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Abstract

Given a patchwork system of overlapping local institutions, can residents direct public policy? Current approaches to representation at the local level may present a distorted view of how democracy operates because they fail to account for the overlapping nature of institutions. To address this gap, I first implement a framework that incorporates multiple overlapping governing institutions: cities, counties, school districts, and special districts. Second, I use data from more than 500,000 survey responses to estimate a novel measure of local ideological preferences for cities over time. Finally, to assess the impact of ideology on public policy outcomes, I use a Bayesian within-between random effects model. This methodology yields three major findings. First, I demonstrate that cross-sectional responsiveness exists. Second, I find evidence for dynamic responsiveness in spending but inconclusive evidence for taxation. Third, I provide descriptive evidence that consolidated governance fosters greater responsiveness. I reframe the responsiveness discussion from a single governing unit to a holistic system of overlapping institutions and provide the strongest evidence to date that local governments respond dynamically to the ideology of citizens.

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Broadly defined, a responsive government is one that follows the will of the public (Dahl, 1971). The last few years have seen representation in local government become more salient because the Black Lives Matter movement's fight to reform politics and the conflict surrounding local governments' COVID-19 policies such as mask mandates and stay-at-home orders. These episodes have centered on whether local governing institutions can represent the will of the public. Overall, the true nature of representation at the local level is hidden because complex institutions are not fully understood or appreciated. Cities, counties, school districts, and special districts all interact to provide local public goods to individuals. Varied levels of accountability, funding streams, and jurisdictional mandates characterize these governing institutions, requiring that the meaning of representation in the local context must take a holistic view that appreciates this complexity and how citizens receive their package of local goods and services.

Overlapping jurisdictions are widespread in the United States' governing structure. Despite the well-developed and widely discussed theories of federalism—the existence and interaction between national and state governments—the patchwork of local governing institutions remains understudied in terms of ideological representation. That patchwork contributes to the ongoing debate around whether representation exists at the local level, with overlap potentially both enhancing representation (by providing additional avenues for a hyper-localized public to receive specialized services) or impeding representation (by adding complexity to a system that already lacks clear lines of accountability).

On the one hand, the *limited city* paradigm suggests that we should not expect responsiveness from municipal government because they are overwhelmingly constrained by their position in the federal hierarchy and the mobility of their residents (Gerber and Hopkins, 2011; Rae, 2003; Peterson, 1981; Tiebout, 1956). Furthermore, cities generally lack competitive elections, residents lack sufficient political knowledge about local issues, and some cities' lack of partisan labels makes it difficult for residents to easily apply heuristics. In addition,

the overlap of governing units—cities, counties, schools, and special districts— has created economic inefficiency, duplication, over-taxation, and complication, making accountability and (thus) responsiveness unlikely (Berry, 2008, 2009; Bollens, 1957).

On the other hand, these constraints do not release municipalities from the electoral pressures experienced by other levels of government. Despite the low turnout and unfavorable conditions (e.g., non-partisan elections), we can observe correspondence between public preferences and local policy for both cities and county governments (Einstein and Kogan, 2016; Sances, 2019; Tausanovitch and Warshaw, 2014).

In this paper, I take seriously the inherent patchwork nature of local governments in the U.S. context to re-examine a basic question of democratic governance. Adopting this perspective offers two distinct advantages, one empirical and one theoretical.

First, moving away from the study of individual municipal governments to the broader set of institutions involved in taxing and spending in a geographic region, we gain a clearer view of the nature of responsiveness at the local level. Specifically, my analysis provides concrete evidence that local governments are indeed cross-sectionally responsive to the policy preferences of constituents. I find evidence of dynamic responsiveness for spending but inconclusive evidence for taxation.

Second, this theory suggests that democratic accountability at the local level remains possible despite fragmentation. Just as it is difficult for scholars to understand the delivery of goods at the local level in this patchwork system, it is difficult for voters to understand where services and taxes originate and which officials should be held accountable. As such, an important implication of this research is that at the aggregate level, local governments are far more responsive when taxing and spending power is concentrated across fewer overlapping institutions.

1 Background: Overlapping Governing Institutions

Local governance in the United States is a patchwork of overlapping and competing jurisdictions that generate revenue and provide a menu of local public goods and services. As of the latest count by the U.S. Census, there are over 90,000 local governments, a category that includes cities, counties, school districts, and special districts. Figure 1 shows the increase of local governments over time, which is tracked through the Census of Governments every five years. However, the growth of local governments are not constant over time. There was an increase of 5,000 local governments between 1992 and 2007, the number of governments remained relatively constant between 2012 and 2017. Most of the variation comes from special-purpose governments.

Special-purpose governments or special districts are governing units that provide an assortment of public goods and services (e.g., water, sewage, fire protection, libraries, or parks) to a specified geographic area. These special districts are important insofar as they constitute a largely hidden—in terms of public knowledge and accountability—governing structure that taxes and spends on behalf of residents. Also, as Berry (2009) notes: "Territorially overlapping, single-function jurisdictions, including 35,000 special districts and 13,500 school districts, today constitute the majority of local governments" (Berry, 2009, p. 1). These local governments have their own funding streams (e.g., property tax assessments, fees, or sales taxes), their own governing bodies, and particular goods and services that they provide to residents. Residents and property owners in these jurisdictions receive a menu or bundle of local public goods not from a single governing entity but from multiple overlapping entities.

Consider, for example, the City of Chicago, Illinois. Residents of Chicago pay local taxes to the city, the county (Cook County), and the Cook County Forest Preserve District.² The

¹Summary Report from the U.S. Census of Governments in the United States 2017: https://www.census.gov/content/dam/Census/library/visualizations/2019/econ/from_municipalities_to_special_districts_america_counts_october_2019.pdf

²Cook County Forest Preserve is one of many special districts that serve residents of the Greater Chicago area.

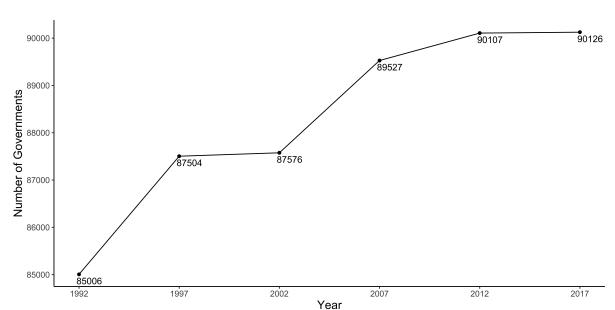


Figure 1: Number of Governments

Notes: Depicts the increase in local governments between 1992 and 2017. Data is from the U.S. Census of Governments, which is collected every five years on years that end in two or seven.

Cook County Forest Preserve District is a special district that stretches across Cook County and manages public monies from property tax assessments to maintain and build forests and natural trails within the county.³ Furthermore, some residents live in special districts within the city itself, such as the Northwest Home Equity Commission, which was created with wide electoral support to levy a special tax assessment on residential properties in Northwest Chicago to provide homeowners with assurance that the value of their property would not decrease regardless of fluctuations and urban degradation.⁴ For example, if a home has been appraised for \$200,000 but the only offer is for \$180,000, the commission covers the difference to ensure the homeowner does not lose money. Such specialized governments appear across the U.S. with varying authority and diverse policy mandates.

³More information about the Cook County Forest Preservation District can be found at: https://fpdcc.com/about/

⁴More information about the Northwest Home Equity Program can be found at https://nwheap.com/about/

Current studies about ideological responsiveness at the local level both under-theorize and overlook the growth and sheer number of local governments. This article seeks to reexamine the responsiveness question within the context of a landscape characterized by overlapping governing institutions. The following section discusses the existing debate surrounding whether local governments are responsive to the views of their constituents, reframing the debate to include the existence and proliferation of this overlap.

2 The Responsiveness Debate in Local Government

2.1 The Limited City Paradigm

In City Limits, Paul Peterson argues that cities are constrained by economic pressures to address the interests of business and secure economic growth. Cities aim to maintain and attract businesses to sustain economic growth, but providing certain social services—such as increased welfare—increases taxes and raises the likelihood that they will move out of the city. Such disincentives limit the capacity of cities to pursue policies the public wants, leading to what Peterson calls a "lack of ... partisan impact on local policy outcomes" (Peterson, 1981, p. 174). Arguments in this vein pertain to the limited city paradigm.

The limited city paradigm implies that cities are unable to meet the definition of responsive government. That is, cities are limited in their actions by characteristics of their political, social, and economic environments; many early scholars confirmed that cities are mostly unresponsive to constituents (Morgan and Watson, 1995; Peterson, 1981; Ruhil, 2003). This view suggests, for example, that competition between cities (Peterson, 1981) and the primacy of higher levels of government (Derthick, 1970; Ladd and Yinger, 1989) reduce municipal governments to a subservient role, precluding them from effectively responding to the will of the public.

Furthermore, turnout in local elections is low (Bullock III, 1990; Caren, 2007; Holbrook

and Weinschenk, 2014). For a sample of 38 large cities over 25 years, Caren (2007) finds an average voter participation rate of 21%. Similarly, Holbrook and Weinschenk (2014) find that the average turnout across 144 cities between 1996 and 2011 was 25.8%. These numbers are low relative to federal and state elections. Furthermore, Progressive Era reforms—such as non-partisan elections and a professional administrator implementing policies (i.e., councilmanager systems)—deprive residents of useful heuristics for gathering information about candidates and add an unelected layer between the people and the administration of policy (Marschall, 2010).

Beyond the constraints and limits observed in individual cities, overlapping jurisdictions further discourage expectations of responsiveness. In terms of goods and services, overlapping jurisdictions are considered wasteful, duplicative, and inefficient (Bollens, 1957). Furthermore, ignoring concerns about the provision of goods and services, these overlapping institutions (especially special districts) have low visibility, reducing the extent to which we should expect accountability (Burns, 1994; Wood, 1961). Indeed, some have suggested that overlapping institutions are *intended* to obscure accountability to allow governments to run more like "business" (Walsh, 1978).

Furthermore, as Berry (2008, 2009) recognizes, residents face a common-pool resource problem: Their incomes are taxed by multiple overlapping local governments, making it unlikely that any one municipal structure fully feels the pressure of their decision because it is distributed across all of the other units. That is, if one governing unit—for example, a special district—overtaxes residents who subsequently voice their disagreement ("voice") or move ("exit"), other government units (e.g., the city) are likely to be punished. Additionally, the fact that citizens are rarely able to distinguish the lines of accountability further complicates responsiveness in local government.

Twentieth-century institutional reformers considered the increase in local governments a danger to democracy due to the additional obstacles to democratic accountability introduced (The Challenge of Local Government Reorganization, 1974; Burns, 1994; Wood, 1961). This prompted them to advocate for a single larger governing institution instead of the increasing fragmentation of local government.⁵

Taken together, much of the literature suggests that responsiveness in local government does not and should not exist given the overwhelming constraints on their ability to change or implement policies, the dearth of institutions that easily facilitate accountability from the residents, and the existence of multiple overlapping institutions. However, although the limited city paradigm may raise valid concerns about the future of representation in local government, there are reasons to believe that the link between policy and the people persists.

2.2 Local Governments as Small-Scale Democracies

In contrast to the limited city paradigm, several theoretical frameworks position local governments as small-scale democracies. First, demand exists for uniquely local goods and services. Second, supply (in terms of government's ability to enact policy at the margins) of these goods and services is available. Third, given that a political market aligns preferences from right to left, the median voter theorem suggests elections incentivize officials to follow the will of their constituents. Lastly, scholars of the public choice school of economics have consistently argued that fragmentation and overlapping governance can increase responsiveness by providing additional avenues for citizens to get what they want in terms of public goods (Ostrom, 2010; Ostrom, Tiebout and Warren, 1961; Ostrom and Whitaker, 1999; Tiebout, 1956).

Americans demand services that local governments provide, including good schools, safe environments, and on-time waste collections (Capps, 2014). Most respondents to an Atlantic Media/Siemens State of the City poll indicated that they were happy with the services provided by their local government, which included roads, education, and police protection.⁶

⁵See Goodman (2019) for a review of local government fragmentation in the United States.

⁶The Atlantic Media/Siemens State of the City Poll (Capps, 2014) asked: "When you think about the

A majority even believed that services represented excellent or good value for their local taxes. Furthermore, findings from the Gallup Poll Social Series suggest that Americans have more confidence and trust in their local government than their state government (McCarthy, 2018). According to one observer, "Americans trust their local governments because they are tasked with doing things we want: keeping us safe, educating our children, cleaning the streets" (Hendrix, 2019). Hence, local governments have the power to provide the services their constituents trust them to deliver.

Second, local governments also have some power to shape local public policy according to the will of residents (Sances, 2019; Tausanovitch and Warshaw, 2014). I do not mean to suggest that cities have the *unconstrained* ability to adjust policies in the direction sought by constituents—indeed, some local governments (i.e., counties) are effectively constrained by the state government in terms of spending on health, hospitals, and education (Sances, 2019).⁷ I simply mean that local governments generally have *sufficient* control over their own resources to enact policies in the direction their constituents want on a broad set of issues. For example, liberal cities spend and tax more (Tausanovitch and Warshaw, 2014), and counties can change their tax revenue with the changing partisan composition of voters (Sances, 2019).

It remains true that localities have limited control over policies. However, local governments can alter the administration of state and federal policies to accomplish their goals (Rosenfeld, 1979). The federal government routinely delegates implementation of national policies to the local level through grant programs like the U.S. Department of Housing and Urban Development's Community Development Block Grant (CDBG).⁸ Through this program, the federal government funds local efforts to address issues of poverty, housing, and

public services where you live, like roads, education, and police, do you think these services are an excellent value for the local taxes you pay, a good value, a poor value, or a very poor value for your local taxes?"

⁷Furthermore, cities have been effectively constrained in their ability to implement certain policies, such as minimum wage ordinances.

⁸Information on the Community Development Block Grant can be found athttps://www.hud.gov/program_offices/comm_planning/communitydevelopment

infrastructure with few regulatory restrictions. Rosenfeld et al. (1995) discuss this level of discretion in their analysis of CDBG funds:

"Ultimately, CDBG delegates partial decision making responsibility to local political and administrative officials. These individuals have the opportunity to define local community development programs within broad or narrow federal parameters. The extent to which they exercise this opportunity and do so without abuses to the legislation will vary, not only with federal policies, but also with local economic, political, and administrative characteristics" (Rosenfeld et al., 1995, p. 57)

As with other federal grant programs, local governments strategically apply for money and use the funds for geographic and political reasons (Rosenfeld et al., 1995; Rosenfeld, 1979). Rosenfeld et al. (1995) point out that the political environment can shift the use of CDBG funds toward social service provisions and limit spending on economic development in the short term. In other words, local governments have the relative autonomy to change public policy at the margins to respond to the will of the public.

Given that a political market exists and preferences can be aligned on a left-to-right scale, an electoral incentive exists for officials to follow the will of the public (Mayhew, 1974). This process may involve adaption or selection. When elected officials pursue policies incongruent with the will of their constituents, voters can sanction them by selecting an opposing candidate on election day (Ansolabehere, Snyder and Stewart, 2001; Lee, Moretti and Butler, 2004; Poole, 2007).

While in office, electoral officials are continually under pressure to adapt to the will of the public out of fear of voter sanctioning (Caughey and Warshaw, 2018; Erikson and Wright, 2000). For example, Kousser, Lewis and Masket (2007) find that a Republican surge in California prompted experienced Democrats to moderate their voting record in

⁹Although I argue that both can occur, I am agnostic as to which mechanism is operating at the municipal level. Future research should explore this question. Notably, Caughey and Warshaw (2018) find that dynamic responsiveness operates through adaptation on the state level. However, as they acknowledge, this contradicts the majority of the research in the congressional literature, which suggests selection as the main contributor to responsiveness (Ansolabehere, Snyder and Stewart, 2001; Poole, 2007).

the state legislature out of fear of losing their recall elections. Similarly, Caughey and Warshaw (2018) find evidence that policy changes occur even when the partisan composition of the state does not. That is, "evidence supports the hypothesis that the adaptation of reelection-motivated incumbents to shifts in public sentiment is an important, and perhaps the dominant, mechanism of responsiveness" (Caughey and Warshaw, 2018, p. 261).

Scholars of public choice theory and advocates of polycentricity argue that the multiplicity of overlapping institutions may increase responsiveness (Ostrom, 2010; Ostrom, Tiebout and Warren, 1961; Ostrom and Whitaker, 1999; Tiebout, 1956). Polycentricity is a "social system of many decision centers having limited and autonomous prerogatives and operating under an overarching set of rules" (Aligica and Tarko, 2012, pg. 237). The patchwork of local governments or metropolitan governance is traditionally considered a polycentric system because there exists a multiplicity of semi-autonomous decision centers that compete, cooperate, or interact both vertically and horizontally.

Overlapping governance creates hyper-local avenues through which residents might have their voices heard. It also creates the opportunity for policies to be tailored to the demands of those residents. For example, according to early research on polycentricity and overlapping governance, creating neighborhood-sized governments within cities—which, for example, gives residents control of the police force—could increase responsiveness compared to larger and consolidated districts (Ostrom and Whitaker, 1999). The authors of that work note the importance of giving local control to small cities given the greater diversity in American metropolitan and the general dissatisfaction among Black Americans governed by larger, unrepresentative institutions.

Furthermore, Tiebout (1956) provided a model that does not rely on the direct connection between citizens, elected officials, and policy through representative institutions. According to that model, residents only need to know the level of public goods a particular set of governments provides, with residents registering their satisfaction by moving or staying.

According to some researchers point out, "one implication of a Tiebout type model is that representative institutions may not matter very much. Elected politicians are incentivized to pursue policies that retain and attract like-minded citizens" (Tausanovitch and Warshaw, 2014, pg. 606). Furthermore, the Tiebout model and the lesser importance of traditional electoral institutions provide substantial insight into responsiveness in a patchwork of overlapping governments.

The preceding discussion suggests that there are reasons why we may or may not expect responsiveness at the local level. Considering the competing arguments and the available insights into overlapping governance, I ask three questions:

RQ1: Given overlapping governance, does cross-sectional responsiveness exist?

RQ2: Given overlapping governance, does dynamic responsiveness exist?

RQ3: Does consolidated governance modify the effect of public opinion on policy outcomes?

3 Data

3.1 Fiscally Standardized Cities as the Unit of Analysis

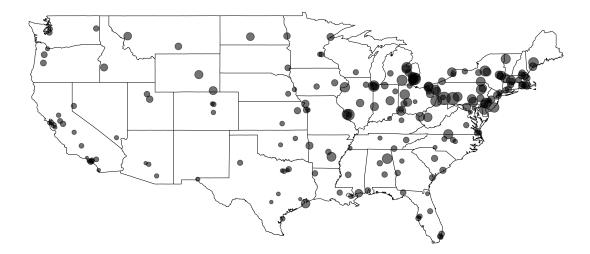
To examine the relationship between local ideological preferences and local public policy, I analyze data from the Lincoln Land Institute's Fiscally Standardized Cities (FiSC) dataset (Langley, 2013).¹⁰ This data contains annual finances for over 200 cities between 1977 and 2017. For the purposes of this article, I use the ten years between 2007 and 2016.¹¹ As Figure 2 shows, the cities contained in the sample stretch across the United States. A list of the cities appears in Appendix A.

The FiSC database provides two unique advantages for studying representation at this

¹⁰ The Lincoln Institute of Land Policy's FiSC Database can be accessed at the following website: https://www.lincolninst.edu/research-data/data-toolkits/fiscally-standardized-cities/search-database

¹¹I choose these years because they include data that can be used to estimate ideological preferences.

Figure 2: Map of Cities in Sample



Notes: Depicts a map of the United States where each point is a city featured in my sample. The size of each point is apportioned by the population size in 2016. I do not show the sample's two cities in Alaska, Anchorage and Fairbanks.

level. First, it enables comparisons between municipal budgets (the traditional measure used by researchers) and FiSC (the measure I use). The FiSC measurements of revenue and expenditures captures all goods, services, and revenue generation from all local governing units within a geographic city. These units include not only the general purpose municipality but also the wide range of special governing units that can tax and spend on behalf of residents. This aggregation involves apportioning spending and taxation by population. Consider, for example, a county that has one million residents, of which half a million reside in the principal city (municipality). Half of the county's expenditures and taxation are assumed to be distributed to the city. If, for example, a school district stretches across multiple cities, its expenditures and tax revenue are divided by the population covered by the school district.

¹²While most of the current work does not consider this complexity, Christopher Berry's book, *Imperfect Union*, addresses how representation is inhibited by the multitude of special-purpose governments like school districts, fire districts, and special business authorities (Berry, 2008, 2009). Stone (2014) also accounts for overlapping jurisdictions to provide a measure of public good provision for the Dallas-Fort Worth-Arlington metropolitan statistical area using geographic information systems.

For a visual representation, refer to Figures 3 and 4. I plot the trends over time for expenditures and tax revenue per capita by layer of local government for the City of Cincinnati, Ohio. In both figures, Plot A represents the municipality, the traditional measure used by researchers to examine budgets and policy outcomes. Plots B–D represent expenditures and tax revenue per capita apportioned to the city at the levels of county, school, and special district. Plot E represents the culmination of taxation and spending. For the purpose of this project, I use the FiSC measure of public goods provision.

Using the culmination of expenditures and taxation is important for the study of representation in local politics. First, it is possible for responsiveness to exist at one level and not the other. For instance, imagine a city that becomes more conservative and reduces spending on affordable housing. This would be seen as a responsive city. However, imagine that the same city reduces its spending on affordable housing, but the county government, which serves the same residents (among others), begins to spend more on affordable housing. It would be hard to suggest that these residents live under a responsive regime. As such, the FiSC measure better describes the world as it is.

This is not the first time someone has considered reframing the unit of analysis. Stone (2014) argues in favor of shifting the provision of local public goods toward an overlapping government combination as the unit of analysis. In examining the Dallas-Fort Worth-Arlington consolidated metropolitan statistical area in Texas, he finds that overlapping government combinations are distinct from their constitutive components and more accurately describe property tax rates.¹³

¹³While my approach shares many similarities with that of Stone, I depart from his analysis in a few ways. First, I evaluate responsiveness cross-sectionally and over time for over 200 cities. Meanwhile, he explores public goods provision—proxied by an ad valorem property tax rate—in a metropolitan area for a single time period. Second, the FiSC I use simplify the aggregation of public goods provision (taxation and spending) by weighting by population, while Stone uses geographic information systems to stack government layers. I argue that my approach is better suited to my inquiry because the data contains a multitude of cities across time (ten years) and space (across the United States rather than a single state), making my conclusions more generalizable.

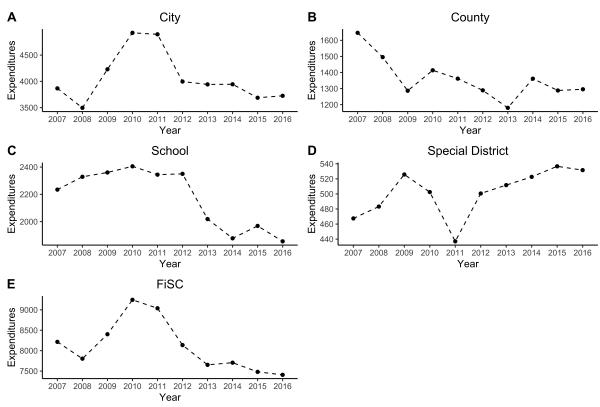


Figure 3: Cincinnati, OH: Expenditures by Layer of Government

Notes: Depicts expenditures per capita in Cincinnati, Ohio. Plot A represents municipality-only spending, while Plots B–D represent spending apportioned to the city at county, school, and special district levels. Plot E is the culmination of spending from the overlapping entities or, simply put, the summation of city, county, school, and special district spending apportioned to the city.

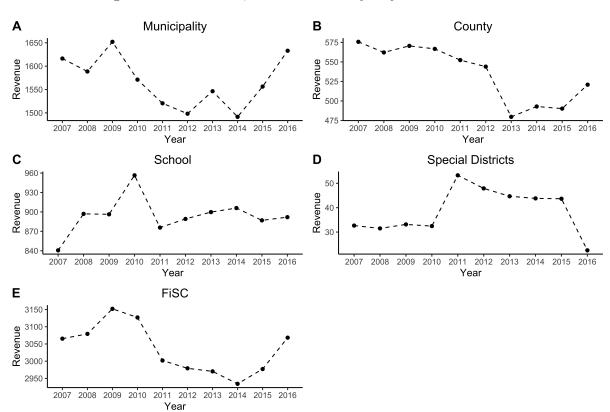


Figure 4: Cincinnati, OH: Taxation by Layer of Government

Notes: Depicts expenditures per capita in Cincinnati, Ohio. Plot A represents municipality-only tax revenue, while Plots B–D represent taxation apportioned to the city at the county, school, and special district levels. Plot E is the culmination of taxation from the overlapping entities or, simply put, the summation of city, county, school, and special district taxation apportioned to the city.

3.2 Outcome: Local Government Finances

I use two measures of policy output: tax revenue and expenditures per capita. Figure 5 depicts the median tax revenue and expenditures per capita for the cities in my sample. Tax revenue usually comes from sales and property taxation. In my sample, the median tax revenue ranges from \$1,752 to \$1,900. Expenditures can be classified into eight categories: education services, social services and income maintenance, transportation, public safety, environment and housing, government administration, interest on general debt, and miscellaneous activities. The median expenditures range from \$5,701 to \$6,422 per capita.

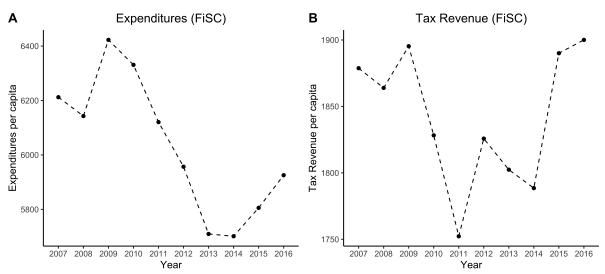


Figure 5: Median of Dependent Variables

Notes: Depicts the two dependent variables used for the main analysis. Panel A shows the median expenditures per capita for FiSC, while Panel B shows the median revenue generated per capita.

3.3 Ideological Preferences

To examine cross-sectional and dynamic responsiveness at the geographic city level (FiSC), I create a novel measure of local ideological preferences. First, I compile a super survey of over 500,000 respondents from the Cooperative Congressional Election Surveys, Gallup Poll Social Series, and the Annenberg Election Surveys. Second, I isolate the key ideological measure (self-placement ideology) and key demographic variables (race, age, gender, and education) from the surveys. Third, I estimate ideological preferences as a function of the demographic variables using Gelman et al. (n.d.) dynamic multilevel regression and post-stratification (MRT). The MRT model resembles the traditional multilevel regression and post-stratification (MRP) models with the inclusion of time smoothing parameters (γ) and time intercepts. As the following shows, I include demographic intercepts with interactions to improve the model's performance.

$$x_{it} = \gamma_1 \text{year std} + \gamma_2 \text{year std sq} + \alpha_{r[i]}^{\text{race3}} + \alpha_{e[i]}^{\text{education3}} + \alpha_{g[i]}^{\text{gender2}} + \alpha_{l[i]}^{\text{location}} + \alpha_{t[i]}^{\text{year}} + \alpha_{r[i],t[i]}^{\text{race3,year}} + \alpha_{e[i],t[i]}^{\text{education3,year}} + \alpha_{g[i],t[i]}^{\text{gender2,year}} + \alpha_{l[i],t[i]}^{\text{location,year}} + \epsilon_{it}$$

$$(1)$$

In Appendix B, I provide additional information on the estimation of local political preferences and the model specification. In Appendix C, I provide evidence that the cross-sectional and dynamic variation of the measure can be validated using vote share across three presidential cycles and other ideological measures.

The measure of ideology ranges empirically from -0.7 (Oakland, CA in 2016) to 0.52 (Colorado Springs, CO in 2009). The average city in the dataset has a conservatism score of 0.055 (Tampa, FL in 2008). To visualize the measure over time, Figure 6 depicts conservatism for five cities: Atlanta, GA; Cincinnati, OH; Columbus, OH; New York, NY; and San Diego, CA.

O.0
Atlanta GA

Cincinnati OH

Columbus OH

New York NY

San Diego CA

Year

Figure 6: Ideology 2007–2016: Five Select Cities

Notes: Depicts conservatism over time for five cities: Atlanta, GA; Cincinnati, OH; Columbus, OH; New York, NY; and San Diego, CA.

3.4 Modeling Strategy

I follow Achen's (1978) conception of responsiveness, defined as the difference between the average opinion of citizens and policy output. In a statistical model, this is represented by the coefficient of the public opinion variable. This approach has been used by many other researchers on responsiveness (Tausanovitch and Warshaw, 2014; Caughey and Warshaw, 2018; Stimson, MacKuen and Erikson, 1995).

While fixed effect models are the typical estimators used by political scientists to analyze panel data, I use a Bayesian within-between random effects model. The within-between random effects model simultaneously estimates both the within- and between-unit effects of explanatory variables by separating higher-level variances (between cities) and lower-level variances (within cities) (See Mundlak, 1978; Bell and Jones, 2015).

The argument for using fixed over random effects has centered on the random effects assumption that predictors in the model do not correlate with unobserved time-constant heterogeneity. Thus, practitioners have gravitated towards using the Hausman test to ex-

amine whether random effects modeling assumptions are violated (Greene, 2012). Recent studies have questioned the usefulness of the Hausman test because it only considers whether the between- and within-unit effects differ and fails to evaluate whether the researcher should make a bias-variance trade-off (Bell and Jones, 2015; Clark and Linzer, 2015).

Importantly, the debate between fixed effects and random effects is largely "imaginary" (Mundlak, 1978). By directly modeling time-invariant heterogeneity by including group-level means, the within-unit effects of random effects models become equivalent to the coefficients of fixed effects models. In Appendix D, I verify that my within-between effects estimates are equivalent using a two-way fixed effects model and a pooled cross-sectional linear regression.

Using the within-between random effects models offers several advantages. First, I can model the dynamic and cross-sectional variation using a single approach. Second, I can interpret the between-unit effects of time-varying variables. For instance, the group-level mean for ideology indicates a cross-sectional relationship between ideology and policy. Third, I can interpret time-invariant variables. For example, I can assess whether places with consolidated cities spend more or less on average. In general, this random effects approach tries to provide a "richer description of the relationship under scrutiny," while fixed effects models attempt to eliminate context (Subramanian et al., 2009, p. 373).

For a better understanding of the model, consider the following equation:

$$y_{jt} = \beta_0 + \beta_1 (x_{jt} - \bar{x}_j) + \beta_2 \bar{x}_j + \beta_3 z_j + (\mu_j + \epsilon_{jt})$$
 (2)

subscript j denotes cities, t denotes time (year), y_{jt} are government policy outcomes (taxes per capita and total expenditures per capita), x_{it} are time-varying independent variables, \bar{x}_j are averages of time-varying variables, and z_i are time-constant independent variables. As such, β_1 represents mean-centered time-variant variables (ideology) and the within-unit effects. β_2 represents the between-unit effects or cross-sectional responsiveness. β_3 represents the effect of time-constant independent variables such as consolidated city. The two error components (μ_j and ϵ_{jt}) represent the aggregated unobserved group-level effect and the

unobserved level-1 effect.

I include the following time-varying variables in the models I present in the main text: population (logged), median household income, share of Black residents, and income inequality. Similar to conservatism, these time-varying variables also have an invariant (or between-unit effect) component that corresponds to group means. For example, these group means represent the time-constant association of being a city with a high income rather than a low income. I also include consolidated government as a time-constant indicator. Consolidated government exists where the city and county are merged or the city functions as an administrative unit of the state (as does a county).

4 Results

I separate the results into three parts. First, I visually examine the bivariate relationship between ideology and policy cross-sectionally and dynamically. Second, I report my main results regarding the impact of ideology on public policy using between-within random effects models with covariates. Finally, I explore the extent to which consolidated governance either fosters or inhibits responsiveness.

4.1 Preliminary Analysis

Figures 7 and 8 show the cross-sectional relationship between conservatism and policy over time. In each year, a negative relationship exists. Indeed, geographic cities with more conservative residents tend to tax and spend less. While the correlations between conservatism and expenditures range from -0.45 to -0.49, the correlations for taxes range from -0.42 to -0.49. However, Figure 9 shows a less clear dynamic relationship.

Figure 9 shows the relationship between ideology and policy, with each line representing a city. If all cities were responsive, we would expect each grey line to point in the negative

direction. It is apparent that some cities are responsive—in the sense that the relationship between ideology and policy is negative—while other cities are actually positive. Nonetheless, many cities tend to have a relatively small slope across the ten years of my sample.

The main takeaways from this preliminary visual analysis suggest that although crosssectional representation may exist in a robust fashion, dynamic responsiveness may be less clear. In the main results section, I examine whether these bivariate results hold up under further analysis.

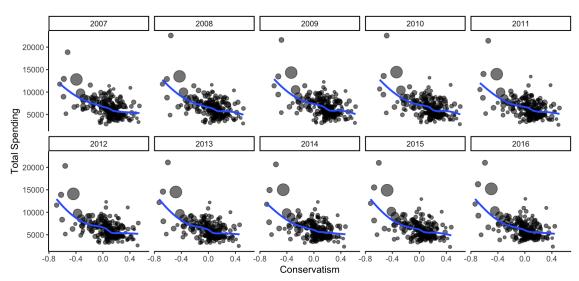


Figure 7: Bivariate: Total Spending and Ideology 2007–2016

Notes: Depicts the bivariate cross-sectional relationship between conservatism and total spending per capita by year. Each dot represents a city. Each dot's appearance indicates relative population size. The negative relationship for every year suggests that cities that are conservative tend to spend less than liberal cities.

2008 2009 2010 2011 9000 6000 3000 Tax Revenue 2012 2013 9000 6000 3000 -0.4 0.0 0.4 Conservatism -0.8 -0.8 -0.8 -0.8 -0.8

Figure 8: Bivariate: Tax Revenue and Ideology 2007–2016

Notes: Depicts the bivariate cross-sectional relationship between conservatism and tax revenue per capita by year. Each dot represents a city with dot size indicating relative population. The negative relationship for every year suggests that conservative cities tend to generate less revenue than liberal cities.

Α Expenditures per capita (FiSC) Exbeuditures ber capita
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100000
100000
50000 0.0 Conservatism -0.8 -0.4 0.4 В Revenue per capita (FiSC) 20000 Revenue per capita 15000 10000 5000 0.0 Conservatism -0.8

Figure 9: Bivariate: Conservatism and Policy Outcomes

Notes: Depicts the bivariate relationship between ideology and policy. Each line shows the relationship within a city.

4.2 Main Results: Ideology's Impact on Public Policy

Table 1 summarizes the results for conservatism's impact on expenditures per capita and taxes per capita. All models include the same control variables: population (logged), median household income, share of Black residents, income inequality, and consolidated government. Given that the results are from a Bayesian within-between random effects model, I show the lower and upper 95% credible intervals in brackets and split the table into two panels: between-unit effects (Panel A) and within-unit effects (Panel B). Panel A (or between-unit effects) estimates are equivalent to the coefficients in a pooled cross-section model. Panel B assesses whether cities dynamically respond to the changes in ideology within their population. For simplicity, if the credible intervals do not contain 0, I highlight the coefficient with an asterisk (*).

Table 1: Results: Impact of Ideology on Expenditures and Taxation

	Expenditures	Taxation
A. Between-Unit Effects		
Intercept	-2747.91	-3470.26*
	[-7587.77, 2205.63]	[-5629.74, -1288.07]
Ave. Conservatism (Cross-sectional)	-3273.69*	-1125.86*
	[-4808.82, -1742.47]	[-1805.18, -423.13]
B. Within-Unit Effects		
Conservatism (Dynamic)	-3293.64*	-254.64
	[-5256.02, -1340.93]	[-970.36, 455.89]

Notes: The dependent variables for this analysis are expenditure per capita and taxation per capita. I report the 95% credible intervals in brackets. Table entries are coefficients from a Bayesian within-between random effects model performed in R. Panel A corresponds to between-unit effects, while Panel B corresponds to within-unit effects.

I find evidence that cross-sectional responsiveness exists for both expenditures and tax revenue. Cities with conservative residents tend to spend \$3,300 less per capita and collect \$1,100 less per capita in revenue. However, these estimates do not represent a plausible counterfactual for the observed changes in the independent variable. Following the recommendations of Mummolo and Peterson (2018), I isolate the relevant between-unit change in ideology and compute the standard deviation. This provides me with the typical between-

unit variation in ideology. A revised one-standard-deviation increase in conservatism or two cities that are one standard deviation apart is associated with taxing and spending \$254 and \$654 less per capita.¹⁴ These results are analogous to the cross-sectional results reported by Tausanovitch and Warshaw (2014).

I observe similar patterns for dynamic responsiveness. A city becoming one standard deviation more conservative reduces its expenditures by \$33 per capita.¹⁵ While this may seem small, a reduction of \$33 per capita for a city of 400,000 is thirteen million dollars. Although the coefficient on tax revenue per capita is in the correct direction, the credible intervals are imprecise.

4.3 Does Consolidated Governance Foster Responsiveness?

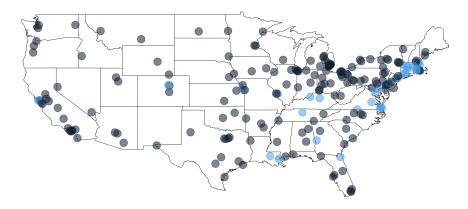
Next, I turn my analysis to how consolidated governments may increase or decrease responsiveness. Consolidated governments are those where the city/municipality and county are merged or the municipality is an administrative unit of the state (in the manner of a county). In my sample, 32 out of the 204 cities feature a consolidated government. Figure 10 shows the geographic distribution of consolidated cities in my sample. Notably, most cases are in the eastern half of the United States.

Similar to the main analysis, I use the Bayesian within-between random effects approach to model the cross-level interaction of ideology and consolidated government. Although competing theories offer different perspectives on how overlapping governments may enhance or impede responsiveness, I generally find evidence that localities with consolidated governments tend to demonstrate stronger responsiveness (See Table 2 Panel C). A direct policy implication of this finding is that we should reduce overlapping governance to increase responsiveness.

 $^{^{14}}$ The standard deviation of residualized (between-unit) ideology is 0.2. Thus, \$3273 x 0.2 = \$654. The calculations for taxation follow the same format.

¹⁵Similar to the cross-sectional results, I compute a more reasonable counterfactual change in within-unit ideology. The standard deviation of residualized (within-unit) ideology is 0.01.

Figure 10: Map of Consolidated Cities in Sample



Notes: Depicts a map of the United States where each point is a city included in my sample. Blue dots are consolidated cities; grey dots are non-consolidated cities. Note that the majority of consolidated cities are in the eastern half of the country.

Table 2: Consolidated Governance

	Expenditures	Taxation
A. Between Unit Effects		
Intercept	-2660.89	-3470.26*
	[-7587.77, 2205.63]	[-5629.74, -1288.07]
Ave. Conservatism (Cross-sectional)	-3279.37*	-1125.86*
	[-4808.82, -1742.47]	[-1805.18, -423.13]
Consolidated Government	293.89	183.53
	[-416.58, 1023.96]	[-152.88, 514.46]
B. Within Unit Effects		
Conservatism (Dynamic)	-3293.64*	-254.64
	[-5256.02, -1340.93]	[-970.36, 455.89]
C. Cross-Level Interactions		
Conservatism*Consolidated Gov.	-1712.52*	-657.24*
	[-2672.73, -745.11]	[-1008.77, -301.05]

Notes: The dependent variables for this analysis are expenditures per capita and taxation per capita. I report the 95% credible intervals in brackets. Table entries are coefficients from a Bayesian within-between random effects model performed in R. Panel A corresponds to between-unit effects, Panel B corresponds to within-unit effects, and Panel C corresponds to cross-level interactions.

5 Conclusion

Residents in the United States live under a patchwork of local governments. Single and unified local governing institutions rarely exist. This makes it important to consider the overlapping nature of governments. Despite the complexities associated with this patchwork composition, I find that citizens are still able to influence some policy issues. While previous studies have examined the relationship between public opinion and public policy, I bring together a new framework that includes overlapping governing institutions, a novel measure of ideological preferences over time, and a seldom-used method to provide new evidence in response to this question. In doing so, I provide evidence that both cross-sectional and dynamic responsiveness exist.

Specifically, I find robust evidence for cross-sectional responsiveness. These results are consistent with the findings of other researchers (Tausanovitch and Warshaw, 2014; Einstein and Kogan, 2016). Indeed, localities with conservative residents tend to spend and tax less on average. I also provide the strongest evidence to date that dynamic ideological responsiveness exists for expenditures. Furthermore, I find that consolidated government moderates the effect of public opinion on public policy. This represents descriptive evidence that consolidated governance fosters greater responsiveness because citizens have clearer lines of accountability.

Although I provide robust evidence of responsiveness in local government, there are inherent limits to the design of this study. First, causal inference remains elusive. Although I have carefully shown cross-sectional and dynamic results, unobserved confounders may render the relationship between public opinion and public policy spurious. Future work should find an instrumental variable or another form of exogeneity for local public preferences. Second, using the fiscally standardized approach is one of many ways to account for the overlapping nature of local governments. Berry (2008, 2009) uses a count of governments within a county, while Stone (2014) uses geographic information systems to stack overlapping governments in

a single metropolitan area. Lastly, this research does not intend to suggest that ideology is the only way to consider responsiveness in local government. Urban politics are awash with theories that may provide insight into responsiveness. Specifically, urban regime theory and racial coalition building may provide a better lens through which to view local governance (See Stone, 1989).

The broader policy implications of this research suggest that we should move away from having multiple overlapping governing institutions and towards more consolidated local governments that feature clearer lines of accountability. Furthermore, we should take seriously the inherent nature of the institutions around us. As overlapping institutions are a fundamental reality of local governance in the United States, future researchers should embrace the complexity rather than ignoring it.

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Appendices

A Cities in Sample

Table 3: Cities in Sample

Akron OH Anchorage AK Anderson IN Antiquon TX Altantic City NJ Bakersfield CA Bayonne NJ Billings MT Bismarck ND Camden NJ Canden NJ Charleston SC Charleston WC Chesapeake VA Cincinnati OH Columbus GA Covington KY Dearborn Heights MI Des Moines IA Durham NC Erie PA Fall River MA Fargo ND Film MI Fremont CA Fremont CA Film River MA Fargo ND Film MI Fremont CA Fr				
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Warren MI Warren OH Warwick RI Washington DC Wheeling WV Wichita KS Wilkes-Barre PA Wilmington DE	Topeka KS	Trenton NJ	Troy NY	Tucson AZ
Wheeling WV Wichita KS Wilkes-Barre PA Wilmington DE	Tulsa OK	University City MO	Utica NY	Virginia Beach VA
	Warren MI	Warren OH	Warwick RI	Washington DC
Worcester MA Yonkers NY York PA Youngstown OH	Wheeling WV	Wichita KS		Wilmington DE
	Worcester MA	Yonkers NY	York PA	Youngstown OH

B Estimating Ideology using MRT

To estimate local ideology, I first collect national surveys asking respondents to place themselves on an ideological scale from liberal to conservative. For these surveys to be included in my dataset, respondents must have identified a valid zip code to help identify their city. I collect nationally representative surveys conducted between 2007 and 2016 from the Gallup Poll Social Series, the Cooperative Congressional Election Surveys (CCES), and the Annenberg Election Surveys (NAES).

To estimate ideology, I use the dynamic multilevel regression with post-stratification model developed by Gelman et al. (n.d.), conducting multiple model specifications to vary the smoothing of year and demographic information. Table 4 describes the variables that enter into the model, with the paper presenting the following model:

$$x_{it} = \gamma_1 \text{year std} + \gamma_2 \text{year std sq} + \alpha_{r[i]}^{\text{race3}} + \alpha_{e[i]}^{\text{education3}} + \alpha_{g[i]}^{\text{gender2}} + \alpha_{l[i]}^{\text{location}} + \alpha_{t[i]}^{\text{pender2}} + \alpha_{l[i],t[i]}^{\text{location}} + \alpha_{e[i],t[i]}^{\text{gender2,year}} + \alpha_{g[i],t[i]}^{\text{gender2,year}} + \alpha_{l[i],t[i]}^{\text{location,year}} + \epsilon_{it}$$
(3)

where γ_1 is the standardized/scaled year variable and γ_2 is the standardized/scaled year variable squared. α with subscripts r, e, g, l, t are random effects for demographics, location, and year. The remaining random effects allow demographic coefficients such as race and gender to vary over time.

In Appendix C, I validate my dynamic measure of ideology by comparing it to changes in Democratic voter share over three presidential cycles. My findings suggest that when cities become more liberal, the two-party vote share for Democratic Presidents increases.

Table 4: Public Opinion, MRT Variables

Variables	Description
Ideology	Self-placement on the ideological scale, [-2,2]
Year	Categorical year variable, 10 Levels [2006-2016]
Year Std.	Standardized/scaled year variable
Year Std. Sq.	Standardized/scaled year variable squared
Location	Categorical unique city
State	Categorical State 51 Levels [including DC]
Race3	Categorical Race Variable, 3 Levels [White, Black, Other]
Gender2	Categorical Gender Variable, 2 Levels [Male, Female]
Education3	Categorical Education Variable, 3 Levels [HS or less, Some College, BA or higher]

C Validation of Local Ideological Preferences

To validate the dynamics of ideology, I collect city-level Democratic presidential vote shares for 21 cities in California and Virginia across three Presidential cycles: 2008, 2012, and 2016. Figure 11 depicts the cross-sectional relationship between ideological conservatism and Democratic vote share. In all presidential years, conservatism is negatively associated with the Democratic vote share. However, this approach does not verify the existence of a dynamic relationship. As such, I model the relationship between ideology and vote share using a fixed effects model. Table 5 shows a statistically significant negative relationship between conservatism and the Democratic presidential vote share. When cities become more conservative, the vote share of the Democratic Party candidate decreases.

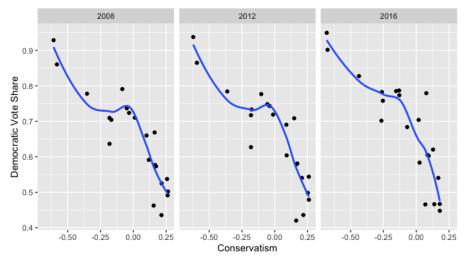


Figure 11: Democratic Vote Share

Notes: Depicts the cross-sectional relationship between conservatism and the Democratic vote share in three presidential elections. The data includes 21 cities across California and Virginia.

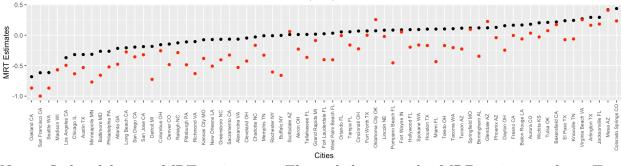
 $^{^{16}}$ The pooled correlation between conservatism and Democratic vote share is -0.87. The correlations by year are -0.88, -0.87, and -0.86 for 2008, 2012, and 2016.

Table 5: Ideology on Vote Share

	Dependent variable:		
	D. Vote Share		
Conservatism	-1.047^{***}		
	(-0.038)		
Constant	0.774***		
	(0.008)		
City FE	Yes		
Year FE	Yes		
Observations	63		
\mathbb{R}^2	0.984		
Adjusted \mathbb{R}^2	0.975		
Residual Std. Error	0.022 (df = 39)		
F Statistic	$105.052^{***} (df = 23; 39)$		
Note:	*p<0.1; **p<0.05; ***p<0.0		

Here, I provide evidence that my MRT-based measure of ideology is comparable to Tausanovitch and Warshaw's cross-sectional MRP-based measure. For purposes of comparison, I restrict my analysis to the year 2008. Figure 12 shows the extent to which the MRT and MRP measures are ordered similarly. The estimates are correlated at the 0.83 level.

Figure 12: MRT Estimate of Conservatism (2008) vs. MRP



Note: Ordered by my MRT estimates. The red dots are the MRP estimates from Tausanovitch and Warshaw (2013, 2014).

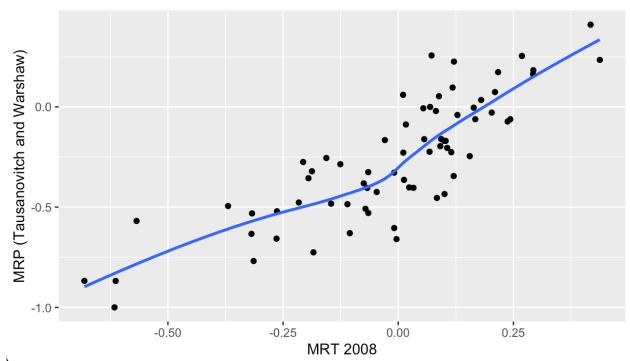


Figure 13: MRT Estimate of Conservatism (2008) vs. MRP

Note: Depicts the cross-sectional relationship between the MRT-based estimate of conservatism for cities in 2008 and the MRP-based estimate of conservatism used by Tausanovitch and Warshaw (2013, 2014). The estimates are correlated at the 0.83 level.

D Comparing Pooled Cross-Sectional, Two-Way FE, and Within-Between Models

Although not frequently used in political science, within-between models can recover estimates as pooled cross-sectional and two-way fixed effect estimators. As Table 6 shows, the coefficients are approximately identical. I report estimates from the frequentist variant of the within-between random effects model.

Table 6: Comparing Coefficients: Expenditure

	Model Coefficient	Within-Between Model
Two-Way FE	-3,371	-3,356
Pooled Cross-Sectional	-3,231	-3,289

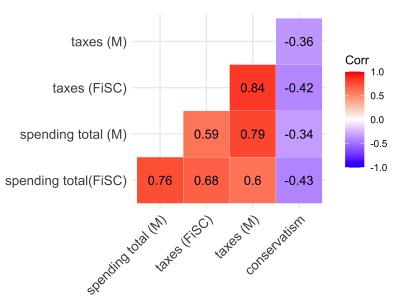
E Responsiveness using Fiscally Standardized Cities vs. Municipalities

In this section, I investigate how much more we learn about representation in local government by using fiscally standardized cities rather than the traditional measure of public policy. As Figure 14 shows, both measures are highly correlated. Specifically, the measures of expenditures per capita and revenue per capita are correlated at 0.76 and 0.83, respectively. Furthermore, the correlation between ideology and policy takes the same general pattern between the two measures, although the relationship seems larger for fiscally standardized measures. This is largely borne out after running the models. Figures 15 and 16 visualize the results.

This association, however, does not tell the whole story. One might be interested in the extent to which one measure demonstrates a stronger relationship with policy. Using the traditional measure may over or underestimate the extent to which representation truly exists. To evaluate this claim, I use Zellner's seemingly unrelated regressions to model the errors across the fiscally standardized and municipality models (Zellner, 1962). Following the system of equations, I test the extent to which the slopes using the fiscally standardized measures are greater than the slope of ideology using the traditional measure.¹⁷ To make the comparisons at the same level, I scale the dependent variables by subtracting the mean and dividing by the standard deviation.

¹⁷See Mize, Doan and Long (2019) for further discussion of testing coefficients across models using seemingly unrelated regressions.

Figure 14: Correlations



Notes: Reports the bivariate correlation matrix of the dependent variables and the explanatory variable of interest in the analysis. "FiSC" refers to fiscally standardized cities or the measure I use in the main analysis. "M" refers to municipality, the traditional measure of municipal budgets.

The following two tables reproduce the coefficients from the seemingly unrelated regression and the linear hypothesis test of the coefficients across the equations. First, I compare these scaled results to the main results found earlier in the paper. Second, I examine the extent to which using one set of dependent variables enables finding a stronger relationship with public opinion.

As shown in Panel A of Tables 7 and 8, all coefficients are in the expected direction. That is, conservatism is negatively associated with expenditures and tax revenue per capita cross-sectionally and dynamically. Differing from the main results in Table 1, I can find evidence of within-unit effects for tax revenue dynamically in fiscally standardized cities. The only coefficient that is indistinguishable from zero is the within-unit effect for expenditures for municipalities.

Next, I examine whether we see greater responsiveness when using fiscally standardized

cities rather than municipalities. As shown in Panel B in Tables 7 and 8, I find evidence that using municipalities underestimates the extent to which responsiveness exists cross-sectionally. Similarly, I find evidence that using municipalities underestimates responsiveness expenditures dynamically (see Table 7 Panel C). The results are the opposite for revenue generation dynamically (see Table 8 Panel C).

Overall, I argue that measuring the provision of local public goods using fiscally standardized measures better represents the functional state of local democracy. Using traditional measures of fiscal policy may sometimes over- or under-estimate the extent to which responsiveness exists.

Α FiSC (Within Unit Effect) В FiSC (Between Unit Effects) Expenditures dollars per capita Expenditures dollars per capita 10000 7000 8000 6500 6000 0.00 0.05 -0.50 -0.25 0.00 0.25 Conservatism (Within Effect) Conservatism (Between Effect) C Municipality (Within Unit Effects) D Municipality (Between Unit Effects) Expenditures dollars per capita dollars per capita 3000 3000 2700 Expenditures dollars per capita 9000 2000 2000 6000 0.00 0.05 0.00 0.25 -0.10 -0.05 0.10 -0.50 -0.25 Conservatism (Within Effect) Conservatism (Between Effect)

Figure 15: Conditional Effects: Conservatism on Total Expenditures

Notes: Depicts the conditional effects of ideology on total expenditures per capita for standardized cities (Plots A and B) and municipalities (Plots C and D). While Plots A and C show within-unit effects, Plots B and D show between-unit effects. All plots depict a negative relationship, suggesting that policy moves with ideological change.

Α FiSC (Within Unit Effect) В FiSC (Between Unit Effect) Tax Revenue dollars per capita dellars per capita dollars per capita d Tax Revenue dollars per capita 0.10 0.00 0.25 0.00 -0.25 Conservatism (Within Effect) Conservatism (Between Effect) C Municipality (Within Unit Effect) D Municipality (Between Unit Effect) Tax Revenue dollars per capita Tax Revenue dollars per capita 2000 1500 1000 500

Figure 16: Conditional Effects: Conservatism on Total Taxation

Notes: Depicts the conditional effects of ideology on tax revenue per capita for standardized cities (Plots A and B) and municipalities (Plots C and D). While Plots A and C show within-unit effects, Plots B and D show between-unit effects. Plots B and C depict a negative relationship, suggesting that cities that are conservative tend to record low levels of taxation and spending. Although Plots A and C reveal a slightly negative relationship, the intervals are wide, and the slope is relatively flat.

0.00

Conservatism (Between Effect)

-0.25

-0.50

0.25

0.50

0.10

0.05

-0.10

-0.05

0.00

Conservatism (Within Effect)

Table 7: Seemingly Unrelated Regression: Expenditures

D 1.4	CIID
Panel A.	SUR
FiSC Model: Conservatism (Between)	-1.99***
	(.116)
FiSC Model: Conservatism (Within)	-1.38***
	(.135)
Municipality Model: Conservatism (Between)	-1.61^{***}
	(.021)
Municipality Model: Conservatism (Within)	15
	(.182)
Panel B. Between	ZScore
Linear Hypothesis With Restriction:	-3.26***
Panel C. Within	ZScore
Linear Hypothesis With Restriction:	-5.88***

^{***}p < 0.001; **p < 0.01; *p < 0.05; p < 0.1

Table 8: Seemingly Unrelated Regression: Revenue

Panel A.	SUR
Revenue (FiSC) Model: Conservatism (Between)	-2.84***
	(.092)
Revenue (FiSC) Model: Conservatism (Within)	608***
	(.099)
Revenue (M) Model: Conservatism (Between)	-1.90***
	(.015)
Revenue (M) Model: Conservatism (Within)	96***
	(.138)
Panel B. Between	ZScore
Linear Hypothesis With Restriction:	-10.16***
Panel C. Within	ZScore
Linear Hypothesis With Restriction:	2.28***

^{***}p < 0.001; **p < 0.01; *p < 0.05; p < 0.1

F Additional Tables

Table 9: Results: Ideology on Expenditures and Taxation

	Expend. FiSC	Expend. City	Taxes FiSC	Taxes City
	(1)	(2)	(3)	(4)
Within Effects				
Conservatism	-3356.54	-2399.75	-262.68	-67.47
	[-5347.84, -1418.66]	[-3905.96, -872.32]	[-981.83, 437.715]	[-558.65, 436.14]
Log(Population)	-949.62	-1191.99	-186.73	-89.19
	[-1624.13, -268.44]	[-1713.72, -673.17]	[-427.84, 57.530]	[-254.73, 79.44]
Median Household Income	0.08	0.04	0.03	0.02
	[0.07, 0.09]	[0.03, 0.05]	[0.03, 0.04]	[0.01, 0.02]
Black Share	3641.03	1511.96	1042.00	548.51
	[2033.02, 5223.82]	[252.64, 2757.69]	$. \ [466.55, 1606.37]$	[140.27, 956.08]
GINI	102.90	942.49	1338.63	423.69
	[-2340.74, 2507.89]	[-940.46, 2809.56]	[457.06, 2224.36]	[-179.59, 1027.56]
Between Effects				
Intercept	-2802.85	-4943.54	-3557.59	-2177.06
	[-7909.46, 2397.48]	[-9418.89, -519.46]	[-5758.88, -1411.16]	[-4175.21, -250.01]
Ave. Conservatism	-3289.59	-2012.47	-1120.29	-886.92
	[-4793.95, -1809.58]	[-3467.99, -570.44]	[-1818.86, -444.18]	[-1491.71, -286.39]
Ave. Log(Population)	150.82	30.02	-19.88	-62.15
	[-139.14, 448.79]	[-252.53, 304.74]	[-153.91, 115.51]	[-181.42, 60.67]
Ave. Median Household Income	0.03	0.02	0.03	0.02
	[-0.01, 0.06]	[-0.01, 0.05]	[0.02, 0.04]	[0.01, 0.04]
Ave. Black Share	1298.66	584.70	435.23	296.76
	[-294.69, 2836.51]	[-993.28, 2079.06]	[-280.96, 1183.75]	[-358.74, 930.94]
Ave. GINI	13153.16	13619.55	9539.86	6062.36
	[3291.63, 22862.90]	[5114.04, 22459.24]	[5390.09, 13968.08]	[2300.99, 9897.61]
Consolidated Govt	298.40	2865.55	183.53	1059.0
	[-451.05, 1042.47]	[2168.67, 3562.59]	[-152.88, 514.46]	[761.77, 1357.09]
Pseudo-R ² (Fixed Effects)	0.29	0.40	0.32	0.38
Pseudo-R ² (Total)	0.96	0.96	0.98	0.99
Num. obs.	2031	2031	2031	2031

^{*} indicates that zero is not in the credible interval.

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Table 10: Ideology on General Expenditures with Covariates

	Dependent variable:			
	Expend. FiSC	Expend City	Expend. FiSC	Expend City
	2WFE	2WFE	FD	FD
	(1)	(2)	(3)	(4)
Conservatism	$-3,371.070^*$	$-2,404.332^*$	-1,030.598*	-1,166.655*
Low(Donulation)	(1,645.824)	(1,184.969)	(525.451)	(550.403)
Log(Population)	-948.606 (715.950)	-1,191.204* (457.237)	$ \begin{array}{c} 121.274 \\ (361.333) \end{array} $	-215.474 (281.149)
Median Household Income	0.080*	0.037*	0.030*	0.010
	(0.016)	(0.013)	(0.008)	(0.007)
Black Share	3,627.028*	1,521.112	742.991	418.728
	(1,409.442)	(1,008.984)	(742.732)	(785.717)
GINI	99.762	940.432	597.476	-93.110
	(2,616.679)	(1,851.809)	(1,201.118)	(955.069)
Constant	12,167.960	17,942.720*		
	(8,597.033)	(5,460.019)		
City FE	Yes	Yes	<u>-</u>	_
Year FE	Yes	Yes	-	-
First-Diff	-	-	Yes	Yes
Observations	2,031	2,031	1,827	1,827

 $^{^{\}ast}$ indicates statistical significance at the 0.05 level. Errors clustered on location.

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Table 11: Ideology on Tax Revenue with Covariates

	Dependent variable:			
	Taxes FiSC	Taxes City	Taxes FiSC	Taxes City
	2WFE	2WFE	FD	FD
	(1)	(2)	(3)	(4)
Conservatism	-266.547	-70.612	-714.932	-348.809
	(563.228)	(364.800)	(389.403)	(207.489)
Log(Population)	-189.120	-89.053	71.166	56.285
,	(200.124)	(122.632)	(149.237)	(93.764)
Median Household Income	0.033*	0.015*	0.013*	$0.007*^{'}$
	(0.004)	(0.003)	(0.003)	(0.002)
Black Share	1,045.648*	547.217	119.812	147.645
	(412.322)	(285.920)	(255.085)	(256.580)
GINI	1,340.664	425.069	424.253	40.268
	(786.735)	(450.929)	(443.553)	(346.020)
Constant	1,396.719	1,786.145	· · · · ·	,
	(2,417.409)	(1,552.792)		
City FE	Yes	Yes	-	_
Year FE	Yes	Yes	-	_
First-Diff	-	-	Yes	Yes
Observations	2,031	2,031	1,827	1,827

 $^{^{\}ast}$ indicates statistical significance at the 0.05 level. Errors clustered on location.

Table 12: Ideology on Public Policy (Cross-Sectional)

	$Dependent\ variable:$			
	Expend. FiSC	Expend. City	Taxes FiSC	Taxes City
	(1)	(2)	(3)	(4)
Conservatism	-3,257.412*	-2,086.059*	-1,144.058*	-902.055^*
	(924.155)	(858.149)	(355.849)	(382.014)
Log(Population)	154.671	33.999	-16.927	-56.338
-	(152.089)	(157.609)	(83.584)	(76.081)
Median Household Income	0.025	0.022	0.029*	0.022*
	(0.017)	(0.019)	(0.009)	(0.010)
Black Share	1,359.542	$\hat{6}26.23\hat{5}$	$\hat{471.713}$	308.143
	(841.058)	(800.337)	(361.250)	(322.596)
GINI	11,777.250*	12,816.520*	8,738.471*	5,629.503*
	(4,301.903)	(3,671.825)	(2,543.635)	(1,899.954)
Consolidated Govt	304.504	2,877.525*	181.429	1,065.292*
	(428.360)	(467.020)	(190.560)	(210.387)
Constant	-1,949.800	-4,394.894*	-2,999.829*	-1,886.183*
	(1,987.896)	(1,881.059)	(835.641)	(804.259)
City FE	No	No	No	No
Year FE	Yes	Yes	Yes	Yes
Observations	2,031	2,031	2,031	2,031

 $^{^{\}ast}$ indicates statistical significance at the 0.05 level. Errors clustered on location.