−0.032
	(0.025)	(0.025)	(0.025)
Race: Other	−0.021	−0.006	0.033
	(0.021)	(0.021)	(0.021)
Female	−0.013	−0.004	0.003
	(0.011)	(0.011)	(0.011)
College	−0.022*	0.004	−0.012
	(0.011)	(0.011)	(0.011)
Income: Second Quartile	0.016	0.013	−0.008
	(0.015)	(0.015)	(0.015)
Income: Third Quartile	−0.014	0.010	−0.013
	(0.016)	(0.016)	(0.016)
Income: Fourth Quartile	−0.017	0.006	−0.020
	(0.017)	(0.017)	(0.017)
Looking for Work	−0.021	−0.003	−0.013
	(0.018)	(0.018)	(0.018)
Homeowner	0.005	−0.012	−0.001
	(0.013)	(0.013)	(0.013)
Years in MSA: 1-5	−0.017	−0.006	−0.017
	(0.030)	(0.030)	(0.030)
Years in MSA: 6-10	−0.012	0.014	0.006
	(0.031)	(0.031)	(0.031)
Years in MSA: 11-15	−0.026	−0.005	−0.027
	(0.032)	(0.033)	(0.033)
Years in MSA: 16+	−0.037	−0.014	−0.024
	(0.025)	(0.025)	(0.025)
Intercept	0.076*	0.039	0.050
	(0.033)	(0.033)	(0.034)

Table A-10: Partisanship – Factor: Governance

	Consolidate local government	More power to the state
Party: Weak Dem.	−0.001	0.031*
	(0.015)	(0.016)
Party: Lean Dem.	−0.023	−0.030
	(0.018)	(0.017)
Party: Independent	0.015	0.020
	(0.015)	(0.015)
Party: Lean Rep.	−0.001	0.009
	(0.019)	(0.019)
Party: Weak Rep.	−0.022	0.016
	(0.017)	(0.017)
Party: Strong Rep.	−0.003	0.023
	(0.016)	(0.016)
Age: 31-50	−0.013	−0.015
	(0.013)	(0.013)
Age: 51-65	−0.006	−0.031*
	(0.014)	(0.014)
Age: 65+	0.001	−0.040*
	(0.016)	(0.016)
Race: Black	0.013	0.034*
	(0.014)	(0.014)
Race: Latino	−0.013	−0.004
	(0.021)	(0.021)
Race: Other	0.022	0.038*
	(0.019)	(0.018)
Female	−0.013	−0.006
	(0.010)	(0.010)
College	0.022*	0.004
	(0.010)	(0.010)
Income: Second Quartile	0.005	0.007
	(0.013)	(0.013)
Income: Third Quartile	−0.012	−0.011
	(0.014)	(0.014)
Income: Fourth Quartile	−0.005	−0.018
	(0.015)	(0.015)
Looking for Work	0.011	−0.000
	(0.016)	(0.015)
Homeowner	−0.003	0.003
	(0.011)	(0.012)
Years in MSA: 1-5	−0.012	−0.005
	(0.026)	(0.025)
Years in MSA: 6-10	−0.008	0.030
	(0.027)	(0.026)
Years in MSA: 11-15	0.019	0.020
	(0.029)	(0.028)
Years in MSA: 16+	−0.006	0.007
	(0.022)	(0.021)
Intercept	0.022	−0.018
	(0.029)	(0.029)

Table A-11: Partisanship – Factor: Workers and Entrepreneurship

	Limit unions' power	Expand unions' power	Worker training vouchers	Tax breaks to entrepreneurs
Party: Weak Dem.	−0.002	−0.058*	−0.040*	−0.017
	(0.019)	(0.020)	(0.019)	(0.019)
Party: Lean Dem.	0.009	−0.025	0.011	−0.012
	(0.022)	(0.023)	(0.022)	(0.022)
Party: Independent	0.057*	−0.052*	−0.015	−0.027
	(0.020)	(0.019)	(0.019)	(0.020)
Party: Lean Rep.	0.100*	−0.086*	0.032	0.021
	(0.025)	(0.025)	(0.025)	(0.025)
Party: Weak Rep.	0.065*	−0.095*	−0.033	−0.007
	(0.021)	(0.022)	(0.021)	(0.021)
Party: Strong Rep.	0.054*	−0.139*	−0.054*	−0.019
	(0.021)	(0.021)	(0.020)	(0.020)
Age: 31-50	−0.010	−0.007	0.013	0.003
	(0.017)	(0.017)	(0.016)	(0.017)
Age: 51-65	0.017	−0.016	0.049*	0.020
	(0.018)	(0.018)	(0.018)	(0.018)
Age: 65+	−0.001	−0.026	0.033	0.026
	(0.021)	(0.021)	(0.020)	(0.021)
Race: Black	0.017	0.014	0.005	−0.004
	(0.018)	(0.018)	(0.018)	(0.018)
Race: Latino	−0.019	0.002	−0.027	−0.047
	(0.027)	(0.028)	(0.027)	(0.027)
Race: Other	0.008	−0.007	0.020	−0.004
	(0.024)	(0.025)	(0.024)	(0.024)
Female	0.007	0.011	0.007	−0.004
	(0.012)	(0.012)	(0.012)	(0.012)
College	0.004	−0.011	−0.018	−0.009
	(0.013)	(0.013)	(0.013)	(0.013)
Income: Second Quartile	−0.007	−0.016	−0.043*	−0.029
	(0.017)	(0.017)	(0.017)	(0.017)
Income: Third Quartile	−0.021	−0.016	−0.034	−0.019
	(0.018)	(0.018)	(0.018)	(0.018)
Income: Fourth Quartile	−0.009	−0.039*	−0.051*	−0.012
	(0.019)	(0.019)	(0.019)	(0.019)
Looking for Work	−0.015	−0.029	0.009	−0.015
	(0.021)	(0.020)	(0.020)	(0.020)
Homeowner	0.011	0.010	0.017	0.002
	(0.015)	(0.014)	(0.015)	(0.015)
Years in MSA: 1-5	−0.030	0.004	0.007	−0.003
	(0.033)	(0.033)	(0.033)	(0.033)
Years in MSA: 6-10	−0.051	0.013	0.025	−0.010
	(0.034)	(0.034)	(0.034)	(0.034)
Years in MSA: 11-15	−0.078*	−0.069	−0.038	−0.045
	(0.036)	(0.036)	(0.036)	(0.036)
Years in MSA: 16+	−0.042	−0.017	−0.021	−0.032
	(0.028)	(0.027)	(0.028)	(0.028)
Intercept	−0.037	0.025	0.050	0.086*
	(0.037)	(0.037)	(0.038)	(0.037)

Table A-12: Partisanship – Factor: Local Services

	Affordable housing	Public transportation	Public safety and crime prevention
Party: Weak Dem.	−0.006	−0.015	0.027
	(0.017)	(0.017)	(0.017)
Party: Lean Dem.	0.031	0.033	0.052*
	(0.020)	(0.020)	(0.020)
Party: Independent	−0.024	−0.013	0.034
	(0.018)	(0.018)	(0.017)
Party: Lean Rep.	−0.044*	−0.044*	0.030
	(0.022)	(0.022)	(0.022)
Party: Weak Rep.	−0.029	−0.034	0.055*
	(0.019)	(0.019)	(0.019)
Party: Strong Rep.	−0.029	−0.034	0.061*
	(0.018)	(0.018)	(0.018)
Age: 31-50	0.013	0.018	0.039*
	(0.015)	(0.015)	(0.015)
Age: 51-65	−0.004	−0.013	0.006
	(0.016)	(0.016)	(0.016)
Age: 65+	−0.011	0.015	0.036
	(0.019)	(0.019)	(0.019)
Race: Black	0.032	−0.001	0.021
	(0.017)	(0.017)	(0.016)
Race: Latino	0.011	0.055*	0.027
	(0.025)	(0.025)	(0.024)
Race: Other	0.024	0.013	−0.021
	(0.021)	(0.021)	(0.022)
Female	0.028*	−0.009	0.033*
	(0.011)	(0.011)	(0.011)
College	−0.004	0.018	0.006
	(0.011)	(0.011)	(0.011)
Income: Second Quartile	−0.001	0.000	0.027
	(0.015)	(0.015)	(0.015)
Income: Third Quartile	−0.014	0.001	0.002
	(0.016)	(0.016)	(0.016)
Income: Fourth Quartile	−0.024	0.020	0.007
	(0.017)	(0.017)	(0.017)
Looking for Work	−0.012	−0.016	0.003
	(0.018)	(0.018)	(0.018)
Homeowner	−0.030*	−0.029*	0.009
	(0.013)	(0.013)	(0.013)
Years in MSA: 1-5	−0.026	0.010	−0.011
	(0.030)	(0.030)	(0.030)
Years in MSA: 6-10	0.019	0.015	0.012
	(0.031)	(0.031)	(0.031)
Years in MSA: 11-15	0.000	−0.007	−0.018
	(0.033)	(0.033)	(0.033)
Years in MSA: 16+	−0.005	0.009	−0.007
	(0.025)	(0.025)	(0.025)
Intercept	0.076*	0.019	−0.032
	(0.033)	(0.034)	(0.033)

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