The Weak Leviathan? Testing Partisan Theories of Political Influence on Defense Procurement in Congressional Districts: 98th-102nd Congress*

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Abstract

Analyses of federal spending across congressional districts have tended to ignore the institutional, geographical, and longitudinal context in which these districts are located. This neglects other sources of political influence, such as Senators, other representatives, party leaders, and Presidents. A decade-long data set (98th-102nd Congress, or 1983-1992) of defense procurement awards was collected and fitted to a Bayesian multilevel time series cross-sectional model. Partisan hypotheses from the modern literature on political determinants of federal spending are tested. There is little evidence that the Democratic party has been successful in steering defense spending towards Democrat districts, voters, members of the Armed Services committee, and Democratic state Congressional delegations–at a time period when Democrats were the Congressional majority and would have been expected to be able to do so.

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1 Introduction

The 2004 defense appropriations bill passed in August 2004 included a record 2,000 earmarks worth nearly $9 billion. These included three Piper airplanes for Montana, an artificial lung for Pennsylvania, and brown tree-snake eradication in Hawaii and the Pacific Islands (help for fisheries in Alaska was turned down). None of these items were requested by the Department of Defense. John McCain of Arizona, who prides himself a "pork-buster", didn't even bother to read aloud his speech opposing these earmarks. It also appears that these were financed by reductions in payments for military training and maintenance (Wheeler 2004*a*). Just 10 days after September 11, 2001, the National Defense Authorization Act included amendments which established the Fort Des Moines Memorial Park and Education Center, made improvements to the Rocky Flats National Wildlife Refuge, and altered contract arrangements at the US Army Heritage and Education Center at Carlisle Barracks, PA (Wheeler 2004*b*).

To what degree are members of Congress successful in influencing flows of federal benefits in general, and defense procurement awards in particular, to their particular geographic constituencies? Differences in the level of federal benefits across congressional districts are in fact real and enduring over time. Texas' 18th congressional district (CD), represented by G. T. "Mickey" Leland (Democrat), received $3,459 in total federal expenditures (in current, per-capita dollars) in the 98th Congress. New York's 23rd CD, represented by Samuel Stratton in the same Congress, received some $43,310. The histogram below counts the benefits (in expenditures per capita) received by all districts in the 98th-102nd congresses. The mean expenditure per capita was $9,258, and the median $8,339. These differences are all the more striking given that they include the large entitlement programs and are adjusted for population.

Furthermore, this variation is even more pronounced in the various subcategories of federal spending. Compare Minnesota's 7th CD represented by Republican Arlan Stangeland, which received a scant $9 per person in defense procurement dollars in the 100th Congress, with Virginia's 1st CD (Herbert Bateman, Republican), which enjoyed $18,048 in the same Congress. The median defense procurement award is $575, and the mean $1361.

One way of measuring the inequalities in geographic distribution of benefits is to calculate coefficients of variation, which is merely the standard deviation of a variable divided by its mean. A zero indicates completely equal distributions, and higher numbers are increasingly unequal. Table 1 shows that defense procurement is highly unequal in distribution across districts, at least in relation to general spending.

What causes these differences? Political scientists have examined political mechanisms for these disparities, looking at a number of factors. These include the electoral connection (Stein

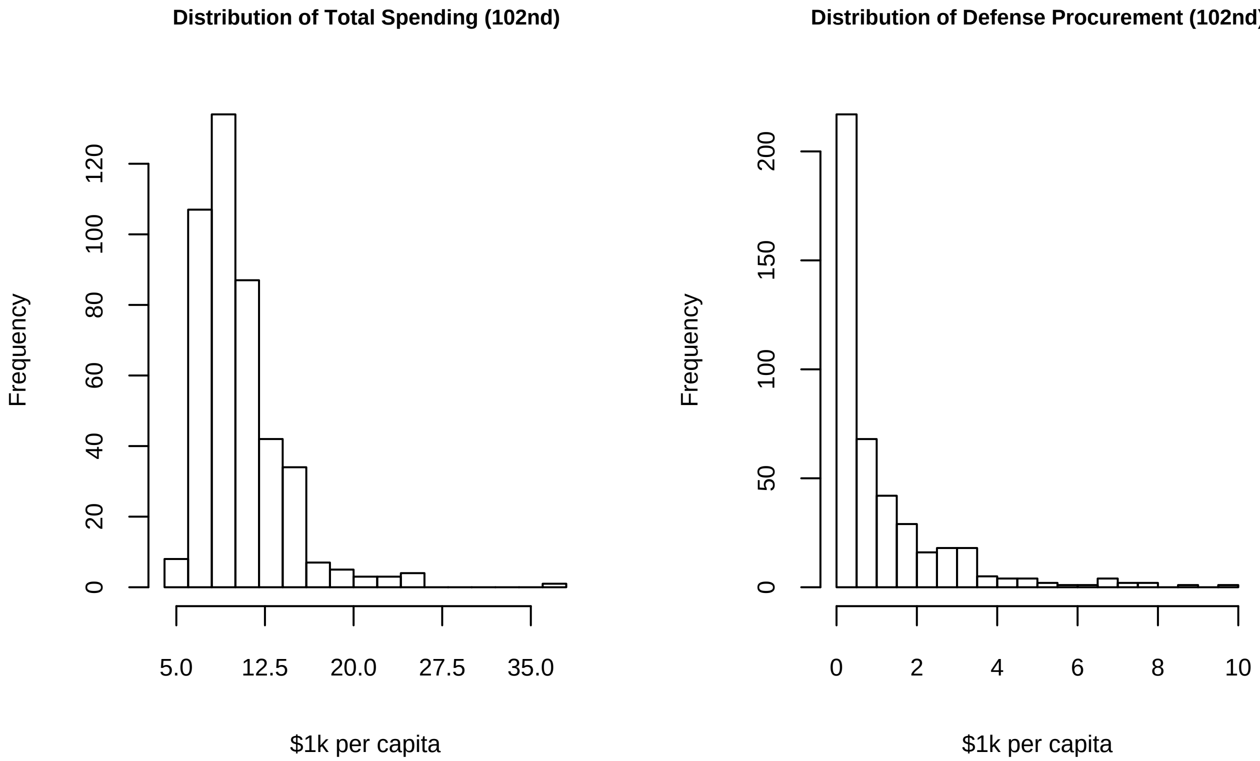

Figure 1: *Histograms of total federal spending and defense procurement spending across congressional districts in the 102nd Congress.*

and Bickers 1995; Alvarez and Saving 1997), the institutional structure of Congress with its committees encouraging distributive log-rolling (Arnold 1979; Ray 1980; Weingast and Marshall 1988; Rich 1989; Shepsle and Weingast 1995). Less work has been done to apply theories of partisan influence to distributive policies (Levitt and Snyder 1995; Bickers and Stein 2000; Rundquist and Carsey 2002).

One fundamental problem with the existing literature is that these analyses have tended to ignore the institutional and geographical contexts in which these districts are located. That is, districts are viewed atomistically, separate from the states in which they naturally belong, or the time-period they exist in. To the extent that these influences matter and vary in their importance geographically, district measurements naturally "cluster" and are clearly non-independent. Analyses that ignore this clustering effect have biased estimates of the true influence of individual representatives.

One way of taking these multiple contextual sources of influence into account is a multilevel model design. Such an approach, advocated for example by Steenbergen and Jones (2002), easily

Spending Type	Coefficient of Variation
Defense Procurement	1.32
Defense Employment	1.84
Civilian Procurement	1.86
Civilian Employment	0.68
Total Spending	0.35

Table 1: *Variation in Disparities, 102nd Congress*

handles data at multiple levels of analysis. The natural hierarchy of districts being located within states, while simultaneously 'belonging' to various time periods, can easily be incorporated into a hierarchical model. In turn, Bayesian inference provides a well-developed method of estimating these models. Bayesian hierarchical or multilevel models are also rather well suited to time series cross-sectional data (Western 1998), common in the spending literature.

To test extant theories of congressional influence on federal spending, I build a new time-series cross-sectional data set that uses the rich and almost unutilized expenditure data found in the Consolidated Federal Funds Report (CFFR). This expenditure data is much more comprehensive than the much more commonly used Bickers-Stein Federal Awards Assistance Data (FAADS), as I explain in section 4.1. Specifically, I use CFFR data on defense procurement awards, which is not present in FAADS. The multilevel data innovation I employ means that I directly incorporate information at four levels of analysis (district-congress, district, state, and state-congress).

I find little support for the numerous partisan hypotheses present in the literature. In fact, one striking finding is that districts with larger numbers of Democratic voters have tended to do worse in terms of defense spending. The lesson of this paper is that a more complex and structured analysis of congressional district data is warranted in testing theories of political influence on federal spending.

1.1 Why defense procurement?

The flexibility of the multilevel data set created for the larger project is that any spending category can be chosen, at any level of aggregation. Using defense procurement in this paper as an outcome variable of choice is worthwhile on a number of grounds. Such spending is quite big. In fiscal 2001, defense procurement contracts totaled $149 billion, a not insignificant amount. Furthermore, Wheeler (2004*b*) claims that politically-motivated procurement decisions come at the expense of critical readiness resources. Defense procurement decisions literally have life-and-death consequences, and thus costs more than money are involved when such decisions are made on technically inappropriate criteria such as distributive politics.

There is strong controversy about whether defense procurement is in fact politically influenced or not. On the one hand, the large sums of money and number of jobs associated with military procurement make it natural for politicians to be interested in influencing fund flows. Furthermore, politicians always claim that their efforts help win new contracts and defend old ones.

On the other hand, many analysts of military procurement have noted a lack of significance for political variables (Goss 1972; Mayer 1991; Rundquist and Carsey 2002). Mayer argues that "the Pentagon does not, indeed can not, distribute defense contracts (as opposed to bases) for political purposes. Political explanations of contracting decisions describe neither process nor outcomes adequately." (Mayer 1991). In terms of partisan influence, Arnold (1979) argued that this was unlikely in the context of defense spending because incohesive parties limited their ability to be important in disciplining agencies who had control over the geographic distribution of government goods.

This skepticism about whether distributive politics are actually operative in defense procurement stems from several sources. One reason is institutional. Defense procurement decisions ("source selection") are made within the context of institutional safeguards.[1] Essentially, decisions are said to be made on policy, rather than political grounds. Second, the national security context of defense spending enforces a high barrier for competence, as the downside to shoddy products made by politically-connected insiders could be very high (Goss 1972). Empirically, the evidence of political effects has been mixed (Owens and Wade 1984; Rundquist and Carsey 2002).

So is there room for politics at all in influencing defense decisions over geography? Mayer (1991) argued that politics is operative in the arena of military employment and bases, simply because institutional barriers are lower to political interference and lobbying by politicians. Yet, since these barriers are enacted and maintained by Congress itself, one wonders how exogenous they really are. Furthermore, as Mayer admits, contractors themselves quite often choose subcontractors from locales to maximize political influence in Washington. It is common for major weapons systems to be produced by contractors located far and wide, or narrowly in important geographic constituencies. Luckily, my data source allows me to track exactly where money is appropriated for use, rather than merely where the prime contractor is located.[2]

[1] These include the Federal Acquisition Regulation (FAR), implemented in 1983, amendments to this regulation (Mayer 1991, 137), and regulations of individual branches of the military. Award decisions can be appealed at various levels, both administratively and judicially.

[2] The [CFFR] collects procurement statistics on a quarterly basis from most federal government departments and agencies, and provides these data according to the place of performance rather than the location of the prime contractor (Bureau 2003).

2 Literature

The modern concept of distributive politics–the study of who gets what national resources and why–in the academic literature can be traced to Lowi (1964) and Mayhew (1974). Lowi wrote that distributive policies like defense procurement "are characterized by the ease with which they can be disaggregated and dispensed unit by small unit .... These are policies that are virtually not policies at all but are highly individualized decisions that only by accumulation can be called policy. They are policies in which the indulged and the deprived, the loser and the recipient, need never come into direct confrontation (1964:690)". Mayhew argued that politicians used the tools of incumbency to deliver federal spending to their constituents in order to claim credit during the re-election campaign."How much particularized benefits count for at the polls is extraordinarily difficult to say, but it will be hard to find a Congressman who thinks he can afford to wait around until precise information is available. The lore is that they count.(1974:57)".

The field of distributive politics has been dominated by analyses of Congress, where massive geographic differentiation of states and districts seems to have created natural conditions for log-rolling behavior. This same rich variation begged for analysts to use it to explain public policy outcomes. Indeed, a rich spending literature arose which sought to answer why various members of Congress appeared to have varying ability to deliver the goods to their districts.

One obvious place to look in explaining patterns of distributive politics is partisan factors. Arguments about the consequentiality of American political parties have raged for many decades in political science. Most recently, Cox and McCubbins (1993); Aldrich (1995) argued for the leading role of majority political parties, while Krehbiel (1998) took the opposing view. Yet much of the debate has been mostly theoretical or tied to roll call voting in Congress. These are certainly important. Much of the argument has ignored actual policy outcomes, however, which is ultimately what we ought to be concerned about.

2.1 Geographic Distribution: Party and Legislators

Do Democrats and Republicans differ systematically in their ability and willingness to provide distributive benefits for their districts? The electoral connection of Mayhew (1974) would seem to suggest there should be no difference on the subject of pork between the left and the right, as both are eager to do what is necessary to get re-elected.

But while individual propensity for local benefits may not differ, the opportunities for gathering those benefits may in fact vary according to a legislator's party. Party could matter in geographic distributive politics if majority party privileges translated into easier access to federal largesse. In other words, the party caucus represents a coalition that provides selective benefits to members.

Recent empirical work shows some support for these claims, though not in the defense context. Balla et al. (2002), in a study of academic earmarks, find that districts represented by majority party House members received higher levels of these expenditures than those represented by the minority, though the number of these awards tended not to vary between the parties. Alvarez and Saving (1997) find some evidence that majority party status has contributed to higher spending for Democratic districts, at least for the 101st Congress.

In sum, the very simple hypothesis follows from these lines:

H1: Districts represented by Democrats will benefit more than those represented by Republicans.

2.2 Geographic Distribution: Party and Voters

The empirical literature on party and expenditures includes work on several levels. At the aggregate level, do Democratic majorities behave differently than Republican majorities at the level of overall budgets and appropriations? Since dollars are the clearest possible signal of policy priorities, to the extent that Republicans and Democrats have different party platforms and aggregate ideological differences, we might not be surprised that dollars requested and spent change as Democrats or Republicans come to control Congress.

Empirically, there has been some evidence that Democrats and Republicans choose different spending priorities at the budgetary level. (Kiewiet and McCubbins 1991) presents evidence that Democratic Congresses have significantly cut down on presidential appropriations requests for defense, and while increasing budget resolution amounts for nondefense spending. Su, Kamlet and Mowery (1993) found that increasingly Democratic-dominated congresses lead to higher entitlement and discretionary spending, and lower spending on defense. Bickers and Stein (2000) established that Republicans and Democrats were generally as likely to engage in pork-barrel politics. However, while Democrats generally preferred spending on entitlements in their reign, Republicans tended more towards contingent liabilities expenditures. This is a consequence of the different constituencies for the two parties.

Yet these studies do not speak to the topic at hand. The Democratic caucus may well desire overall lower levels of defense spending, but within the context of a given pool of dollars, it would be difficult to believe they were willing to cede money to Republicans.

Levitt and Snyder (1995) found that partisan factors accounted for some of the geographical distribution of federal expenditures, despite the presence of divided government and preference conflicts within the majority party. Specifically, Democrats were partially successful in the late 1970s–at the height of their ascendance and after a long tenure as the majority party–in creating federal programs designed to aid Democratic voters. The majority party, in other words, was able to discriminate on a programmatic, not geographic, basis.[3] They find evidence that the Democrats, during their long tenure as the majority party, were able to create new programs that disproportionately benefited Democratic voters. For these programs, the number of Democrats in a district is highly correlated with the amount of expenditures.

In short, if Democratic majorities in the 1980s could translate into disproportionate benefits for programs that tended to favor their core constituencies, we would expect that those geographic constituencies would do better over the time period than comparable Republican ones.

H2: Districts with predominantly Democratic voters should benefit more than those with predominantly Republican voters.

Similar to Levitt and Snyder (1995), I measure districts' support for the Democratic party by averaging the Democratic share of the presidential elections in the 1984 and 1988 elections. This is a better measure of the Democratic proclivities of individual districts because congressional elections are influenced to some degree by incumbency.

2.3 Delegations

Perhaps membership in the majority party works its effects at a higher level of aggregation, such as the state delegation level. Thus, while Democrats might not be able to target individual districts, they may be able to target states that are represented by more Democratic delegations in the House and the Senate.

Another reason may account for the possibility of a majority party delegation benefiting from federal funds: it stands to reason that state delegations should cooperate with each other to bring benefits back home that cross district boundaries. This is because federal benefits are often assigned geographically in a way that crosses district boundaries. If a state delegation were overwhelmingly of the majority party, it might be better able to cooperate for the greater state good and get resources from Congress as a whole and the majority party caucus in particular.

The empirical record is small. Rundquist and Carsey (2002) did not find support for the notion that state Senate and House delegations that were more Democratic obtained any more

[3]Of course, insofar as voters are distributed non-uniformly across districts, programmatic discrimination in favor of Democratic voters will tend to lead to geographic discrimination.

defense contracts than those that were less so.

H3: States with House delegations (Senate or House) dominated by the majority party (Democrats) will do better in regards to expenditures.

2.4 Parties and Committees

It could be the case that parties structure or affect the way committees advantage their members in terms of defense expenditures. In other words, membership on a committee may not tell us all we need to know with regards to institutional advantages offered by it. Since the majority party selects the chairman of the committee and receives a majority on it, they are entitled to significant agenda control power.

Carsey and Rundquist (1999) and Rundquist and Carsey (2002) conclude that Democratic members of the House (and Senate) Armed Service committees obtain more benefits for their constituencies than do Republican members of those committees. Thus, membership on such committees is not sufficient in and of itself to benefit districts. Majority party membership on such committees is the critical ingredient.

This line of argument can be summed up as an interaction:

H4: Democrats on the Armed Services Committee will do better than Republicans on that committee.

2.5 Political Controls

I include controls for seniority (number of years served in Congress), as well as party and committee leadership (both minority and majority party).

Since districts belong in states, and states are the primary geographic units in the federal system, it makes sense to include Senate and presidential predictors in the model. After all, the hierarchy of the federal government means that presidential politics should affect districts just as they do states. Consequently, I include partisan and electoral hypotheses for both the president and the Senate.

For the Senate, I include the partisan composition of the Senate state delegation. For the President, I include the average winning margins for the President across states.

2.6 Other Controls

The most important control for defense procurement is including the number of major military installations in a district. This is because much spending is local, and these installations will likely demand many expenditures.

I include a host of demographic and fiscal controls to account for the differing abilities of districts to accomplish defense procurement goals of the Pentagon. These include the urbanization of the district, its location near a coastline, its population, and its income level. State-level controls include state wealth and geographic area.

Given the proximity of the Pentagon in Washington, DC to a number of congressional districts in Maryland and Virginia, I expect these districts to get a larger quantity of procurement dollars than others further away. I also control for districts which contain state capitol, as these are sometimes advantaged by federal policies which shunt distributive benefits through the states.

3 Accounting for Context

3.1 How to Account for Context

Single members of the House represent congressional districts, but the federal policies that affect these districts frequently spill across geographic boundaries. In the context of federal procurement this can mean a number of things: a procurement winner that straddles district lines, subcontracting of work to nearby companies in other districts, or simply the commuting of citizens from non-winning areas where they live to winning districts where they work.

In addition, these districts are embedded in states that are represented by two senators and a President; plus a federal agency (Defense) that has no geographic limitations to its policy jurisdiction. Levitt and Snyder (1997) write "the inflow of federal funds to a district is affected by the decisions of a large number of actors, not simply by a representative acting in isolation."

Decisions about locating defense contracts may be much more affected by decisions at the state level than the district level. Furthermore, the spillovers of district benefits onto neighboring districts limits credit-claiming opportunities by MCs and thereby decreases their incentives to labor on their district's behalf. On the other hand, spillovers may encourage intrastate cooperation between Representatives, regardless of party.

Few analysts have attempted to come to grips with the context issue. Levitt and Snyder (1997) were among the first to identify the inherent externalities that accompany federal policies whose impact crosses district boundaries. Not accounting for this externality was a form of omitted variable bias.

Lee (2003) argues that because districts are merely electoral rather than administrative, the persistent lack of findings in the distributive politics literature come as no surprise. She instead chooses to study congressional earmarks because these policies are more directly attributable to individual MCs, and finds significant political effects.

Bickers and Stein (1999) found that a high density of governmental jurisdictions led to greater awards to individual districts. New awards and dollars flowed more strongly to those districts that were in closer proximity to others. This finding was, however, conditional on the type of program and the party of the district's representative.

Milligan (2003) argued that large district areas lowered the possibilities for spillover, and increased the incentive to free-ride on neighboring districts' federal benefits. Including district area in his model of defense procurement decreased the effect of Senate malapportionment.

These authors use interesting methodological approaches to address the lack of context information in older models of distributive politics. Perhaps the intuitionally simplest approach of all is to include information about the context in the model itself. Creating such a multilevel model is the approach of this paper.

3.2 Why district level?

Rundquist and Carsey (2002) argue that a state level analysis of defense procurement is superior to a district-level analysis for several reasons. First, data availability on defense procurement awards is better for states than for districts. This is because government statistics record awards to states for a considerably longer period. In addition, state boundaries do not change after a decennial census, unlike districts. Finally, states constitute more "meaningful" political subdivisions. This is a point made by Lee (2003).

These points are valid ones and point to real problems with using district-level data, but they do not obviate the need for such an analysis. At most, these critiques demand that a district-level analysis not be done as a mere substitute for a state-level analysis.

Let us examine each of these objections in turn. It is true that the CFFR data for counties (and by extension districts) exists only since 1983. It is also the case that reapportionment clearly demands that district-level analyses be performed at most within a decennial period.

These facts make our lives as scholars more difficult, but data availability problems ought not dictate our questions. It is also the case, however, that what district data lacks in longitudinal variation, it makes up for in cross-sectional variation. After all, there are 435 congressional districts, and only 50 states. Because of aggregation, it is inevitable that districts are far more diverse cross-sectionally than states. Furthermore, because defense procurement is so heavily trended, cross-sectional variation is in some sense more desirable than longitudinal variation.

Because the government does not report procurement data by congressional district, we have to employ some method for translating existing county data to congressional districts. Most of the time, we simply add the awards for each county that composes a given congressional district to get a total district award figure.

Since counties sometimes cross-district borders, the question arises of how to allocate county awards to these districts. The method employed in this paper is to divide those awards among the various districts by weighting the awards by weighting by population. For example, Jefferson County in Alabama has 537,179 (or 82.4%) of its residents present within the 6th congressional district, and 114,346 (or 17.6%) in the 7th. If Jefferson County is given $1000 of military procurement, we would credit the 6th district with $824 and the 7th with $176.

How prevalent are these split counties? In the 98th-102nd congresses, 77% of counties were wholly contained within a single congressional district, while 23% of counties were split. The mean "split" amongst counties (not adjusted by population) is 86%. Within split counties, the median population was 62,358, while non-split counties had a median population of 19,226.

There will be inevitable measurement error in this approach. Nevertheless, we know that measurement error in the dependent variable does not lead to biased or inconsistent estimates, as long as the error is independent. The consequence of such measurement error is rather in inflating standard errors and thereby missing potentially significant predictors.

Traditional methods of performing district-level analyses have flaws. Most of them have been done as single cross-sections, ignoring the dynamics of the distributive politics process, and inadvertently lowering the sample size. Even more importantly, they have not taken account of the political 'action' occurring at the state level. That is, they have ignored context effects. A multilevel model allows us to simultaneously estimate the effect of predictors at the individual level (here, district-years), while accounting for the spatial and longitudinal context that a particular observation is contained within.

Another reason to want to do a district-level analysis is the nature of representation. Since states are represented by Senators elected at-large, studying Senatorial delegations makes more sense than doing so for the House. Unlike the Senate, individual Representatives represent discrete geographical constituencies. This 'monopoly' on representation gives them an undeniable amount of responsibility for policy consequences in that district. Of course, these policies occur in the context of Senate and presidential, not to mention agency, authority.

Furthermore, the aggregation inherent in doing a state-level analysis blurs the effects of institutional, partisan, and electoral motivations on individual members of congress. The micro-theories underlying these explanations are premised on MCs as individuals engaging in instrumentally rational behavior. Coalitions based on party or ideology make sense because they are chosen by individuals. Of course, geographic coalitions-say intrastate cooperation by a House and/or Senate delegation, aren't chosen and are obviously important. They should be treated as context, or group-level effects. Testing these theories should be at least attempted on the individual level, subject to data limitations.

Finally, aggregation inevitably entails the loss of intrastate cross-sectional and longitudinal variation. Nydia Velazques (D)'s 12th Congressional District in New York City and Vito Fossella's (R) 13th in Staten Island are rather different. Sample size is severely restricted, making it more difficult to test theories of political behavior.

4 Data

The advantage of a multilevel model is its ability to directly incorporate data at multiple levels of analysis, at the cost of increased complexity. The multilevel data set in this paper information at four levels of analysis: the individual-level (district-congress) and three group levels (districts, states, and state-congresses). The outcome variable is measured at the individual (district-congress) level.

The individual-level data is assembled as a time-series cross section with 435 congressional districts over 5 congresses (the 98th to the 102nd, or 1983-1992). This time period was selected because it entailed no large-scale redistrictings, which would undermine any attempt to trace political effects to individual House districts.

This corresponds to an era of divided government, with Democratic political control of the House and Republican control of the presidency. Models dropping uncontested elections did not change the results.

Time is measured in Congresses rather than years because data on districts is far less available than that for states. Indeed, much demographic information is only available only every decennial census. A ten-year or five-congress period was selected because the constituencies are different across redistrictings. It would not make much sense to analyze spatial data across constituencies that change geographic boundaries.

On the other hand, I have numerous data at other levels of analysis that conditions and

Table 2: *Data Hierarchy*

Name	Level	Description	Observations
District-Congress	Individual	Time-series cross-section of all congressional districts in 5 Congress (98th-102nd Congress)	2175
District	Group	Time-invariant cross-sectional data on all congressional districts	435
State	Group	Time-invariant cross-sectional data on all states	50
State-Congress	Group	Time-series cross-section of all 50 states over 5 Congresses	250

structures that individual-level data. The first group-level data that I have is time-invariant data on the districts themselves. For this, I have 435 observations. The second is time-invariant data on the states. The data on the states is taken from Shor et al. (2003), and restricted to this given time range. Finally, I have time-series cross-sectional data on states over this time period.

4.1 Description of Dependent Variable

The outcome variable I will be examining is the per-capita federal spending amounts on defense procurement across all congressional districts over the course of five Congresses (98th-102nd). Expenditure data was obtained from the Consolidated Federal Funds Report (CFFR), which collects data from Federal agencies for spending in the entire United States. The CFFR is a superset of the more commonly used Federal Awards Assistance Data (FAADS) (Bickers and Stein 1998), a commonly used data set in the distributive politics literature. FAADS excludes, for example, procurement and wage information, two large portions of the federal budget. Levitt and Snyder (1995)[964] note that "the absence of data on military procurement and wages [in FAADS] is unfortunate, because there may be significant differences in the distributions of military and other expenditures."

Since there are wide variations in this spending total, I took the natural log of the per capita spending amount to smooth out these big differences.

4.2 Explanatory Variables

The control variables were taken from the Census Bureau's Current Population Survey (CPS), an annual survey that gathers data on nearly 100,000 individuals across all states. Data was aggregated at the district level. The data is chiefly composed of demographic and employment variables, though some voting questions are asked biennially in November in the "Voter Supplement File" (Census Bureau, 1983-2001). Income data is from the Bureau of Economic Affairs. Presidential vote totals were taken from Congressional Quarterly.

5 Methodology

The data for this paper is time-series cross-sectional in nature, a form increasingly popular in political science research. It allows analysts to increase the number of observations to analyze complex models as well as taking account of dynamics. On the other hand, it is also accompanied by a host of well-studied difficulties (Stimson 1985).[4]

I employ a multilevel model here. Multilevel modeling accounts for the variation in an outcome variable measured at the lowest level of analysis, while using explanatory information from that level as well as others (Steenbergen and Jones 2002).[5] In short, multilevel modeling allows the researcher to combine data sources from multiple sources directly (Gelman N.d.). A two-stage regression is a similar, though clumsier, way of integrating such data(Gelman 2005*b*,*a*).

Multilevel models have been introduced and applied in multiple contexts in political science research (Gelman and King 1993; Western 1998; Steenbergen and Jones 2002).[6] These models incorporate data at multiple levels of analysis to yield a best fit. For example, states and years can be modeled to predict presidential electoral outcomes (Gelman and King 1993), individual and state-level covariates can be simultaneously modeled to predict issue attitudes by state (Park, Gelman and Bafumi 2004), or individuals, nations and parties can be modeled to predict support for European integration (Steenbergen and Jones 2002).

To estimate the multilevel model, I employ Bayesian inference. This is done using Markov Chain Monte Carlo (MCMC) methods and, specifically, a Gibbs sampler contained within `WinBugs`. Essentially, the Bayesian framework combines prior (non-sample) information with sample data to produce a posterior distribution of parameter estimates. The mean and standard deviation of this distribution is then comparable to OLS and maximum likelihood parameter estimates. See Gelman et al. (2003); Jackman (2000*a*,*b*) for introductions to this methodology.

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[4]These include (1) serial correlation, (2) heteroscedasticity, and (3) contemporaneous correlation. First, due of the time-series aspect to TSCS data, the errors are serially correlated. Second, the assumption of homoscedastic (equal) variances on the error term is violated. The source of this is usually unit heterogeneity, especially when there is large variation on the dependent variable. Third, errors can violate the assumption of cross-sectional independence. That is, errors can be correlated across cross-sectional units (or panels) within time. This is usually due to common shocks felt across all units, or to unmodeled relationships between units.

[5]This approach was popularized in educational research, where it was used to explain the variation in student performance using student-level information as well as school-level variables (Raudenbush and Bryk 1992).

[6]Also see a forthcoming edition of *Political Analysis* devoted to the analysis of multilevel data sets.

Common approaches to TSCS data (e.g., Beck and Katz (1995); Kristensen and Wawro (2003)) have some difficulties. They are often asymptotic in time, which is problematic when the time period is small (Beck 2001). The Bayesian approach has a more reasonable assumption about the variability of estimated parameters and the fixed, nonstochastic character of the data (Western and Jackman 1994). Estimation of slow-moving and time-invariant predictors–a common situation in such data–is easier in the Bayesian framework (Western and Jackman 1994; Western 1998). Bayesian methods allow us to estimate varying intercepts for *all* the units in the sample, rather than arbitrarily dropping one. Bayesian methods allow for easier estimation of multilevel models, which are often very difficult to fit with maximum-likelihood-based estimators.

The multilevel structure of TSCS data makes "partial pooling" an optimal estimation strategy by borrowing strength from the various levels. The traditional alternatives to multilevel modeling are "no pooling" (e.g., fixed effects) - running regressions in each context; and "complete pooling" - ignoring difference between groups. Both approaches have problems. No pooling assumes that varying contexts make individual-level observations completely noncomparable, a very strong assumption. It can give unacceptably variable inferences. No pooling is especially problematic here as there are only 5 observations per district, given the number of Congresses in the sample. Complete pooling suppresses variation that can be important, and carries the extremely strong assumption that context is irrelevant, and that micro-level variation is all-important. Partial pooling is a compromise between the two extremes. (Gelman et al. 2003).

Most importantly, under quite general conditions, the BML approach offers performance advantages. In other work (Shor et al. 2005) I show with Monte Carlo simulations that compared with the most commonly employed estimators for such data, I find that the Bayesian multilevel model is (1) equally unbiased on average, (2) considerably more efficient, and (3) reports higher quality standard errors. Moreover, the BML is more general and flexible, which offers researchers additional advantages for TSCS data.[7] The Appendix shows a comparison of various estimators for the model presented here.

5.1 The Multilevel Model

The general form of the multilevel model is the following:

$$y_{it} = \alpha_i + \gamma_j + \delta_k + \tau_t + \lambda_j t + (X\beta)_{it} + \epsilon_{it} \tag{1}$$

[7] Unfortunately, MCMC methods are extremely computationally-intensive, often hundreds of times slower than their classical counterparts. This cost is falling over time, as computing hardware and software improve and cheapen thanks to Moore's Law.

$$\text{where } \epsilon_{it} \sim N(0, \sigma^2_{\epsilon(i)}).$$

Where y_{it} stands for estimated spending in a given district i (1 to 435) and congress t (1 to 5, or the 98th to 102nd). j is a state indicator (1 to 50). X is the matrix of district-congress predictors and B the coefficients to be estimated. j is the estimated time trend (or slope) of spending for the state of the given district-congress. It is a linear trend in time t. This is the corrective for the autocorrelation present in budgetary data, which allows for a separate trend for every state.

α is the indicator for district i (1 to 435), γ is an indicator for state j (1 to 50), δ is the indicator for state-congress k (1 to 250), and τ the indicator for congress t (98 to 102).

To take account of the varying variability of the errors across units (panel heterogeneity), $\sigma^2_{\epsilon(i)}$ is subscripted i, indicating the estimation of a new error variance parameter per state.

The multilevel nature of the model is revealed in the α, γ, δ, and τ terms. The varying intercepts for districts, states and state-congresses are themselves outcomes with means and variances that are estimated, allowing for the partial pooling described above.

$$\alpha \sim N(\mu_\alpha, \sigma_\alpha), \mu_\alpha = (Um), \sigma_\alpha \sim U(0, 1000) \tag{2}$$

$$\delta \sim N(\mu_\delta, \sigma_\delta), \mu_\delta = (Wp), \sigma_\delta \sim U(0, 1000) \tag{3}$$

$$\gamma \sim N(0, \sigma_\gamma), \sigma_\gamma \sim U(0, 1000) \tag{4}$$

$$\tau \sim N(0, \sigma_\tau), \sigma_\tau \sim U(0, 1000) \tag{5}$$

They are normally distributed with means derived from the product of the matrices of district- and state-congress-level data (U, W) multiplied by the district- and state-congress-level predictors (m, p). Their group-level variances σ_α, σ_γ, σ_δ and σ_τ are random (which is what makes this a random coefficient model), and are given very vague and uninformative uniform priors.

These indicators are useful for two reasons. First, we can include the variation in the data unexplained by group-level predictors. Second, they allow us to explicitly control for the context effects of space and time. District, time, and state indicators allow us to control for the inevitable problems of contemporaneous correlation and heteroscedasticity in the data. The advantage of

Bayesian methods, as opposed to the more classic approach, is that collinearity does not prevent the estimation of any the indicators, even in the presence of time-invariant parameters.

Note that these group level indicators can be considered "random intercepts with fixed slopes" since they modify the individual-level constant but do not vary with the level of any individual-level parameters. The assumption here is that causal factors affecting federal spending do not differ in different districts and years. For now, this assumption seems reasonable enough, given the high similarity of districts to each other relative to cross-country comparative research.

5.2 Bivariate Correlations

Before we get into the results of the estimation, it is useful to examine the bivariate relationships between the outcome variable of logged per-capita defense procurement spending and the predictors chosen to operationalize the hypotheses.

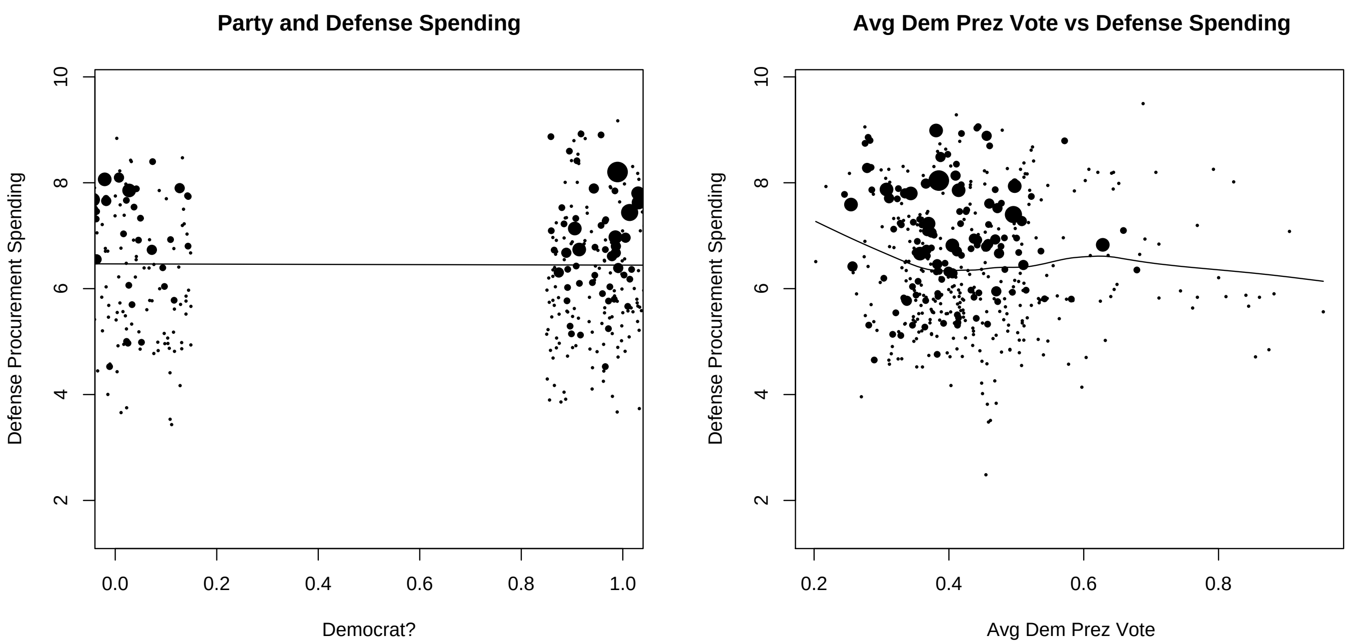

Figure 2: *Plot of actual logged defense procurement spending per capita versus (a) legislator party and (b) average Democratic presidential vote in each district of the 102nd congress. The estimated correlation is plotted as the slope of the line. The size of the points reflect the number of major military installations in that district. Party is coded as 1=Democrat, and is jittered for visibility.*

Figure 2 shows that the predicted relationships of Hypotheses 1 and 2 do not seem to hold, at least in a bivariate sense. From eyeballing the figure, it appears as if there is no relationship between legislator party and defense procurement spending, and that there is a slight negative relationship between the presidential party vote of the district and defense procurement spending. They also show that the number of major military installations do not seem to vary much by legislator party or constituency.

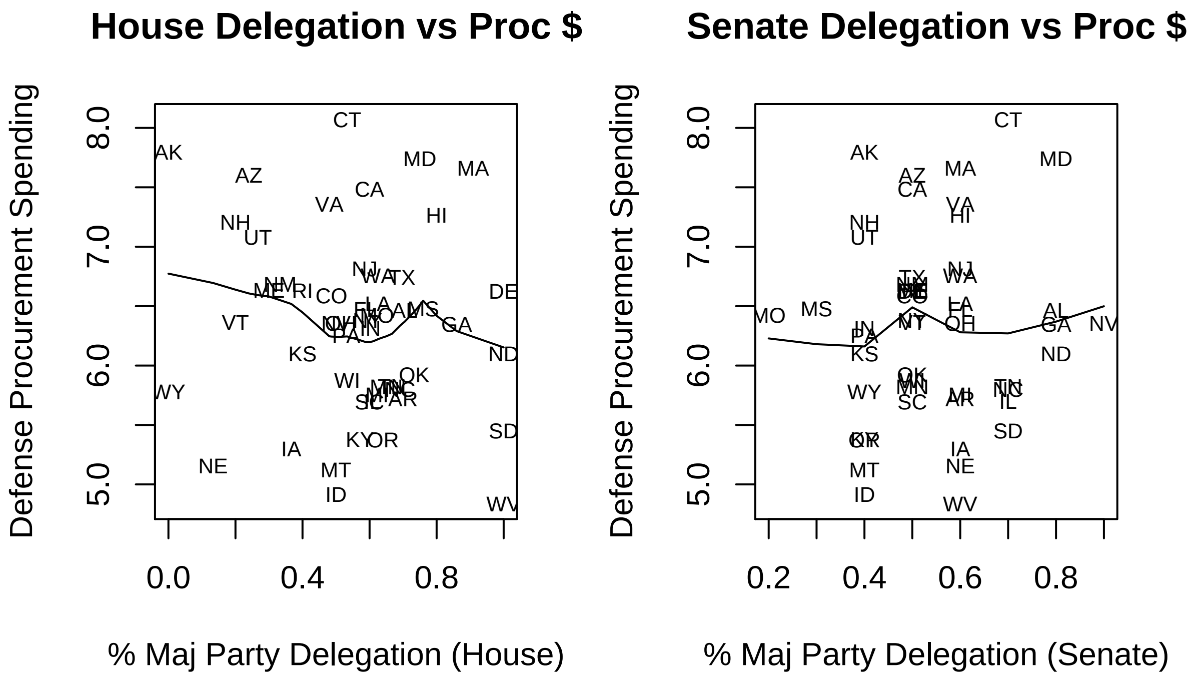

Figure 3: *Plot of actual logged defense procurement spending per capita versus (a) average proportion (98th-102nd congress) of the House state delegations that were members of the chamber majority party (b) average proportion of the Senate state delegations that were members of the chamber majority party. A lowess line is plotted.*

Figure 3 shows that the hypothesized delegation effects do not appear to hold. In the case of the House, moreover, it appears that–on average in this decade–increasingly Democratic delegations (for example, Delaware, the Dakotas, West Virginia, Georgia, Massachusetts) are associated with slightly lower defense procurement spending than Republican delegations (for example, Alaska, Wyoming, Arizona, New Hampshire, Utah, Vermont).

In sum, simple bivariate plots shed some doubt on the hypothesized relationships of party and distributive politics. This is not definitive evidence, obviously. For that, we turn to the estimation in the next section.

5.3 Estimation

The Bayesian multilevel models are estimated with Markov Chain Monte Carlo (MCMC) techniques as implemented in the `Winbugs` 1.4 software package (Spiegelhalter, Thomas and Best 2002). The model code is presented in the Appendix. The model was run with two chains of 35,000 iterations each. One-half of the iterations were discarded as a burn-in. The chains converged successfully for all the parameters of the model, as measured by the Gelman-Rubin-Carlin `Rhat` statistic. This statistic approaches 1 when a parameter achieves convergence in its multiple chains.

In this section, I will break down the results of the empirical model described in the last section. I will first describe the aggregate model fit and check the predictions of the model against the actual outcomes. Then, I will present and discuss the parameter estimates, along with showing graphical plots of the effect of the significant predictors.

5.4 Model Fit

The multilevel model's predicted defense procurement spending amounts per district-congress was checked against the actual 2175 measures of the dependent variable. The resulting plot is displayed below. The strong fit is shown by how closely the points are clustered around the 45-degree line. There appear to be very few outliers. The root mean squared error, a standard measure of model fit, is only 0.287.

The average Box-Jenkins autocorrelation coefficient was low, at -0.01, indicating that the linear time trend was effective at managing the severe autocorrelation present in the dependent variable.

Alternative estimators including simple OLS, OLS with panel-corrected standard errors, and fixed effects were employed as well. Results from these estimators are shown in the Appendix. Results were generally comparable, though as predicted, the standard errors of the classical estimators were too small for the group-level predictors.

5.5 Parameter Estimates

The following table summarizes the parameter estimates from the fitted models. Since the dependent variable is logged total expenditures in a given district-congress, the parameter estimates are fairly easy to interpret. A one-unit change in a predictor leads to an ex-1 percentage change in the dependent variable. For relatively small estimates (which most of these are), ex percentage is approximated by x percentage. For example, a -0.05 parameter estimate should

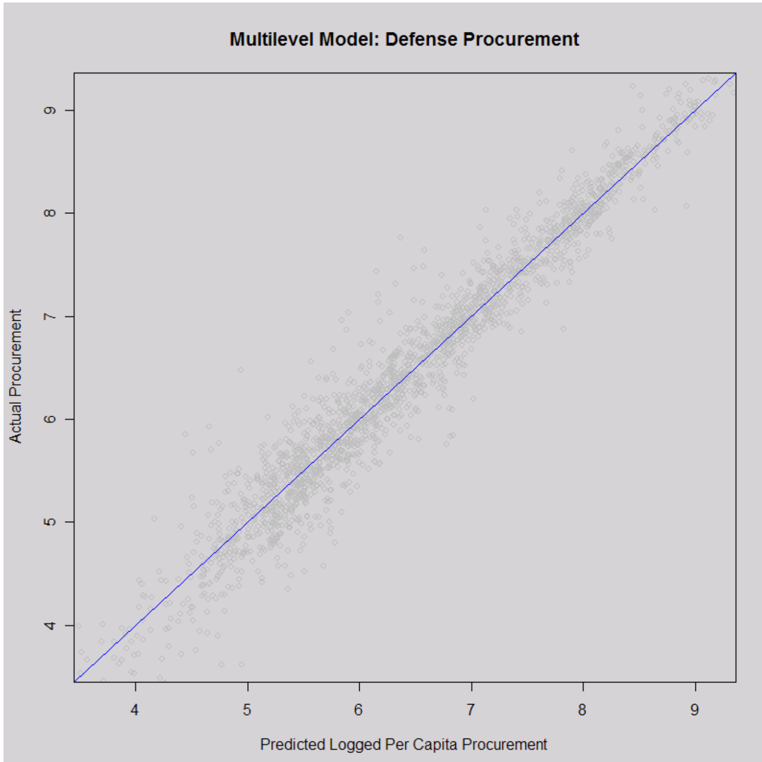

Figure 4: *Plot of predicted logged defense procurement spending per capita versus actual spending.*

be interpreted as meaning that the predictive effect for a one-unit increase in that variable is 5.1 percent less defense procurement spending per capita in a district-congress.

We can see in Table 4 only one of the estimated coefficients was statistically significant. The proportion of Democratic voters in a district is negatively related to district procurement awards. Democratic House members did not obtain more defense procurement money, state House and Senate delegations dominated by Democrats did not bring more money to their state, and Democratic members of the Armed Services committee did not do better than Republican members of the committee.

Turning to defense wages, do we see similar patterns? We can see in Table 5 that we do not. The more Democrats in a given district, the less the defense wage expenditures that are made, but the uncertainty of the estimate is high, so that 0 is included in a 95% interval. The other predictors are not significant.

Do these patterns exist in nondefense spending? Interestingly, Table 6 the pattern reverses itself. Democratic voters seem to be rewarded with grants spending by the majority party in this 10 year time period. Civilian procurement, on the other hand, (Table 7) does not show partisan effects.

	Mean	SD	2.5	97.5
constant	6.78	0.25	6.29	7.23
District Income (DC)	−0.72	0.23	−1.13	−0.27
Seniority (DC)	0.00	0.00	−0.00	0.01
Democrat (DC)	0.02	0.03	−0.05	0.08
Armed Svcs Comm (DC)	−0.01	0.05	−0.11	0.08
Dem*Armed Svcs (DC)	0.05	0.08	−0.10	0.22
Log Grants Per Capita (DC)	0.03	0.02	−0.01	0.07
District Avg Dem Vote (D)	−2.30	0.43	−3.12	−1.47
District Area (D)	−0.34	0.04	−0.41	−0.27
Proximity to DC (D)	1.52	0.45	0.61	2.41
District Coastal? (D)	0.06	0.11	−0.18	0.28
Milt Installations (D)	0.41	0.07	0.28	0.54
Foreign-Born Population (D)	−1.15	1.05	−3.20	0.92
State GSP (SC)	0.00	0.01	−0.03	0.03
House Delegation Maj Party (SC)	0.00	0.02	−0.03	0.04
Senate Delegation Maj Party (SC)	−0.00	0.01	−0.03	0.02
Prez Win Margin (SC)	−0.00	0.02	−0.05	0.04
Log State Population (SC)	0.00	0.01	−0.03	0.04
N	2175			

Table 3: *Outcome variable: logged defense procurement expenditures. Multilevel model posterior estimates: mean, standard deviation, and 95% interval. DC = individual level of analysis (district-congress); D = Time-invariant district level of analysis; SC = State-congress level of analysis.*

5.6 Predictive Effects

We can examine further the effect of individual predictors on the outcome variable, controlling for the effect of the other predictors. One effective expository method of doing this is using predictive plots. Here, the outcome variable is plotted on the y-axis and the variable of interest is plotted on the x-axis. The slope of the plotted line represents the effect of given predictor on the calculated prediction of the outcome. The values (not the slopes) of the other predictors are held at their means. Consequently, these plots are intuitive in the sense that one gets a feel for the direct effect of the predictor on the outcome for the actual range of values of the predictor.

The number of Democratic voters hypothesis proved significant, but in the 'wrong' direction according to Levitt and Snyder (1995). The number of such voters, as proxied by the average Democratic presidential vote share in 1984 and 1988, is negatively associated with district benefits. A one standard deviation (.12) increase from the mean of this variable (.44) results in a drop of spending of nearly 25%, or some $319 per capita, quite a large substantive effect.

This result is very odd, given our expectations of Democratic gain in this time period of nearly

	Mean	SD	2.5	97.5
Democrat (DC)	0.01	0.03	−0.05	0.08
Dem*Armed Svcs (DC)	0.05	0.08	−0.10	0.21
District Avg Dem Vote (D)	−2.37	0.49	−3.38	−1.43
House Delegation Maj Party (SC)	0.00	0.01	−0.03	0.03
Senate Delegation Maj Party (SC)	−0.00	0.01	−0.03	0.02
N	2175			

Table 4: *Outcome variable: logged defense procurement expenditures. Multilevel model posterior estimates: mean, standard deviation, and 95% interval.*

	Mean	SD	2.5	97.5
Democrat (DC)	0.01	0.01	−0.01	0.02
Dem*Armed Svcs (DC)	−0.03	0.02	−0.08	0.01
District Avg Dem Vote (D)	−0.80	0.61	−1.85	0.24
House Delegation Maj Party (SC)	0.02	0.02	−0.01	0.07
Senate Delegation Maj Party (SC)	−0.02	0.01	−0.04	−0.00
N	2175			

Table 5: *Outcome variable: logged defense procurement expenditures. Multilevel model posterior estimates: mean, standard deviation, and 95% interval.*

dominant Democratic control of Congress. Potential explanations, to be explored later, include several possibilities. The first is that Democrats' policy priorities were for nondefense policy areas at the expense of defense spending. Yet, given an agreed spending pie (the size of which should be affected by these priorities), why should Democrats have acquiesced in benefiting Republicans geographically, rather than their own voters? Second, we may be seeing the effect of prime contractors who are strategically distributing subcontracts to important districts, which happen to be dominated by Republican voters. Third, the President himself, or the Department of Defense, may be systematically pushing procurement awards to Republican voters. Finally, there may be an issue of endogeneity, where procurement awards may actually be creating Republican voters. These alternative explanations remain to be explored in future work.

Given the expectation by Mayer (1991), we might think that defense employment expenditures would be far more likely to be manipulable than defense procurement. But that isn't the case.

Contrast this with grants, where the majority party appears able to direct expenditures towards its voters. However, Democrats themselves seem to do just very slightly worse (about 5%) than Republicans for grants spending.

	Mean	SD	2.5	97.5
Democrat (DC)	−0.05	0.03	−0.10	0.01
Dem*Armed Svcs (DC)	−0.02	0.07	−0.15	0.11
District Avg Dem Vote (D)	1.56	0.27	1.02	2.10
State GSP (SC)	0.05	0.03	−0.01	0.11
House Delegation Maj Party (SC)	−0.03	0.06	−0.17	0.08
N	2175			

Table 6: *Outcome variable: logged grants expenditures. Multilevel model posterior estimates: mean, standard deviation, and 95% interval.*

	Mean	SD	2.5	97.5
Democrat (DC)	0.03	0.04	−0.05	0.10
Dem*Armed Svcs (DC)	−0.01	0.11	−0.21	0.19
District Avg Dem Vote (D)	−0.04	0.16	−0.40	0.24
House Delegation Maj Party (SC)	−0.03	0.06	−0.17	0.06
Senate Delegation Maj Party (SC)	−0.02	0.03	−0.08	0.03
N	2175			

Table 7: *Outcome variable: logged civilian procurement expenditures. Multilevel model posterior estimates: mean, standard deviation, and 95% interval.*

5.6.1 Controls

Procurement awards appear to be redistributive, as lower procurement awards are granted to richer districts. Districts close to DC get larger procurement awards, as do increasingly urbanized districts. DC-adjacent districts received nearly five times the procurement awards that non-neighbors did, while completely urbanized districts received more than six times the awards than the most rural of districts. Income, proximity to the capitol, and urbanization all tap into district capacity. However, state wealth, as measured by GSP, was not significant in modifying district awards, nor was the presence of a coastal body of water.

In an analysis of military and federal employment, Milligan (2003) argued that spillovers in small districts created disincentives for representatives to work hard for federal benefits. Districts with large areas were thus advantaged, rather than through the effect of state population (large districts tend to come from less populous states). I find the opposite to be the case.

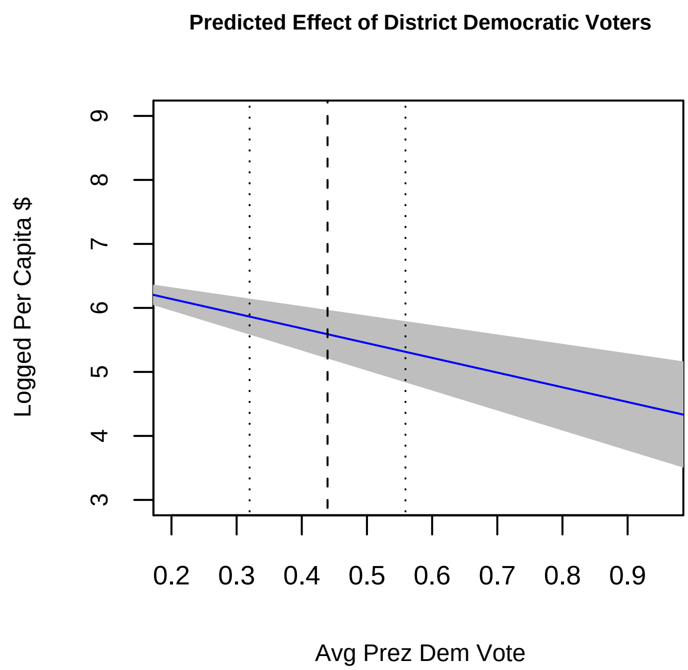

Figure 5: *Predicted effect of varying amount of support in districts for Democratic presidential candidates, 98-102nd Congress, on* **logged defense procurement expenditures***, holding other predictors constant at their means. The shaded region represents a 95% posterior interval. The dashed line represents the mean of the variable, and the dotted lines 1 standard deviation from the mean.*

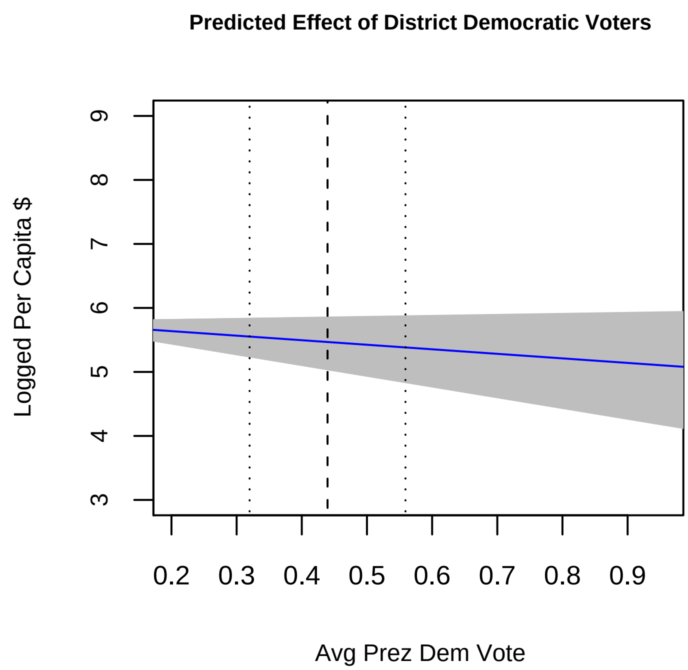

Figure 6: *Predicted effect of varying amount of support in districts for Democratic presidential candidates, 98-102nd Congress, on* **logged defense wage expenditures***, holding other predictors constant at their means. The shaded region represents a 95% posterior interval. The dashed line represents the mean of the variable, and the dotted lines 1 standard deviation from the mean.*

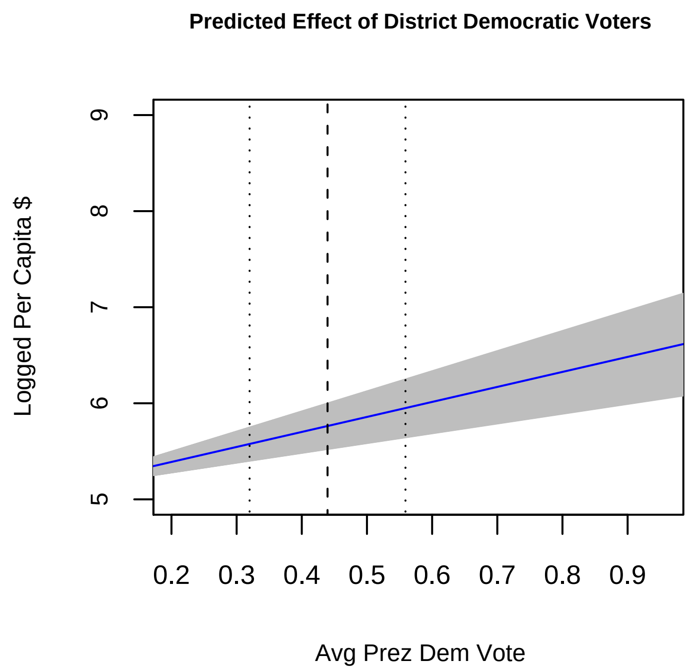

Figure 7: *Predicted effect of varying amount of support in districts for Democratic presidential candidates, 98-102nd Congress, on logged grant expenditures, holding other predictors constant at their means. The shaded region represents a 95% posterior interval.*

6 Conclusion

I have found support for only one of the partisan hypotheses coming out of the distributive politics literature. Democrats in Congress throughout the 98th to the 102nd Congress have not been able to effectively target their particular House districts. Nor have state delegations to the Senate and House dominated by Democrats been able to deliver more for their states. Democratic members of the House Armed Services committee have also not been able to do any better than their Republican counterparts.

On the other hand, I have found that, for defense procurement at least, the proportion of Democratic voters in a given district is negatively associated with defense procurement awards. This is contrary to the common notion, strongly associated with Levitt and Snyder (1995), that Democrats could at least target their voters, if not their own districts. So the partisan effect on distributive politics seems to benefit Republican voters. The cause of this is still unclear, and remains to be investigated.

One objection to these negative results is that defense procurement is a "Republican" program that Democrats would be unlikely to pursue vigorously. While it may be true that Democrats, on the whole, prefer a smaller procurement budget than Republicans, it does not follow that–once such a budget is set in the appropriations process–those Democrats will voluntarily abjure an obvious source of political benefits for their members or districts. That such an attempt is not successful is a finding contrary to expectations.

On the other hand, the Democratic voter hypothesis does operate in the expected direction for grants spending, a highly discretionary portion of the budget. Thus, the results seem to bear out Arnold (1979)'s claim that distributive politics differ based on the type of government benefit.

Another point of the paper is methodological. Understanding the vast differences in spending requires, to some extent, understanding distributive politics. Yet, when trying to find the causes of variation between congressional districts, scholars have taken an overly atomistic view of their unit of analysis. They have failed to incorporate data from other sources of influence at different levels of analysis. Doing so does affect our findings – a predictor at a more aggregated level of analysis has an effect on the outcome variable of interest at a less aggregated level.

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Appendices

A Correlation Table

	lnincome	servicet	democrat	armed	dem.armed	pavgdvote.d	lnarea.d	dc.d	coast.d	gsp.sc	hmajpdeleg.sc	smajpdeleg.sc
lnincome	1.00	0.01	−0.01	−0.11	−0.11	0.27	−0.71	0.10	0.23	0.40	−0.03	0.03
servicet	0.01	1.00	0.13	−0.02	0.01	0.10	−0.09	−0.07	0.02	0.04	0.04	−0.02
democrat	−0.01	0.13	1.00	0.01	0.22	0.49	−0.24	−0.01	0.10	0.03	0.25	0.01
armed	−0.11	−0.02	0.01	1.00	0.76	−0.11	0.10	0.04	0.04	−0.04	−0.02	0.01
dem.armed	−0.11	0.01	0.22	0.76	1.00	−0.03	0.05	0.06	0.03	−0.04	0.05	0.01
pavgdvote.d	0.27	0.10	0.49	−0.11	−0.03	1.00	−0.52	0.02	0.08	0.15	0.06	−0.01
lnarea.d	−0.71	−0.09	−0.24	0.10	0.05	−0.52	1.00	−0.07	−0.21	−0.36	−0.12	−0.02
dc.d	0.10	−0.07	−0.01	0.04	0.06	0.02	−0.07	1.00	−0.08	−0.08	0.05	0.09
coast.d	0.23	0.02	0.10	0.04	0.03	0.08	−0.21	−0.08	1.00	0.16	0.05	0.04
gsp.sc	0.40	0.04	0.03	−0.04	−0.04	0.15	−0.36	−0.08	0.16	1.00	−0.07	−0.08
hmajpdeleg.sc	−0.03	0.04	0.25	−0.02	0.05	0.06	−0.12	0.05	0.05	−0.07	1.00	0.11
smajpdeleg.sc	0.03	−0.02	0.01	0.01	0.01	−0.01	−0.02	0.09	0.04	−0.08	0.11	1.00

B Estimator Comparison

	OLS Beta	OLS SE	PCSE	FE Beta	FE SE	BML Mean	BML SE
constant	7.41	0.22	0.20	8.32	0.78	7.12	0.19
District Income (DC)	0.21	0.15	0.16	−0.17	0.17	−0.86	0.21
Seniority (DC)	−0.00	0.00	0.00	0.01	0.00	0.00	0.00
Democrat (DC)	0.10	0.06	0.02	0.00	0.06	0.02	0.03
Armed Svcs Comm (DC)	0.54	0.12	0.11	0.50	0.11	0.00	0.05
Dem*Armed Svcs (DC)	−0.02	0.16	0.09	0.04	0.14	0.07	0.08
District Avg Dem Vote (D)	−2.54	0.27	0.15	−2.57	0.26	−2.79	0.35
District Area (D)	−0.20	0.02	0.01	−0.30	0.02	−0.32	0.04
Proximity to DC (D)	1.49	0.16	0.06	1.69	0.31	1.55	0.52
District Coastal? (D)	0.13	0.05	0.01	0.01	0.06	0.14	0.12
State GSP (SC)	0.08	0.01	0.01	−0.79	3.11	0.01	0.03
State House Delegation Maj Party (SC)	−0.42	0.14	0.10	−0.08	0.08	0.00	0.02
State Senate Delegation Maj Party(SC)	−0.10	0.07	0.08	−0.22	0.29	−0.00	0.02

Table 8: *Outcome variable: logged defense procurement expenditures. Estimators are OLS (Ordinary Least Squares), PCSE (Beck-Katz Panel-Corrected Standard Errors), FE (Fixed Effects for states). For Bayesian multilevel model (BML), DC = individual level of analysis (district-congress); D = Time-invariant district level of analysis; SC = State-congress level of analysis.*

C Multilevel Estimator Code

```
model {
      for (i in 1:n)
            {
            y[i] ~ dnorm (mu[i], tau.y[state[i]])

            mu[i] <- beta1 + d.trend.state[state[i]] * (cong[i]-mean(cong[]))
            + xi.district*a.district[district[i]] + xi.state*a.state[state[i]]
            + xi.cong*a.cong[cong[i]] + xi.statecongress*a.statecongress[state[i],cong[i]]
            + mu2[i]

            mu2[i] <- b.lnincome*lnincome[i]
            + b.servicet*servicet[i]
            + b.democrat*democrat[i]
            + b.armed*armed[i] + b.dem.armed*dem.armed[i]
            }

      constant <- beta1 + xi.district*mean(a.district[]) + xi.state*mean(a.state[])
                + xi.cong*mean(a.cong[]) + xi.statecongress*mean(a.statecongress[,])

      for (i in 1:ndistrict)
            {
            z.district[i] <- xi.district*(a.district[i] - mean(a.district[]))
            a.district[i] ~ dnorm (mu.district[i], tau.district)

            mu.district[i] <- d.pavgdvote*pavgdvote[i]
            + d.lnarea*lnarea[i]
            + d.capitol*capitol[i] + d.coast*coast[i]
           }

            d.pavgdvote.adj <- xi.district*d.pavgdvote
            d.lnarea.adj <- xi.district*d.lnarea
            d.capitol.adj <- xi.district*d.capitol
            d.coast.adj <- xi.district*d.coast

      for (j in 1:nstate)
            {
            a.state[j] ~ dnorm (0, tau.state)
            z.state[j] <- xi.state*(a.state[j] - mean(a.state[]))

            tau.y[j] <- pow(sigma.y[j],-2)
            sigma.y[j] ~ dunif(0,100)

            }

     for (t in 1:ncongress)
           {
           a.cong[t] ~ dnorm (mu.cong[t], tau.cong)
           z.cong[t] <- xi.cong*(a.cong[t] - mean(a.cong[]))
           mu.cong[t] <- d.0.cong + d.trend*(t-mean(cong[]))
           }

           d.0.cong.adj <- xi.cong*d.0.cong

      for (j in 1:nstate){
            for (t in 1:ncongress)
                {
                a.statecongress[j,t] ~ dnorm (mu.statecongress[j,t], tau.statecongress)
                z.statecongress[j,t] <- xi.statecongress*(a.statecongress[j,t] - mean(a.statecongress[,]))

                mu.statecongress[j,t] <- d.sc.gsp*m.sc.gsp[j,t]
                + d.sc.hmajpdeleg*m.sc.hmajpdeleg[j,t]
                + d.sc.smajpdeleg*m.sc.smajpdeleg[j,t]
                + d.trend.state[j]*(t-mean(cong[]))
                }
            d.trend.state[j] ~ dnorm(0,tau.trend.state)
```

```
        }
        d.sc.gsp.adj <- xi.statecongress*d.sc.gsp
        d.sc.hmajpdeleg.adj <- xi.statecongress*d.sc.hmajpdeleg
        d.sc.smajpdeleg.adj <- xi.statecongress*d.sc.smajpdeleg

    d.0.cong ~ dnorm(0, .001)

      # district level priors
      beta1 ~ dnorm(0, .001)
      b.lnincome ~ dnorm(0, .001)
      b.servicet ~ dnorm(0, .001)
      b.democrat ~ dnorm(0, .001)
        b.armed ~ dnorm(0, .001)
        b.dem.armed ~ dnorm(0, .001)

      d.lnarea ~ dnorm(0, .001)
      d.capitol ~ dnorm(0, .001)
      d.coast ~ dnorm(0, .001)
      d.pavgdvote ~ dnorm(0, .001)
      d.capital ~ dnorm(0, .001)

      d.sc.gsp ~ dnorm(0, .001)
      d.sc.hmajpdeleg ~ dnorm(0, .001)
      d.sc.smajpdeleg ~ dnorm(0, .001)

      # State-level priors
#      d.lnsqmile ~ dnorm (0, .001)

        d.trend ~ dnorm (0, .001)

      # Hyperpriors
      tau.district <- pow(sigma.district, -2)
      tau.state <- pow(sigma.state, -2)
      tau.cong <- pow(sigma.cong, -2)
      tau.statecongress <- pow(sigma.statecongress, -2)
      tau.trend.state <-pow(sigma.trend.state, -2)

      sigma.district ~ dunif (0,1000)
      sigma.state ~ dunif (0,1000)
      sigma.cong ~ dunif (0,1000)
      sigma.statecongress ~ dunif (0,1000)
      sigma.trend.state ~ dunif (0,1000)

      xi.district ~ dnorm (0,.0001)
      xi.state ~ dnorm (0,.0001)
      xi.cong ~ dnorm (0,.0001)
      xi.statecongress ~ dnorm (0,.0001)

      sigma.district.adj <- abs(xi.district)*sigma.district
      sigma.state.adj <- abs(xi.state)*sigma.state
      sigma.cong.adj <- abs(xi.cong)*sigma.cong
      sigma.statecongress.adj <- abs(xi.statecongress)*sigma.statecongress }
```