City Limits to Partisan Polarization in the American Public*

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Abstract

How pervasive is partisan sorting and polarization over public policies in the American public? We examine whether the barriers of partisan sorting and polarization seen in national politics extend to important local policies that shape economic development. To describe the extent of partisan sorting and polarization over local development policies, we employ conjoint survey experiments in representative surveys of eight U.S. metropolitan areas and a hierarchical modeling strategy for studying heterogeneity across respondents. We find that strong partisans are sorted by party in some of their policy opinions, but rarely polarized. The same voters who disagree about national issues have similar preferences about local development issues suggesting a greater scope for bipartisan problem solving at the local level.

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1 Introduction

How pervasive is partisan sorting and polarization over public policies in the American public? An extensive literature has established that voters have become consistently sorted, whereby individuals with conservative policy positions on national issues are increasingly likely to identify as Republican partisans and those with more liberal policy positions are increasingly likely to identify as Democratic partisans (Abramowitz, 2010; Fiorina, Abrams and Pope, 2005; Fiorina and Abrams, 2008; Levendusky, 2009). Some scholars have argued that the extent of partisan sorting has resulted in a population with more polarized national policy preferences (Abramowitz, 2010) while others have argued that this reorganization of preferences has had little impact on the overall extent to which policy preferences are polarized (Fiorina and Abrams, 2008).

Regardless of the extent of polarization, sorting alone is commonly hypothesized to be a barrier to solving national public policy problems. Rather than each policy option having its own distribution of supporters and opposition and therefore a possibility of cross-cutting cleavages across issues, sorted partisans have consistently opposing views about how to solve social challenges. This sorting of policy preferences is thought not only to reduce the scope for compromise across issues but also may strengthen affective ties to partisan identities which in turn makes bipartisan problem-solving less likely (Abramowitz, 2006; Brader, Tucker and Therriault, 2014; Jacobson, 2003; Mason, 2015; Gerber, Henry and Lubell, 2013).

In this paper, we examine whether the patterns of partisan sorting and polarization documented for national issues extend to a wide range of important local public policies that shape economic development. Do local development policy preferences — e.g. policies designed to attract businesses, policies that educate and train local workers, policies that provide local services, etc. — vary by partisanship and if so, do partisans have opposing and polarized positions?

Evaluating partisan sorting and polarization over local public policies is important for at least two reasons. First, it provides a new lens for understanding partisan conflict and its effect on solving public policy problems. The bulk of the research on sorting and polarization focuses on national policies, but there is less consensus over how far down these divisions extend. While there is evidence that local policies differ according to the partisanship of elected officials (de Benedictis-Kessner and Warshaw, 2016; Gerber and Hopkins, 2011), several features of local politics make it difficult to directly apply findings about mass polarization on national issues to the local level. The media landscape is much different when it comes to local politics, many local elections are nonpartisan, and — where elections are partisan — parties tend to stake out less distinctive positions, potentially because localities compete with each other to retain firms and high-income residents. Studying local public policies can be viewed as evaluating whether partisan identities can be overcome to solve problems when voters are faced with alternative incentives and information.

Second, there is a great deal at stake in local development policymaking in the United States. Where Americans live is a major determinant of their economic opportunities (Chetty et al., 2014). Globalization, technological change, and other trends have generated inequality and poor absolute labor market outcomes for many workers. These trends have also made economic growth more geographically concentrated with some communities faring much better than others. A central problem faced by local governments is how to stimulate economic development amidst technological change and international competition. It is therefore important to gain a better understanding of citizen preferences over local development strategies to understand the overlap between policies that are economically productive and politically feasible. A key question addressed in this paper is whether the partisan polarization observed over national policies and often viewed as a barrier to addressing persistent public policy challenges is also evident in city politics.

We study policy opinions in eight major U.S. Metropolitan Statistical Areas (MSAs): Charlotte, Cleveland, Houston, Indianapolis, Memphis, Rochester, Seattle, and St. Louis. Our analysis is based on a 2018 YouGov survey representative of adult residents in each

MSA.[1] We report the results of identical conjoint survey experiments that task respondents with choosing multiple times between alternative local development plans. Each plan proposed a policy alternative for six different dimensions of local development policymaking: Investment and Taxes, Workers and Entrepreneurs, Local Services, Governance, Education and Higher Education. Conjoint designs are attractive for studying this topic for several reasons. First, they allow for assessment of opinion about a multidimensional array of policies. Second, they are useful for studying partisanship because they directly show which elements of a potential policy proposal would face more or less cross-partisan support and whether partisans have opposing views on a policy or consistent views but with varying intensity.

We present two main sets of results. The initial estimates report the average component-specific effect (AMCE) from the conjoint experiment, which tell us the effect of a policy alternative on support for a development proposal (Hainmueller, Hopkins and Yamamoto, 2014). We find that the following policies (in each issue domain) are preferred to the status quo: free pre-school, paying teachers more (Education); investing in community colleges, spending on local colleges and universities, creating technical vocational programs, spending more on student grant programs (Higher Education); using tax and investment incentives to attract new businesses and stimulate existing companies (Investment and Taxes); providing tax breaks to entrepreneurs (Workers and Entrepreneurs); investing in affordable housing and spending more on public safety and crime prevention (Local Services). In contrast, proposals to either expand or limit union power and to increase investments in charter schools are less preferred than status quo policies. Although there is some heterogeneity in these preferences across MSAs, this broad pattern generally holds across most of the cities.

We then estimate conditional average marginal component effects (CAMCE) for Strong Democrats and Strong Republicans to investigate the extent of heterogeneity across partisans in our sample. In the context of our conjoint experiment, we define sorting as Democrats and Republicans having different CAMCEs — relative to a status quo alternative — for a

[1] The data were originally produced by bgC3. They have allowed us to use the data and to make it publicly available upon publication of this paper.

given policy issue, and polarization as Democrats and Republicans having CAMCEs of opposite signs. The sorting definition is straightforward in that if Democrats and Republicans have different policy preferences, we expect policy attributes to have a different effect on their probability of choosing a development plan relative to the status quo. The polarization definition is useful in that it distinguishes between policies for which Democrats and Republicans simply have differential support and those for which a policy option has opposing effects on the probability that each group supports a development plan. The literature has typically defined sorting as Democrats having consistently more liberal policy views than Republicans, and polarization as extremity of these opinions. In adopting our definitions, we incorporate these existing conceptions into our conjoint experimental design.[2]

We implement two approaches for estimating the CAMCEs for Strong Democrats and Strong Republicans. First, as in Hainmueller, Hopkins and Yamamoto (2014), we estimate the same OLS regression for estimating the overall AMCE in each of the subsamples of interest. This split-sample approach yields point estimates and confidence intervals of the CAMCEs defined by each group. Second, we employ a hierarchical model to estimate CAMCEs for each individual in the sample, conditioned not only on their partisanship but a full profile of observed individual characteristics including race and ethnicity. This analysis complements the first by allowing us to investigate systematic heterogeneity across partisans, while adjusting for potential confounding observed variables. Additionally, it allows us to estimate and visualize the distribution of individual-level marginal component effects, which allows us to investigate not just the average opinion, but also population-level variance in opinions.

We find that even among strong partisans there are many areas of local development policymaking for which Democrats and Republicans have very similar policy preferences. Using our definitions of sorting and polarization, we find strong evidence for sorting on

[2]An important feature of our definitions is that sorting and polarization are defined with respect to a particular status quo. If opposing partisans want to move the status quo in opposite directions, they are polarized by our definition. If they both want to move it in the same direction, but have differential intensity of these preferences, they are sorted.

only 10 of the 20 policies we study. And of those 10, we find polarization on only 3 policies. Partisan differences are most pronounced when it comes to primary and secondary education policy. We find some partisan sorting when it comes to policies related to workers and unions, and on policies related to higher education. However, even in these cases, there is not strong evidence that Democrats and Republicans hold opposing views relative to the status quo.

The paper makes two contributions. First, partisan sorting and polarization is not as pervasive in American political behavior as is often asserted. Existing empirical research on partisan sorting and polarization is largely based on national policy issues and our study provides new evidence on local policies. Research on partisanship in local politics has largely focused on determining the impact of partisan control of local government on public policy outcomes (Peterson, 1981). Recent studies come to somewhat mixed conclusions. Three important papers use regression discontinuity designs to analyze whether partisan control of local government affects policy outcomes. Ferreira and Gyourko (2009) find that the partisanship of mayors has no impact on the size of city government and other outcomes. Gerber and Hopkins (2011) also find a limited impact of the partisanship of mayors on policy outcomes with the exception of the share of the budget spent on public safety, a policy where Democratic mayors spend less and cities have greater discretion than in other policy areas. de Benedictis-Kessner and Warshaw (2016), however, examining a larger set of elections and outcomes, find significant partisan effects, with Democratic mayors spending more and issuing greater debt to do so.

This research is important, but regardless of whether mayoral partisanship has an effect on policy outcomes, it remains unclear whether citizens themselves have different local policy preferences. We could observe or not observe an effect of mayoral partisanship under polarized or not polarized local public opinion if special interests, the policy preferences of mayors, competitive constraints on policy, or other considerations influence outcomes. The literature on policy outcomes often proposes electoral control as an explanation for partisan differences, but direct evidence of divergent partisan preferences is limited. An important exception in this literature is Tausanovitch and Warshaw's (2014) excellent analysis of the correspondence between local public conservatism and local policy. But as they note, their measurement approach relies on the assumption that policy opinions on local issues are not distinct from those on national issues. This may be plausible for their purpose of measuring overall policy conservatism, but is exactly what we examine empirically in order to assess how deep partisan sorting and polarization is in the American public.

Our evidence suggests only modest levels of partisan sorting and polarization over local development issues. This may be good news for the capacity of cities to develop bipartisan solutions to local development challenges, as well as for the potential for partisans to update their policy opinions in response to incentives and information about effective public policy.[3] Our results also provide an additional micro-foundation for why a number of studies have argued that partisanship is a less important determinant of voting behavior in local as opposed to national elections (Kaufmann, 2004; Oliver, Ha and Callen, 2012).

Our paper also contributes to the local political economy literature. A number of studies have documented that since 1980, the convergence across regions in economic development that had characterized most of American history slowed if not reversed itself (Berry and Glaeser, 2005; Ganong and Shoag, 2017). The economics of agglomeration have led to self-enforcing equilibria in which productive firms and high-human capital individuals find it in their interest to locate in cities with other productive firms and workers. Slowing convergence has made the politics of local economic development more pressing than ever before. Our study provides the first extensive, comparable cross-city evidence of what policies individual voters prefer to create economic development in their cities and how those preferences relate to partisan political conflict.

The next section of the paper documents polarization over national issues and discusses reasons why partisanship over local development policies might be different. Section 3 de-

[3] Rugh and Trounstine (2011) report that strategic politicians in diverse cities use issue bundling to develop broad coalitions for municipal bonds. Our findings suggest that there are similar opportunities to build bipartisan coalitions in local politics.

scribes the data and conjoint survey experiment from eight metropolitan areas and reports the baseline AMCE estimates. Section 4 investigates how AMCEs vary by partisanship by presenting split-sample estimates of the conjoint for strong partisans. Section 5 presents a hierarchical modeling strategy for heterogeneity in conjoints and presents estimates that allow us to investigate partisan differences "controlling for" other observed individual characteristics of respondents. The final section concludes with a discussion of the implications of the results for understanding partisanship and the politics of local economic development.

2 Partisan Polarization in Local Politics

The objective of this paper is to answer the descriptive question of whether attitudes towards local development policies — e.g. those designed to attract businesses, policies that educate and train local workers, etc. — vary by political partisanship. In this section, we first show that partisans in the eight metropolitan areas considered in this study, like the American electorate more generally, have substantially different preferences about national policy issues. It is not the case that the tendency for more liberal voters to sort into urban areas eliminates partisan differences over national issues. We then outline why local policy preferences might differ from what we see on national issues. While partisanship appears to be pervasive in American politics, there are reasons to think that voters who disagree greatly about national issues may have fairly similar preferences about many local development issues — whether due to competitive pressures among local governments or a decreased salience of partisan cues about these issues. While we will not test these mechanisms directly, they may be a useful lens through which to interpret our results.

In considering the question of how much partisan sorting and polarization that we should expect to observe about local political issues, it is essential to consider the possibility that voters living in cities do not exhibit the same partisan cleavages as the country more generally, even for national issues. If, for example, Republicans who choose to live in cities are more liberal than other Republicans, we might expect few partisan differences about both national and local policy issues simply because Republicans located in cities are not that different ideologically than Democrats.[4]

However, several features of our data suggest that ideological geographic sorting into the large metropolitan areas that we study is insufficient to eliminate partisan polarization. First, our analysis includes the entire metropolitan statistical area for each city and consequently a great number of suburban residents, who tend to be more conservative (Nall, 2018). Additionally, a number of our MSAs are in relatively Republican states: in all but Seattle at least 24% of the respondents identify as Republicans, which is not lower than those identifying as Democrats. Second, the partisans in our cities have significantly different opinions about national policy issues. Figure 1 reports the results of an OLS regression of several national policy measures on dummy variables for partisanship, controlling for sociodemographic characteristics.[5] There are significant differences in policy positions for all five national issues and the differences between "Strong Democrats" and "Strong Republicans" are large in magnitude — for most issues, Strong Republicans are at least 20 percentage points more likely to express a conservative opinion, relative to Strong Democrats.

We know that voters in our MSA data are divided on national policy issues and that this divide is partly explained by party affiliation. However, is that necessarily the case for local policy issues? In the following we present two potential reasons why partisan sorting and polarization in preferences for local policies could be different than for national policies: competition among jurisdictions for capital and high-income residents, and fewer elite cues about what policies go with which partisan orientations at the local level.

One aspect of local politics that could affect partisanship in preferences over different

[4]There is debate about the extent of partisan geographic sorting, with Bishop (2008) suggesting that it is pervasive. On the other hand, Mummolo and Nall (2017) show that political sorting may be rarer than is often hypothesized. Similarly, Martin and Webster (2018) find that levels of geographic sorting are not sufficient to explain geographic polarization.

[5]For comparability, these control variables are the same as those in our main results. They include: age, race/ethnicity, sex, education, income, employment status, homeownership status, length of time living in the metro region, and MSA indicators.

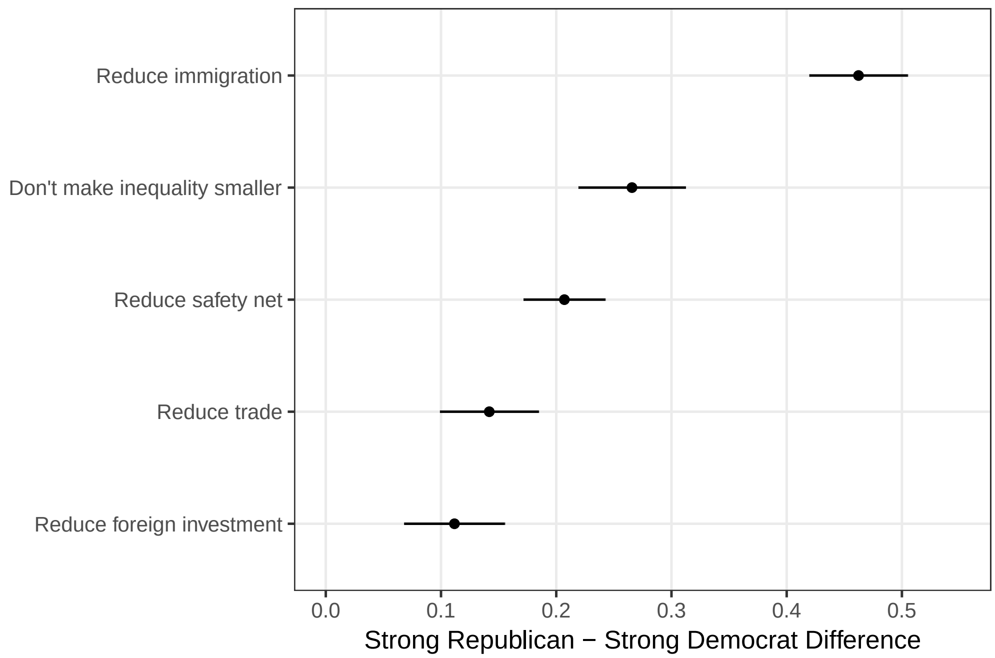


Figure 1: *National Policy Opinions by Partisan Identification.* This plot shows differences in opinions between Strong Republicans and Strong Democrats across a range of national policy issues. The estimates are based on a regression of an indicator for choosing a conservative response to each policy measure on set of dummy variables for partisanship and a number of sociodemographic characteristics. The bars indicate robust 95% confidence intervals. Across all issues, Strong Republicans are at least 10 percentage points more likely to hold a conservative opinion, after controlling for other covariates.

policies, is the fact that cities are in competition with each other. Jurisdictions compete for capital and high-income residents which could make local policy preferences across partisans (and across areas) converge. Peterson (1981) and others have argued that because cities compete for firms and need to attract and retain high-income residents, they will have very similar policies on many local issues. In particular, we would expect this to be relevant for policies that are salient and easy for cities to compete over and for businesses or residents to act upon, such as tax breaks. To the extent that citizens internalize these constraints, their preferred policies may not vary even if they have very different underlying ideological orientations. This is different from national policies, since mobility of capital and residents is greater across areas within a country than across countries which increases competition.

Another mechanism that could limit partisan polarization is the fact that there are fewer elite cues about what policies go with which partisan orientations at the local level — potentially because politicians are attuned to competitive pressures. Hopkins (2018) and others have argued that political behavior has become increasingly nationalized. One of the factors contributing to this trend is that individuals have less information about local politics as they become increasingly reliant on national media sources. This possibility suggests that we should expect variation in the level of partisanship across different local development issues depending on how important the issues are in national political discourse — for instance, the parties have clear positions on issues like rules governing union activity.

A further reason that preferences over local development policies might be less polarized than those over national policies is if voters did not think such policies were important. In that case, they simply might not have well-defined preferences on these issues, rendering average opinion indistinguishable between Democrats and Republicans. However, several pieces of evidence in our survey lead us to conclude that voters pay at least some attention to local politics. First, we asked respondents an open-ended question about what they think is the most important issue facing their metro area. A plurality of respondents say that issues related to the economy and employment are major issues, and other responses are in line with topics covered by our conjoint. Appendix B reports this evidence. Second, we asked a question about whether national or local policies were an important factor in determining the economic performance of their local area over the last 20 years. Respondents tended to attribute just as much responsibility to local economic policies as to national economic policies. This analysis is also presented in Appendix B. Based on this evidence, we conclude that local policies are of high importance to voters, and the specific policies used in our conjoint experiment seem relevant for what voters consider the most important issues facing their metro area.

Alternative predictions point in the opposite direction: that partisan sorting and polarization might be relatively high for local development policies. First, many of these policies are related to left-right positions about the optimal size of government and the role of the state versus markets in organizing economic activity. To the extent that citizens have become more consistently sorted on these issues in national economic policymaking, we might expect similar positions on local issues. Second, de Benedictis-Kessner and Warshaw (2016), Gerber, Henry and Lubell (2013), and others have found significant partisan patterns in local policymaking which seem plausibly related to underlying differences in the policy preferences of voters. Additionally, Tausanovitch and Warshaw (2014) find that local policy questions load onto the same left-right dimension in an ideal point model as national issues, suggesting that local policy preferences might exhibit similar partisan cleavages as national policy questions.

Hence, the question of whether there are partisan divides in preferences for local development policies is ultimately an empirical question, and the remainder of the paper evaluates how deeply partisan polarization pervades American politics. Our research design does not allow us to distinguish between different mechanisms that produce (or limit) sorting and polarization; however, our paper establishes new facts about the extent to which partisanship shapes public opinion on local policies.

3 Local Development Policy Preferences

To measure public preference over local development policies, we report the results of a choice-based conjoint survey experiment that varied attributes of proposed local development plans for eight large U.S. Metropolitan Statistical Areas (MSAs): Charlotte, Cleveland, Houston, Indianapolis, Memphis, Rochester, St. Louis, and Seattle. The surveys were conducted by YouGov in January and February 2018 and are representative samples of the adult population of each MSA.[6] These MSAs were selected based on three main criteria: Each MSA needed to be large enough so that it was possible to construct a representative sample using YouGov's panel and matched sampling methodology; the MSAs needed to be selected from different regions of the U.S.; and the MSAs needed to vary in their economic

[6]See Appendix A for full description of sampling methodology and descriptive statistics.

development success over the last four decades.

3.1 Conjoint Experiment

Consistent with our interest in how individuals think about local public policy problem solving and with recent trends in the drivers of local economic performance, the conjoint experiment is framed in terms of how the MSA should respond to globalization and technological change and implement policies that will generate economic growth and good jobs. The introduction to the conjoint experiment emphasized that increased spending would require tax increases or spending reductions in other areas. See Appendix C for the specific wording of the conjoint introduction.

Respondents were presented with pairs of hypothetical plans for local development. Each plan was composed of six attributes corresponding to six critical areas of local development policymaking: *Investment & Taxes*, *Workers & Entrepreneurs*, *Local Services*, *Governance*, *Education*, and *Higher Education*. For each issue area, a possible value was randomly drawn from an underlying set of potential values that included alternative reform or spending priorities as well as the status quo in that policy area. Table 1 lists each possible value for each dimension.

Respondents were presented with randomly-generated pairs of potential policies for their MSA to adopt as a local development plan and were asked to choose which plan they would prefer to see implemented.[7] Using this style of forced-choice design, we are able to evaluate the direction and relative weight individuals place on each dimension of local development. Respondents were presented with five sets of local development plan pairs. For our analysis, we constructed a binary measure *Local Development Plan Support* that equals one if a respondent selected a particular policy proposal as their preferred choice, and zero otherwise.

We estimate an ordinary least squares regression of *Local Development Plan Support* on dichotomous indicator variables for all treatment categories, with the exception of the

[7]The ordering of the different policy dimensions was randomized for each respondent but was held constant within respondents for each presentation of new policy pairs.

Plan Dimension	Possible Levels
Investment and Taxes	Use tax breaks and subsidies to attract new businesses to the [MSA name] area
	Use tax breaks and subsidies to stimulate investment of existing [MSA name] companies
	Use tax breaks and subsidies to encourage investment by charities and philanthropies
	Keep current investment and tax policies
Workers & Entrepreneurs	Limit unions' bargaining powers
	Expand unions' bargaining powers
	Give training vouchers to existing workers
	Give tax breaks to entrepreneurs that start new businesses
	Keep current policies toward workers and entrepreneurs
Local Services	Spend more on affordable housing
	Spend more on public transportation
	Spend more on public safety and crime prevention
	Keep current local service policies
Governance	Consolidate local government in [MSA name] and surrounding towns
	Give the state of [MSA state name] more power to coordinate policies in [MSA name] and surrounding towns
	Keep current local government structure
Education	Expand charter schools
	Give citizens vouchers that they can use to attend different schools
	Provide more children with free pre-school
	Pay teachers more to attract better teachers
	Keep current elementary and secondary school policies
Higher Education	Invest in community colleges
	Invest in local public universities
	Expand technical vocational training programs
	Expand student grant programs for funding their college
	Keep current higher education policies

Table 1: *Conjoint Dimensions & Attribute Values for Local Development Plans.* This table reports the attribute values for each dimension of the conjoint experiment.

baseline for each conjoint dimension.[8] For the sake of consistency, we take the value that expresses the status quo as our baseline for each dimension. This estimation yields the average marginal component-specific effect (AMCE) for each treatment group relative to the baseline.[9] Standard errors are clustered at the respondent level.

Intuitively, the coefficients give the average change in probability of selecting a development plan with the specific feature over a development plan that contains the status quo policy in that issue domain. Positive coefficients thus indicate that a given feature makes a plan more popular, relative to the status quo.

One of the main advantages conjoint survey experiments is the ability to investigate

[8]The estimates presented employ survey weights that were used to adjust each MSA survey for remaining imbalances after YouGov's matched sampling procedures.

[9]Technically, the additional assumptions that the attributes are fully randomized and there are no profile-order or carry-over effects are also needed. See Hainmueller, Hopkins and Yamamoto (2014) for further discussion.

multidimensional phenomena in an efficient way. This feature makes this approach attractive for studying polarization in policy opinions over local policies, where there may be different patterns of heterogeneity across different policies. Even if Democrats and Republicans have different preferences over the size of government or differential willingness to pay for public goods, we expect the magnitude of those differences to vary across policies. The conjoint allows us to study many policies without focusing arbitrarily on just a few aspects of economic development policy. A related advantage of conjoints for studying local politics is that because there are fewer representative studies of public opinion about local issues, it is less well-known what tradeoffs individuals will make between issues or to put it more simply which issues they weigh more heavily when faced with tradeoffs.

Recent work by Abramson, Koçak and Magazinnik (2019) shows that the AMCE is a function of both the direction and intensity of respondents' preferences, and the sign of the AMCE need not correspond with the preferences that a majority of the population holds. Instead, Abramson, Koçak and Magazinnik (2019) show that the AMCE can be given a structural interpretation as an average of respondents' ideal points. With these results in mind, we refrain from making statements about the median voter based on our results.

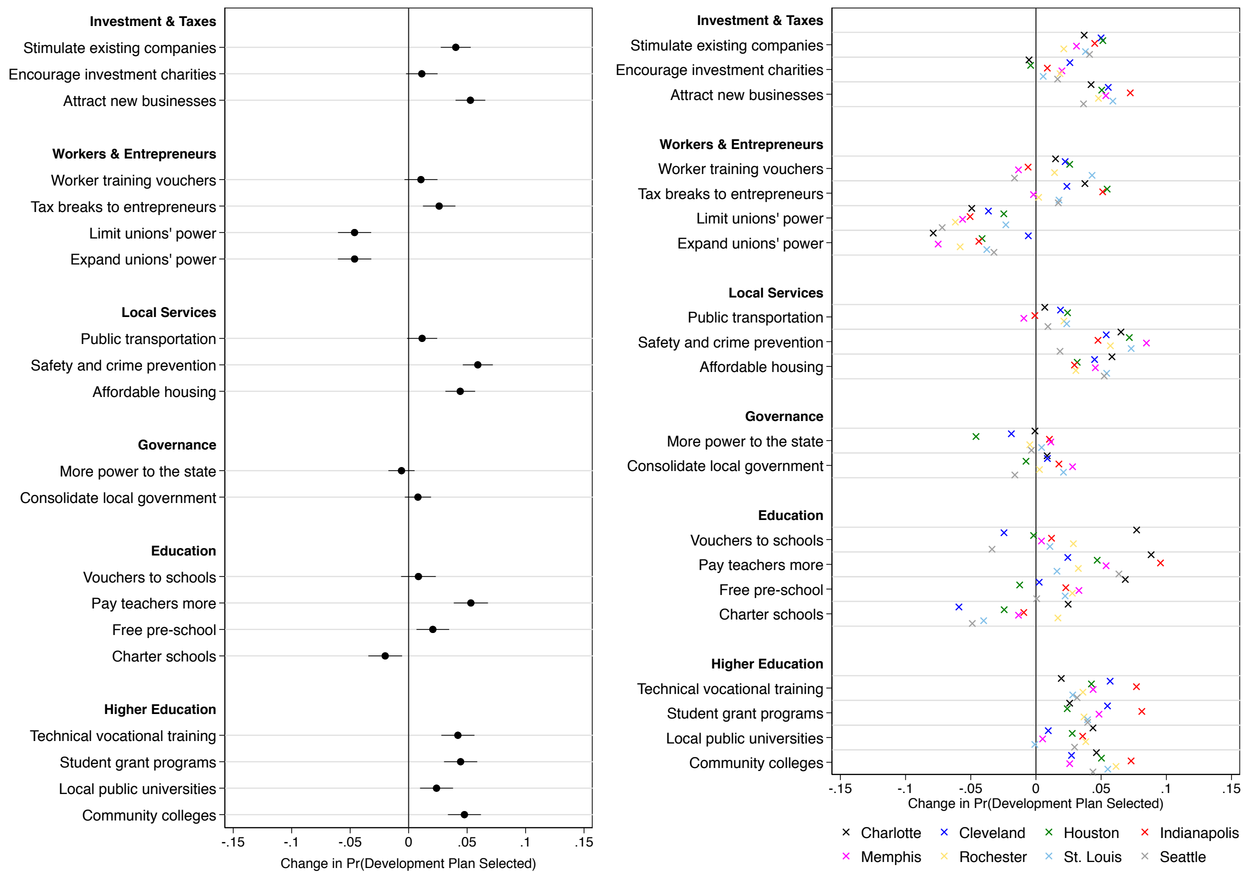
Still, the AMCE is interesting in its own right. First, preference intensity is likely to be important for election-minded politicians if those with the most intense preferences are also those most likely to be mobilized for or against a candidate based on their position on a particular issue. Second, while simple Downsian models predict that only the median voters' preferences determine policy outcomes, other equally plausible political competition models yield equilibrium outcomes that are a function of the average ideal points of all voters (e.g. Lindbeck and Weibull, 1987). Finally, those with relatively intense preference may have an outsized role because they are more likely to be party activists — making the AMCE potentially useful for studying partisan polarization.

3.2 Experimental Conjoint Estimates

Figure 2a presents the conjoint estimates for all the MSAs pooled together.[10] 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 2b 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 2b suggests that although there is some variation across MSAs, the general pattern of estimates is quite similar across communities. Although these average marginal component effects are rich with information about how citizens evaluate different policy alternatives for improving local economic performance, our goal in this paper is to measure and assess the extent to which these opinions vary by party identification. We turn to this analysis in the next section.

[10]See Appendix Table A-5 for the full results.



(a) Pooled Across MSAs

(b) Within MSAs

Figure 2: *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.

4 Partisanship and Local Development

In this section, we examine the extent of sorting and partisan polarization about local development policy. Given the design of our conjoint experiment, sorting is defined as a policy alternative having a different effect on the probability that Democrats and Republicans choose a development plan relative to the status quo. Polarization is defined as the policy alternative having an opposite effect on the two groups, increasing the probability of selecting a plan for one party and decreasing the probability for the other party. This definition is particularly compelling in this setting for which status quo policies are the baseline. Our approach requires that we estimate the conditional average marginal component effect (CAMCE) (Hainmueller, Hopkins and Yamamoto, 2014) for Strong Democrats and Strong Republicans. Our initial CAMCE estimates are based on a split-sample approach in which we employ the same OLS regression used in the previous section for estimating the AMCE for Strong Democrats and Strong Republicans separately.

Figure 3 presents our split sample CAMCE estimates for Strong Democrats and Strong Republicans. Generally, these results show that Democrats and Republicans have broadly similar attitudes towards many of these proposals.[11] The point estimates for Strong Democrats and Strong Republicans are neither statistically nor substantively different from each other on a wide range of policies that we study, indicating an absence of pervasive partisan sorting. Moreover, even when such differences exist, the point estimates have the same rather than opposite signs as we would expect if opinion were polarized. The exceptions to these patterns tend to be a subset of issues relating to primary and secondary education and, to a lesser extent, labor.

Beginning with the top panel, we present the CAMCEs for the Investment & Taxes factor. First, we find that the probability that Strong Republicans and Strong Democrats select a plan is increased if that plan includes subsidies and tax breaks to stimulate existing companies as opposed to the status quo. The CAMCE for Strong Republicans is 3.4 percentage points

[11] Figure A-4 presents analogous estimates for all Democrats and all Republicans.

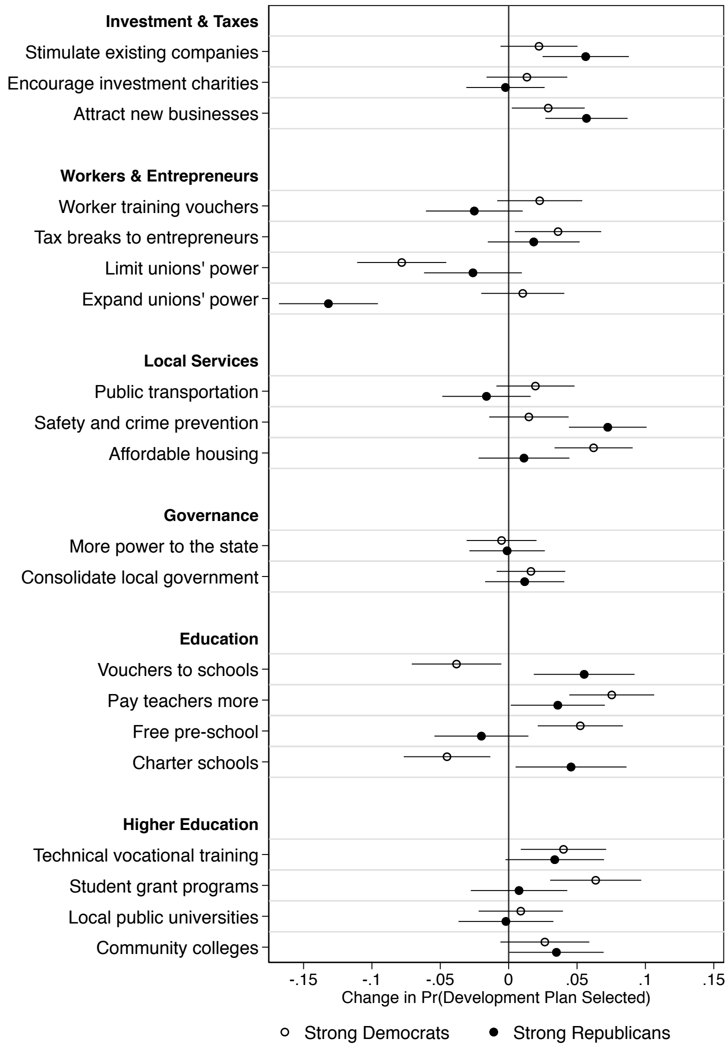


Figure 3: *Split-Sample Results.* CAMCE estimates showing differences between Strong Democrats and Strong Republicans. Points show coefficient estimates from separate OLS regressions, and bars show robust 95% confidence intervals.

higher than for Strong Democrats, but this difference is not statistically significant (p-value is 0.113).[12] Next, the same general pattern holds for a policy of using subsidies and tax breaks to attract new businesses. Democrats and Republican alike support this policy. The CAMCE estimate for Strong Republicans is 2.8 percentage points higher but again this

[12]The estimates reported in Figure 3 use the simple split-sample approach. However, any statements made in the text about whether estimates are different for Strong Democrats and Strong Republicans are based on a pooled regression that interacts the treatments with strong partisan indicators. See Appendix Table A-6.

difference is not significant ($p = 0.173$). On the other hand, respondents from both parties are less enthusiastic about encouraging investments by charities: the estimated CAMCE is indistinguishable from 0 for both groups and there is little evidence of partisan sorting or polarization, again underscoring the partisan consensus that appears on each policy related to Investment & Taxes.

The next panel shows the results for the Workers & Entrepreneurs factor. On this dimension, we find mixed evidence of sorting and polarization. There is almost no difference in the point estimates for the policy of giving tax breaks to entrepreneurs that start new businesses. Respondents of both parties appear on average to view such a policy favorably, a result that aligns neatly with the findings in the top panel. However, when it comes to labor, there is more evidence of partisan differences. In particular, Democrats are more supportive of unions than Republicans. Interestingly, both Democrats and Republicans appear to oppose limiting unions' power — though Strong Democrats are still 5.2 percentage points less likely to support a development plan with this option relative to the status quo than Strong Republicans ($p = 0.035$). But when it comes to *expanding* unions' power, this option has a large negative effect on Republicans but no effect on average for Democrats. On average, the difference between Strong Democrats and Strong Republicans is 14.2 percentage points ($p < 0.001$) — a substantively large and politically meaningful difference. Partisans are clearly sorted in this case and given that the point estimate for Democrats is positive, albeit not significantly different from zero, polarized as well. When it comes to providing vouchers for workers to get training, there is again some evidence of polarization. The point estimate is positive for Strong Democrats but negative for Strong Republicans, and this difference of 4.8 percentage points is statistically significant ($p = 0.046$).

Next, we turn to the results for the Local Services factor. Here, we see evidence of partisan sorting for all three alternatives to the status quo and some evidence for polarization in the area of public transportation. First, consider the proposal to spend more money on affordable housing. The unconditional AMCE reported in the previous section is 4.4 percentage points, indicating some overall support for the policy relative to the status quo. Republicans, however, are less supportive than Democrats. The CAMCE for Strong Democrats and Strong Republicans differs by 5.1 percentage points ($p = 0.023$). Still, the differences are not enough for the issue to have opposing effects on the probability that Democrats and Republicans choose a development plan. Next, consider spending more money on public safety and crime prevention. Here, Republicans are more supportive than Democrats, though respondents of both parties mostly support this policy proposal relative to the status quo. Finally, there is mild division on the issue of spending more on public transportation. On this issue, Republicans tend to be slightly opposed and Democrats tend to be slightly supportive. We will revisit these results in the next section; after controlling for other characeristics of respondents besides partisanship, we find smaller partisan differences over affordable housing and no polarization for any of these issues.

The next factor we consider are two Governance reforms: giving more power to the state and consolidating local governments. Both of these policies, on average, garnered neither support nor opposition relative to the status quo, with AMCEs of -0.6 and 0.7 percentage points reported in the previous section. On the first reform, the point estimates are almost identical for Democratic and Republican partisans and are very close to 0. On the proposal to consolidate local government, the point estimates are positive for both Strong Democrats and Strong Republicans but there is almost no difference between them and the estimates are not significantly different from zero.

Now, we consider the Education factor. This issue domain is where we see the greatest evidence of partisan polarization. We start at the top of this panel with an issue that has received substantial attention in national media: issuing vouchers that citizens can use to attend different schools. As one might expect based on the public debate, the voucher policy option has a positive effect on the probability that Strong Republicans select a development plan, relative to the status quo, but a negative effect for Strong Democrats. The difference between the CAMCEs is 9.3 percentage points and is statistically significant ($p < 0.001$).

There are similar divisions when it comes to expanding charter schools, with this option having opposing effects for Democrats and Republicans — and the difference between them is over 9 percentage points ($p < 0.001$). Third, there are again partisan divergences on the issue of free preschool, this time with the policy option having a positive effect for Democrats and a negative effect for Republicans. The difference between strong partisans is 7.2 percentage points — slightly smaller than on the previous two issues but still quite sizable in the context of the conjoint experiment ($p = 0.002$). Finally, the last education policy proposal, paying teachers more, indicates partisan sorting but not polarization. Paying teachers more has a positive effect on the probability that both Strong Democrats and Strong Republicans choose a development plan relative to the status quo. That said, the difference between the CAMCEs is 3.9 percentage points and is marginally significant ($p = 0.095$).

The final factor we examine, in the bottom panel of Figure 3, is related to higher education policy. There is little evidence of partisan sorting in these estimates and no evidence of polarization. Beginning with investing in community colleges, we see that this policy alternative has a positive effect on the probability that both Strong Democrats and Strong Republicans choose a development plan relative to the status quo and there is virtually no difference in these CAMCEs between the groups. This result resonates with the wave of innovative new community college programs that cities across the country, in diverse political environments, have been able to agree on and, in many cases, successfully implement. Similarly, for the proposal to expand technical vocational training, we see the same pattern. For investing in local public universities, the estimated CAMCEs are nearly zero for both Strong Democrats and Strong Republicans. The fact that the estimates are similar is what is important for the main question of this paper but it is interesting to note that investing in local public universities had a positive and significant AMCE for the full sample as reported in Section 3.2. Finally, for a proposal to expand student grant programs, CAMCE estimate is positive for both Strong Democrats and Strong Republicans but the estimate is 5.6 percentage points larger for Democrats and this difference is statistically significant ($p = 0.023$).

This suggests some sorting on expanding student grant programs but not polarization.

On the whole, we take our split-sample results to indicate that citizens exhibit similar preferences over local policies aimed at spurring economic development. Before discussing the substantive implications of the results, we raise two questions about these estimates. The definitions of sorting and polarization used in this analysis are specific to the experimental conjoint research design that we employ. One might wonder whether this method is well-suited for detecting partisan sorting. Is the absence of evidence of sorting and polarization due to a lack of partisan differences over local issues, or is it due to an inability of this tool to uncover such differences? Two observations suggest that it is the former rather than the latter. First, our estimates do detect partisan differences for some labor and education policies. Second, previous experimental conjoint studies of national policies have uncovered large partisan differences in ACMEs for policies for which other survey methods would also predict partisan differences.[13] Another potential concern about these estimates is whether the presence or absence of partisan differences in the AMCEs is because Strong Democrats and Strong Republicans also have other characteristics which lead them to react similarly or differently to various policy attributes. We investigate this possibility in the next section.

5 Conditional Partisanship and Local Development

The split-sample estimates of the CAMCEs presented in the previous section are unbiased estimates of the AMCEs for each partisan group. Given the CAMCE estimand, there is no bias created by not "controlling for" other individual characteristics in the split-sample estimates. Nonetheless, to fully understand heterogeneity in the AMCEs, it is helpful to define the estimand of interest as the CAMCE, controlling for a wide number of observed characteristics of each respondent. We want to know if the absence or presence of partisan differences is sensitive to conditioning on other potentially relevant characteristics like

[13] See, for example, partisan disagreements over top tax rates in Ballard-Rosa, Martin and Scheve (2017) or differences in the use of electoral heuristics in Hansen, Olsen and Bech (2015).

income and race for predicting local development policy preferences. In this section, we introduce a hierarchical model for estimating CAMCEs conditioned on observed individual characteristics and present these results focusing on differences among Strong Democrats and Strong Republicans.

5.1 A Hierarchical Model for Estimating CAMCEs from Experimental Conjoint Data

Our approach unifies two separate tasks: first, the preference measurement task that traditional OLS analysis of conjoint data enables; and, second, fitting a regression of the estimated preferences on individual-level characteristics.

To motivate the method, consider the more familiar setting of measuring preferences via a standard survey question. For instance, we might directly ask whether respondents support or oppose expanding charter schools. To investigate the correlates of support for charter schools, we could then regress responses on respondent-level covariates.[14] In conjoint experiments, this exercise is not as straightforward, because we must first measure preferences from the choices made in the conjoint tasks and typically respondents do not complete enough tasks to nonparametrically identify individual-level marginal component effects. As such, the conjoint literature has typically focused on estimating AMCEs or simple CAMCEs that can be estimated via split-sample approaches. We refer to this approach as "complete pooling" because it does not explicitly model individual-level heterogeneity in parameter estimates across respondents (Gelman and Hill, 2007).

Alternatively, one could nonparametrically estimate individual-level marginal component effects (IMCEs) if each respondent completed a large enough number of conjoint tasks. In that case, we could run separate OLS regressions for each respondent.[15] These estimates

[14]Indeed, this is exactly the analysis strategy we used in Figure 1.

[15]In order for this estimator to be identified, every respondent must have seen every conjoint level at least once, and each respondent must have seen at least as many profiles as there are conjoint levels (i.e., a simple rank condition for OLS).

would converge to the true IMCEs as the number of tasks grows large. In the limit, we could perfectly measure individual-level parameters, then regress these preference parameters on individual-level covariates — just as we would with traditional survey questions. We refer to this approach as "no pooling" because no information is shared between respondents in estimating parameters. While theoretically possible, this strategy is typically not feasible in practice because each respondent completes only a relatively small number of tasks.

Our proposed method provides an intermediate between the complete-pooling and no-pooling approaches. We use a hierarchical model that allows for individual-level heterogeneity in the way that conjoint levels affect the probability that the respondent prefers a particular profile. We then model these individual coefficients in a second-level regression as a function of respondent-level covariates. We estimate the model using a random-effects framework that allows for partial pooling between similar observations.

We briefly describe the setup here. For more details and further discussion, see Appendix E. Let i index respondents ($i = 1, \ldots, N$) and let j index conjoint profiles ($j = 1, \ldots, J$). If respondent i preferred profile j to the alternative, then we observe $y_{ij} = 1$; otherwise $y_{ij} = 0$. Let X_{ij} denote a vector of dummy variables that specifies the conjoint levels that respondent i saw for profile j.

The first-level regression models conjoint responses as a linear function of the conjoint levels:

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

In this equation, α_i is an intercept term, which may vary at the individual level, that indicates the probability respondent i chooses a profile that features the baseline level of each factor. β_i is a parameter vector that relates the conjoint profile features to the probability of choosing that profile. Finally, ϵ_{ij} is a mean-zero error term. Under the complete-pooling approach, we set $\alpha_i = \alpha$ and $\beta_i = \beta$ for all respondents, and estimate Equation 1 via OLS. Under randomization, β represents the vector of AMCEs.

Instead, we allow for some heterogeneity, allowing elements of β_i to vary as a function of individual-level covariate vector Z_i (which includes a column of 1's as an intercept). In particular, we specify the following linear functional form for element k of β_i:

$$\beta_i^k = Z_i' \gamma_k + \eta_{ik}. \tag{2}$$

The coefficient vector γ_k indicates how the expected individual-level marginal component effect varies as a function of respondent-level covariates, and η_{ik} is a mean-zero error term. Because Z_i may contain several variables, it allows us to characterize how some variable of interest — such as partisan identification — covaries with conjoint preferences after adjusting for other covariates. We set up an analogous model for α_i, the individual-level probability of selecting the status quo as the preferred policy.

It is useful to consider Equation 2 as analogous to the approach taken when modeling answers to traditional survey responses. In that case, we would replace β_i^k on the left-hand side with the actual survey response, and the γ coefficients would be the usual linear regression coefficients. In our case, we are jointly estimating the preference parameter β_i, along with the second-level coefficients γ.

Finally, we place several distributional assumptions on ϵ_{ij} and η_{ik} — namely, that they are normally distributed. We estimate the model in a Bayesian framework using Stan (Carpenter et al., 2017). Estimation in a Bayesian framework is useful for several reasons. It provides a simple method of estimating IMCE parameters and associated uncertainty — a task that is more difficult with maximum likelihood estimation. Additionally, hierarchical models in a Bayesian framework have built-in regularization that helps deal with the multiple comparisons problem (Gelman, Hill and Yajima, 2012) — an attractive feature for our application, where we have many parameters to estimate and many quantities of interest. For more details on estimation, including methods used to assess convergence, see Appendix E.

Our approach allows a richer description of heterogeneity in conjoints, enabling us to make statements of the form, "On average, Democrats are x percentage points more likely than demographically similar Republicans to support a plan that includes expanding union power, relative to the status quo." However, there are several potential limitations.

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.[16]

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 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

[16]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.

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.

Finally, more practically, the hierarchical approach here is more difficult to implement compared to the standard estimator. We provide some practical guidance on implementation in Appendix E.

5.2 Multivariate Estimates

Our main specification models the conditional average marginal component effect as a function of a seven-point party identification scale (with indicators for each response option), along with extensive sociodemographic control variables including: age, race, sex, education, income, employment status, homeownership, length of time living in the region, and MSA indicators. The coefficients on partisanship therefore capture differences between Democrats and Republicans, after (linearly) adjusting for other observable characteristics.

First, to demonstrate the advantage of the hierarchical model, we plot the distribution of estimated individual marginal component effects — in the notation of the previous section, the distribution of the β_i's — in Figure 4. The lines in this figure shows kernel density estimates of the posterior means across all 7,800 survey respondents, while the points show the mean of the distributions — the model-based equivalent of the AMCEs presented earlier in the paper. This figure visualizes the variation in the effect of individual policies' inclusion in a policy bundle on respondents' probability of preferring that bundle.

Next, we can use the second-level regression estimates to investigate the nature of this

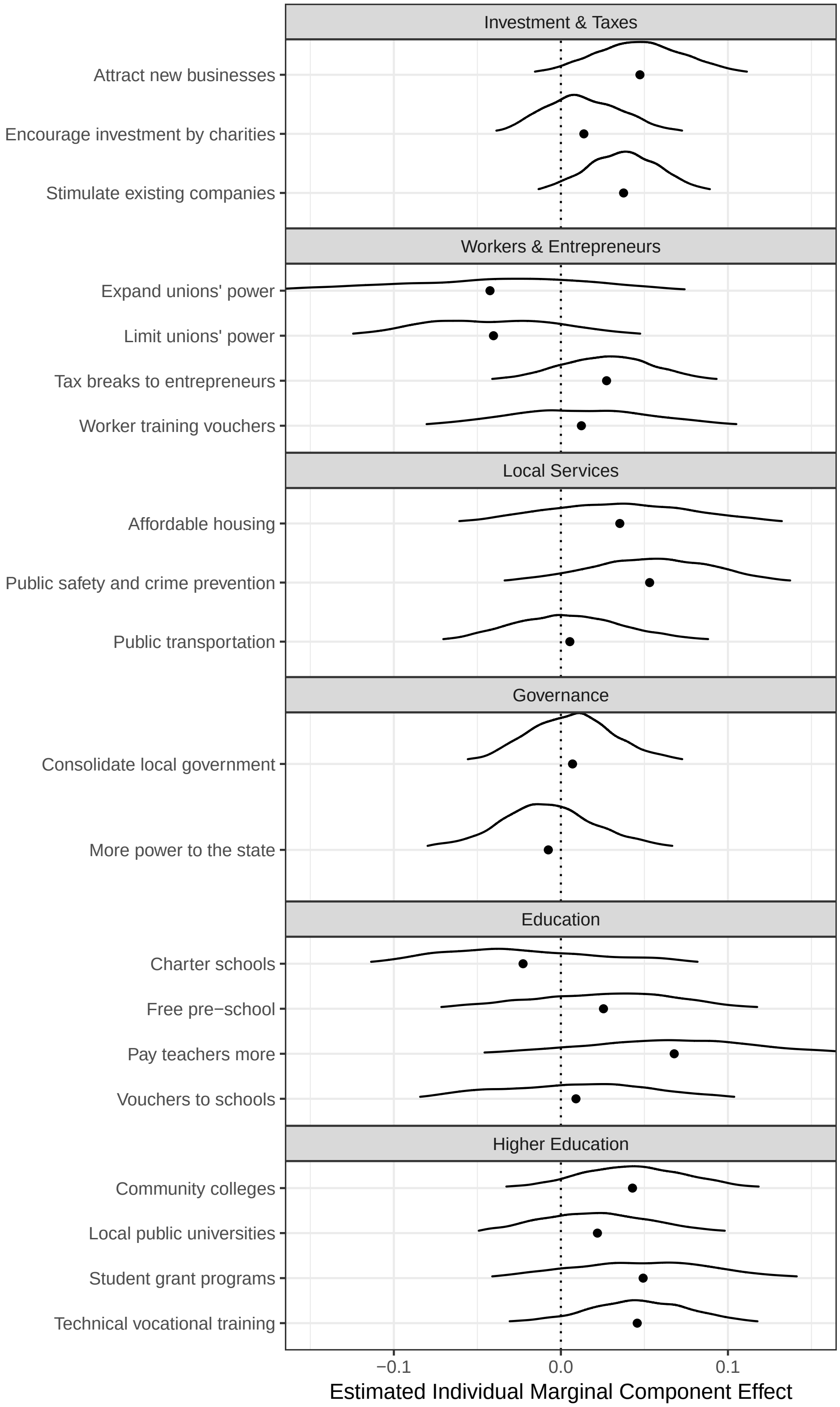


Figure 4: *Estimated Individual-Level Marginal Component Effects.* The lines show a kernel density estimate of the posterior means of the IMCEs, while the dots show the average of the posterior means. Estimates are from the hierarchical model with sociodemographic covariates predicting IMCEs. For readability, we trim the densities to omit the bottom 2.5% of density estimates.

Plan Dimension	Level	Mean	Post. SD	95% CI
Investment & Taxes	Stimulate existing companies	0.018	(0.018)	[−0.02, 0.05]
	Encourage investment by charities	−0.010	(0.018)	[−0.05, 0.02]
	Attract new businesses	0.013	(0.018)	[−0.02, 0.05]
Workers & Entrepreneurs	Worker training vouchers	−0.054*	(0.020)	[−0.09, −0.01]
	Tax breaks to entrepreneurs	−0.019	(0.020)	[−0.06, 0.02]
	Limit unions' power	0.054*	(0.021)	[0.01, 0.10]
	Expand unions' power	−0.139*	(0.021)	[−0.18, −0.10]
Local Services	Public transportation	−0.034	(0.018)	[−0.07, 0.00]
	Public safety and crime prevention	0.061*	(0.018)	[0.03, 0.10]
	Affordable housing	−0.029	(0.018)	[−0.06, 0.01]
Governance	More power to the state	0.023	(0.016)	[−0.01, 0.05]
	Consolidate local government	−0.003	(0.016)	[−0.03, 0.03]
Education	Vouchers to schools	0.105*	(0.020)	[0.07, 0.14]
	Pay teachers more	−0.062*	(0.020)	[−0.10, −0.02]
	Free pre-school	−0.090*	(0.020)	[−0.13, −0.05]
	Charter schools	0.103*	(0.020)	[0.06, 0.14]
Higher Education	Technical vocational training	−0.025	(0.020)	[−0.06, 0.01]
	Student grant programs	−0.048*	(0.020)	[−0.09, −0.01]
	Local public universities	−0.041*	(0.020)	[−0.08, 0.00]
	Community colleges	0.005	(0.020)	[−0.03, 0.04]
Intercept	Strong Rep. - Strong Dem.	0.030	(0.029)	[−0.03, 0.09]

Table 2: *Comparison of Partisan CAMCEs.* Estimated second-level coefficients on the indicator for Strong Republican, relative to Strong Democrat. The first two columns specify the policy proposal. "Mean" refers to the posterior mean of the coefficient, while "post. SD" is the posterior standard deviation. The final column shows the 0.025 and 97.5 quantiles of the posterior distribution, i.e., the central 95% credible interval. Asterisks indicate that the 95% credible interval excludes 0.

heterogeneity, especially as it pertains to partisan sorting and polarization. Table 2 shows the estimated difference between the CAMCEs for Strong Democrats compared to Strong Republicans on each policy proposal, after adjusting for observable sociodemographic variables. The table reports the posterior means, posterior standard deviation, and central 95% credible intervals.

This table is especially useful for understanding sorting, which again we define in our context as a significant difference in CAMCEs. The patterns are broadly similar to what we saw previously. There are minimal differences between Democrats and Republicans across all Investment & Tax policy proposals, giving tax breaks to entrepreneurs, Governance policy proposals, and several Higher Education proposals. We find that the disagreements over unions, worker training vouchers, and Education policy that we documented previously are all robust to inclusion of sociodemographic covariates.

The main differences from our previous results arise in the Local Services dimension. In the split-sample approach, we found some mild differences across all three of these policy proposals. However, after adjusting for covariates, the only significant difference between Democrats and Republicans is on the proposal to spend more on public safety and crime prevention. Strong Republicans have a 6 percentage point higher CAMCE for this proposal, on average, than Strong Democrats. On affordable housing and public transportation, Democrats still have larger CAMCEs but these differences are small and the 95% credible interval includes 0.

We also see a difference in the results for investing in local public universities. There was no evidence of partisan sorting over this issue in the split sample results but once we control for the demographic characteristics of respondents, Strong Republicans have a 4 percentage point lower CAMCE for this policy, on average, compared to Strong Democrats. This difference in the conditioned and unconditioned partisan comparisons is consistent with Republicans having demographic characteristics associated with greater support for higher education but once we control for these characteristics, Republicans may be ideologically more skeptical about higher education investments.

To investigate the extent of partisan polarization, we need a measure of whether Democrats and Republicans stand on opposite sides of an issue — not just whether they have significantly difference CAMCEs, on average. To approach this question, we use the model to generate predictions of IMCEs for each respondent in the sample under two assumptions. First, we create two modified individual-level covariate matrices, $\tilde{Z}^{dem}$ and $\tilde{Z}^{rep}$, which are identical to the actual Z matrix except we set partisanship to Strong Democrat or Strong Republican, respectively. Second, we predict the marginal component effects for each individual under these counterfactual covariate values. Third, we summarize the resulting distributions. The amount of overlap of the two resulting distributions, as well as whether they tend to fall above or below 0, tell us about the extent of partisan sorting and polarization on each issue.

Additionally, we compute the posterior probability that the means of the respective distributions have opposite signs. To do this, we simply compute the counterfactual AMCEs for $\tilde{Z}^{dem}$ and $\tilde{Z}^{dem}$ for each sample drawn from the posterior distribution of parameter values (i.e. the average of the predicted IMCEs). We then compute the proportion of times that the counterfactual AMCEs have opposite signs.

These results are presented in Figure 5, which plots the predicted distribution of conditional average marginal component effects under the assumption that everyone is a Strong Republican (red line) or a Strong Democrat (blue line). The points show means of the respective distributions, and percentages give the probability that the means have different signs.

There are several issues on which partisans are sorted — in the sense of some partisans having different CAMCEs — but not polarized. On the issue of limiting unions' power, while Democrats are much less amenable to this policy than Republicans, there is still substantial overlap in the distributions, and the means of the distributions are both negative (with only a 9.5% probability of having different signs). A similar pattern exists for spending more on public safety, paying teachers more, and expanding student grant programs — all of which have less than 10% probability of the average partisans being on opposite sides of the issue. In these cases, partisans have different CAMCEs in magnitude, but the sign is the same on average. Partisans, then, may differ in the strength of their opinions on these issues relative to the status quo but they do not find themselves in opposition.

There is substantial polarization, however, on three of the primary and secondary education policy proposals: school vouchers, free pre-school, and charter schools. On these issues, the average difference between Democrats and Republicans is so large that shifting the distributions results in almost no common ground. On all three of these proposals, the probability of partisans being on opposite sides of the issue is greater than 95%.

Finally, there is also some evidence of polarization when it comes to labor policies, though

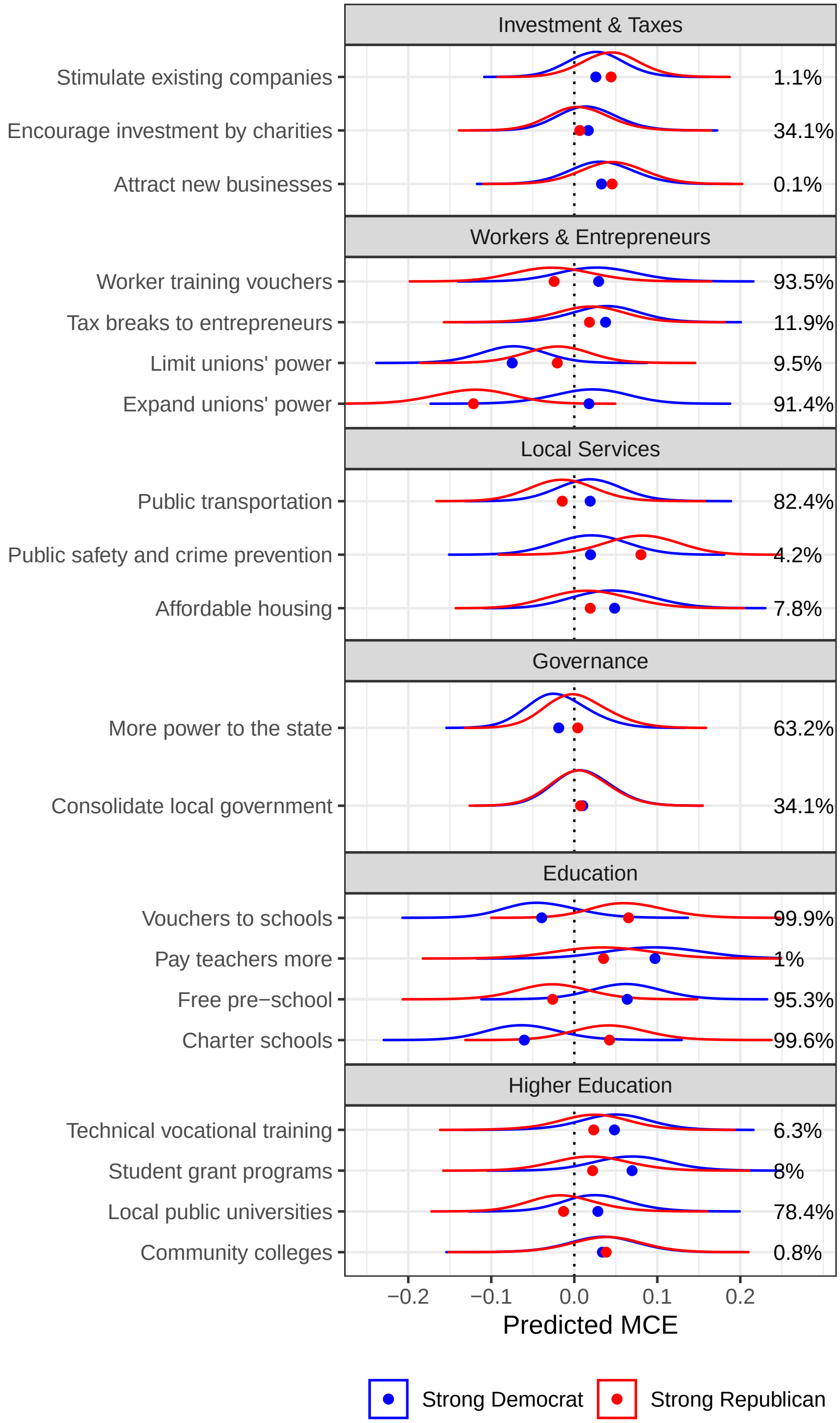


Figure 5: *Simulated Partisan Marginal Component Effects.* Distribution of predicted individual-level marginal component effects, assuming everyone is a Strong Democrat or a Strong Republican, holding other covariates fixed at their observed values. Lines show posterior means of kernel density estimates applied to 500 samples from the posterior; points show posterior means. Percentages refer to the posterior probability that the partisan means have different signs. The omitted default category for each dimension is the status quo.

it does not meet the strict 95% threshold. For worker training vouchers and expanding union power, the probability of partisans standing on opposite sides is roughly 93% and 91%, respectively.

6 Discussion and Conclusion

Partisan polarization seems pervasive in American politics. Academics and pundits point to the increasing divide between Democrats and Republicans as an impediment to solving pressing policy problems. But extant evidence on polarization focuses primarily on national policy issues, with less research on the extent of polarization in subnational policy domains. On the one hand, there is evidence that partisanship of mayors matters for local policymaking, suggesting that citizens, too, may hold divergent views over local policy. On the other hand, there are good reasons to think that polarization over local political economy issues, in particular, would be muted. Residential, capital, and labor mobility within and across regions makes it difficult for localities to pursue dramatically different economic policies, as cities compete to attract high-income residents and businesses. Additionally, and possibly as a consequence, there are relatively few cues from elites about which policies partisans should support. However, if there is polarization and partisan sorting over these local issues, it could have large policy implications. There is increasing economic divergence across metro regions in the U.S., meaning local economic policy is of central importance. Partisan polarization could lead to policy delay and inaction that prevents effective responses to evolving economic conditions.

In this paper, we analyze new data on support for strategies that local governments could pursue to manage the evolving economic environment. We report the results of identical surveys conducted in eight large cities in the U.S. Using a conjoint survey experiment, we measure support for various policy platforms aimed at promoting local economic development. These results contribute to a large political economy literature which focuses on

Plan Dimension	Level	Impact on Support Relative to SQ	Sorting	Polarization
Investment & Taxes	Stimulate existing companies	+		
	Encourage investment by charities			
	Attract new businesses	+		
Workers & Entrepreneurs	Worker training vouchers		✓	
	Tax breaks to entrepreneurs	+		
	Limit unions' power	−	✓	
	Expand unions' power	−	✓	
Local Services	Public transportation			
	Public safety and crime prevention	+	✓	
	Affordable housing	+		
Governance	More power to the state			
	Consolidate local government			
Education	Vouchers to schools		✓	✓
	Pay teachers more	+	✓	
	Free pre-school	+	✓	✓
	Charter schools	−	✓	✓
Higher Education	Technical vocational training	+		
	Student grant programs	+	✓	
	Local public universities	+	✓	
	Community colleges	+		

Table 3: *Summary of Results*. We define sorting as Democrats and Republicans having significantly different levels of support for the policy relative to the status quo (i.e., significantly different CAMCEs, with 95% credible interval excluding 0). Polarization occurs when one set of partisans prefers the policy to the status quo on average and the other opposes it (i.e., Democrats and Republicans having CAMCEs of opposite signs with posterior probability of at least 95%).

the politics of economic development, particularly in the context of increasing geographic inequality in patterns of U.S. growth over the last several decades.

The main contribution of the paper, however, is to study the extent of partisan disagreement on these local issues. We provide a research design employing conjoint survey experiments to study both partisan sorting and partisan polarization. We further develop a hierarchical model for estimating conditional average marginal component effects for strong partisans controlling for other individual characteristics. This methodology provides numerous new ways to study heterogeneity in average marginal component effects that complement commonly used split-sample estimates.

To aid with interpretation of our results, Table 3 presents a concise summary of our findings — both in terms of overall support for the policy change as well as in terms of the extent of partisan sorting and polarization. Across both our split-sample and hierarchical model estimates, there is broad bipartisan support for policies aimed at encouraging business investment. In particular, policies to use taxes and subsidies to encourage investment draw strong support from both sides of the aisle. Additionally, citizens of all political stripes support similar higher education policy proposals, notably investment in community colleges, technical training, and student grant programs. Though these policies are riskier in terms of attracting businesses — because people can move away after they are educated — empirically there is evidence that having skilled workers and innovation spurred by higher education institutions are important components of a thriving local economy (Moretti, 2012). These results are broadly consistent with theories that emphasize the pressure cities are under to compete for firms and high-income residents.

On the other hand, across both estimation strategies, we observe strong evidence of polarization on primary and secondary education policy, specifically on policies related to charter schools, school vouchers, and free pre-school. We also observe some weaker evidence on labor issues — particularly on proposals to provide training vouchers to workers and on expanding union power. Both of these issues are relatively prominent in national political discourse — with Republican politicans pushing for public education reform and labor unions being a core Democratic constituency. Citizens appear to be aligned with their parties on these issues, with Republicans supporting school choice and opposing labor unions, and Democrats supporting traditional public education and supporting labor unions. These differences may reflect the strength of national partisan cues about these issues and the absence of sufficiently clear competing pressures to overcome those associations.

Finally, for several issues, particularly local services, our two estimation strategies yield different results. The split-sample estimates suggest a good deal of partisan sorting over the policy to increase spending on local services but these differences substantially disappear in the hierarchical models that control for other respondent characteristics. We interpret these differences as indicating that while partisans on average react differently to these policy deviations from the status quo those differences are largely a function of differences in sex, race, and homeownership rather than partisanship among otherwise similar citizens.

Overall, we conclude that on many core development issues, there is a relatively broad scope for compromise. Especially when it comes to issues that affect business investment, partisanship appears not to structure public opinion. The low levels of polarization on these sets of issues run in contrast to the partisan divides seen on national policy issues — even among the same set of respondents. The results are consistent with cities being relatively constrained in the policies they can pursue, leaving less room for parties to stake out distinct positions.

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

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	0.34	0.35
Republican	0.29	0.30
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	0.61	0.57
Democrat	0.39	0.41
Republican	0.24	0.23
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	0.48	0.40
Some College	0.70	0.60
In the Labor Force	0.65	0.66
Democrat	0.32	0.34
Republican	0.27	0.26
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	0.30	0.30
Republican	0.32	0.34
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	0.02	0.03
College Degree	0.51	0.36
Some College	0.80	0.60
In the Labor Force	0.65	0.63
Democrat	0.35	0.40
Republican	0.29	0.26
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	0.62	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	0.33	0.32
Republican	0.27	0.27
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	0.58	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	0.36	0.36
Republican	0.24	0.27
Voted Clinton 2016	0.50	0.48
Voted Trump 2016	0.39	0.48
Observations	1,000	1,000

Seattle

Means	*Raw*	*Weighted*
Age	46.00	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	0.41	0.41
Republican	0.16	0.18
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.*

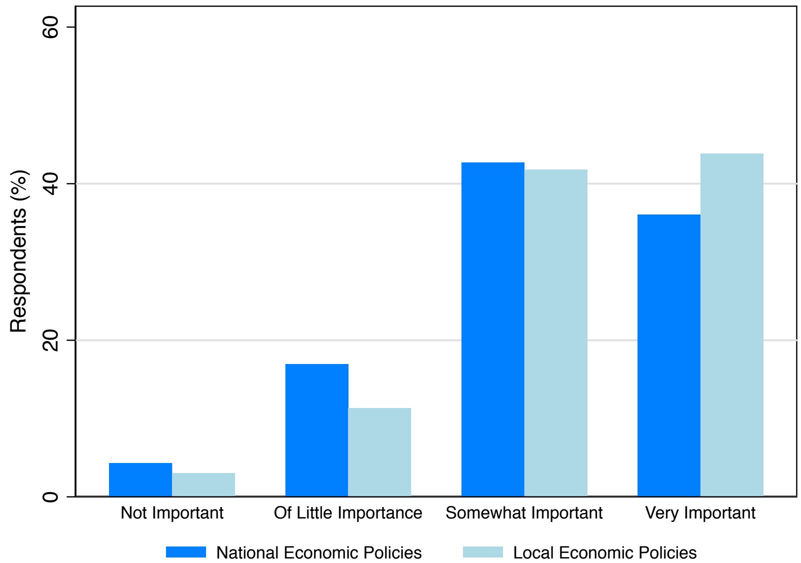

Figure A-1: *Importance of National and Local Policies for MSA Performance.* This graph shows respondents' assessment of the importance of national and local policies, respectively, for changes in the economy in their MSA over the last 20 years.

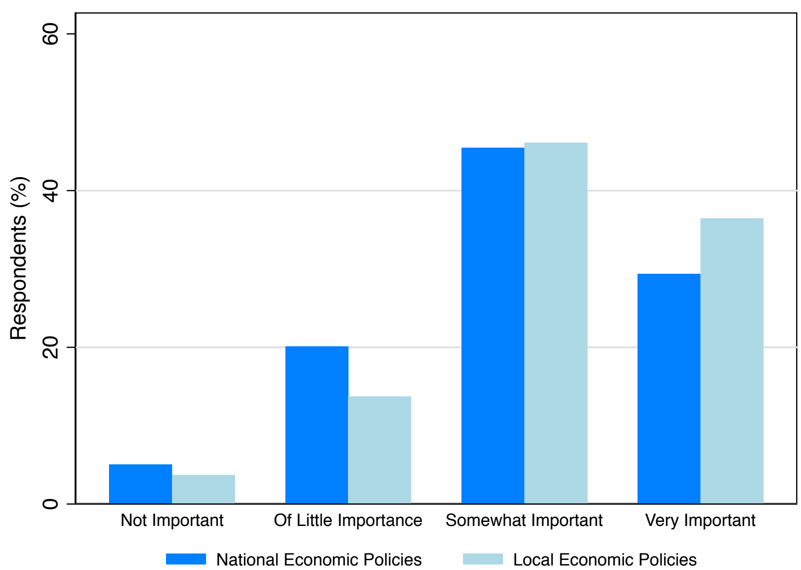

Figure A-2: *Importance of National and Local Policies for MSA Performance - Economy Improved.* This graph shows respondents' assessment of the importance of national and local policies, respectively, for changes in the economy in their MSA over the last 20 years. The graph is based on a subsample of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

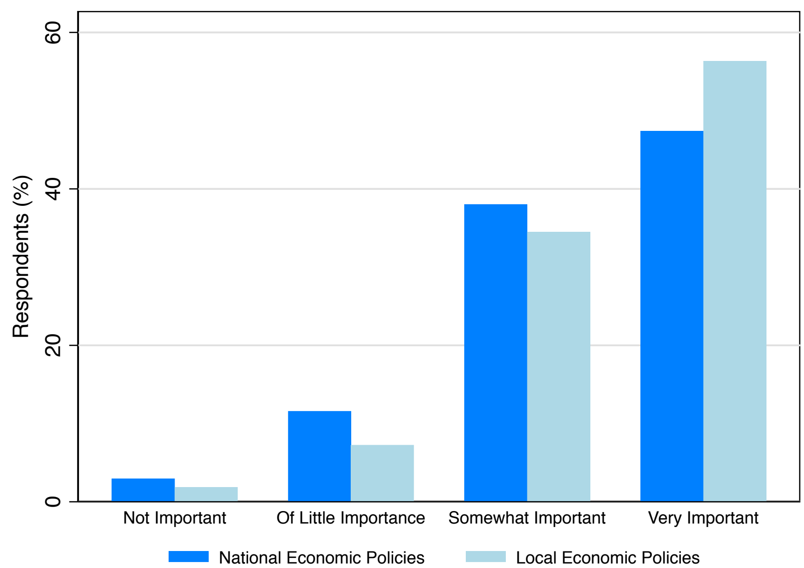

Figure A-3: *Importance of National and Local Policies for MSA Performance - Economy Got Worse.* This graph shows respondents' assessment of the importance of national and local policies, respectively, for changes in the economy in their MSA over the last 20 years. The graph is based on a subsample of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

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. $^*p < 0.05$

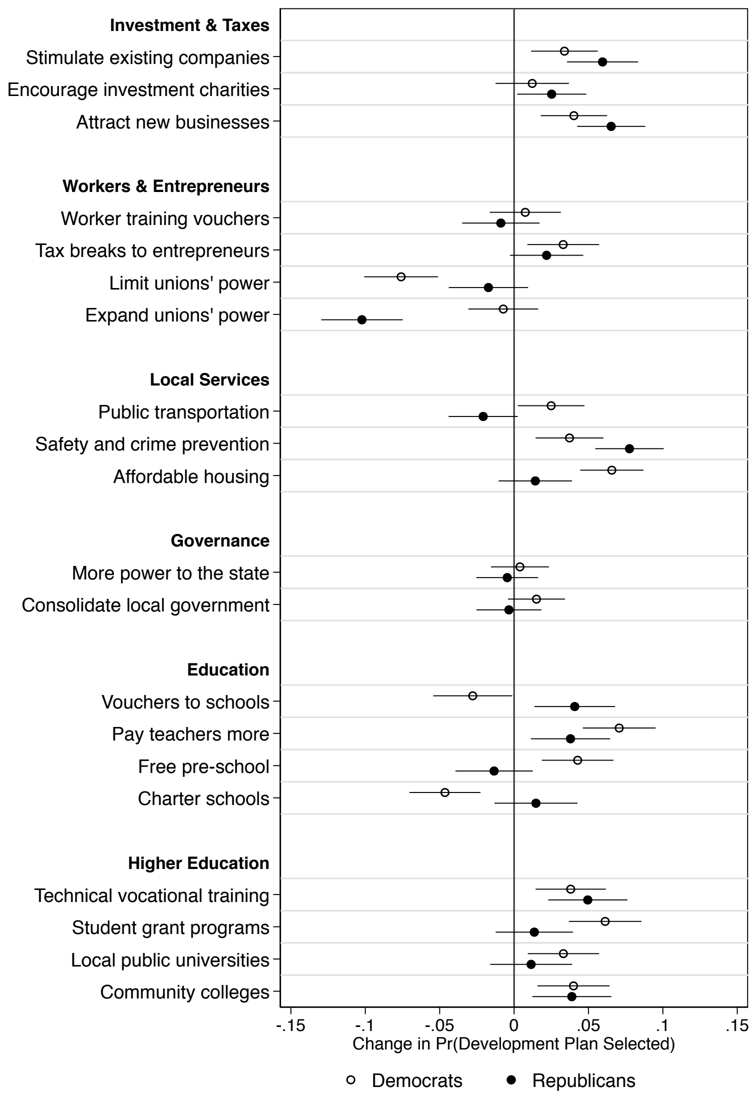

Figure A-4: *Conjoint Estimates of Local Development Policy Preferences by Party Identification.* Party identification is measured in a single question: "Generally speaking, do you usually think of yourself as a Democrat, a Republican, an independent, or what?" The estimates reported here are for "Democrat" 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.

F Hierarchical Regression Tables

Here we report the full set of hierarchical regression results. In terms of the notation used in Section 5.1, 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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