Dan Goldhaber, Lesley Lavery, and Roddy Theobald

CEDR Working Paper 2012-2.2
University of Washington Bothell
Abstract: A large literature on teacher collective bargaining describes the potential influence of the provisions in collectively bargained teacher union contracts on teachers and student achievement, but little is known about what influences the provisions that end up in these contracts. Using a unique dataset of every active teacher collective bargaining agreement in Washington State, we estimate spatial lag models to explore the relationship between the restrictiveness of a bargained contract in one district and the restrictiveness of contracts in nearby districts. Employing various measures of geographic and institutional proximity we find that spatial relationships play a major role in determining bargaining outcomes. But, importantly, these spatial relationships are actually driven by two “institutional bargaining structures”: Education Service Districts (ESDs), which support school districts, and Uniserv councils, which determine who is bargaining on behalf of local teachers’ unions. This suggests that the influence of geographic distance found in previous studies of teacher wages may simply reflect the influence of these bargaining structures.

* This research was made possible in part by generous support from the Bill and Melinda Gates Foundation and an anonymous foundation, and has benefited from helpful comments from the editor, two anonymous reviewers, Katharine Strunk, Sean Reardon, James Cowen, Wilner Jeanty, John Winters, Dick Startz, Ron Wilson, Andy Coons, and participants at the Center for Education Policy Analysis Seminar Series at Stanford University, including Thomas Dee, Erica Greenberg, Brian Jacob, Susanna Loeb, and Eric Taylor. We thank Yangru Fang and Dylan D’Entremont for excellent research assistance, and we thank the CBA coders without whom this project would not be possible: Rahn Amitai, Shijia Bian, Scott Bohmke, Stephanie Burns, Jonathan Humphrey, Angela Kim, Gregory Johnsen, Eric Lei, Hanqiao Li, Yi Li, Wanyu Liu, Xijia Lu, Alex McKay, Courtney Polich, Leah Staub, Annie Saurwein, Bifei Xie, Nancy Xu, Youngzhe Yi, and Wenjun Yu. The statements made and views expressed in this paper do not necessarily reflect those of the study’s sponsors or the institutions with which the authors are affiliated. Any and all errors are solely the responsibility of the authors.

The suggested citation for this working paper is:


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I. The Geography of Collective Bargaining Agreements

Teacher collective bargaining agreements (CBAs) cover a wide array of school district rules and regulations that govern everything from hiring and compensation, to the policies that determine teacher transfers, evaluation, professional development, promotion, grievance, and termination. A large literature on teacher collective bargaining discusses the potential consequences of collective bargaining and specific CBA provisions for school and district finances, staffing, and operations.\(^1\) And recent policy decisions reflect concerns about the potential consequences of specific CBA provisions. For example, the federal government’s Race to the Top grant competition incents states to make dramatic changes in teacher evaluation policies, changes that often must be negotiated as part of the collective bargaining process (Hanover Research 2011). And in response to recent budget woes, the governors of two Midwestern states made it illegal to bargain over some provisions that had previously appeared in teacher CBAs (Greenhouse 2011).

There is indeed some empirical evidence that some CBA provisions may have consequential effects. Hoxby (1996), for instance, concludes that teachers’ unions, empowered by collective bargaining, raise school budgets and the level of school inputs (teacher salaries, per-pupil spending) but have a negative effect on outputs such as student performance. And Levin and Quinn (2003) find that CBA transfer policies can lead urban districts to hire teachers much later than their suburban peers. Finally, there is mixed evidence on whether seniority-based transfer provisions appear to influence the distribution of teacher experience across students (Anzia and Moe, 2011; Koski and Horng, 2007; Moe, 2005). But this empirical literature, with a few exceptions (e.g. Strunk and Grissom 2010; Strunk 2012), has largely ignored the factors that may determine which provisions appear in CBAs in the first place. As Lewin et al (2012) note,

\(^1\) For a review of these issues see Hannaway and Rotherham (2006) or Strunk and Grissom (2010).
“Much of the current political debate has occurred in the absence of empirical evidence about how collective bargaining actually functions.” Lewin and colleagues thus call for a “new generation of empirical research” about the bargaining process itself.

We address this gap in the research using data collected in Washington State to assess how spatial and institutional bargaining relationships between school districts may help explain bargaining outcomes. We first code each provision in each teacher CBA in the state, and then aggregate these to the district level using a methodology developed by Strunk and Reardon (2010) to get a measure of the restrictiveness of each district’s negotiated CBA. This measure of CBA restrictiveness is the extent to which the body of provisions imposes constraints on district management, and should not be interpreted as being normative or, necessarily, as having implications for student outcomes. We then employ a spatial econometric approach (Anselin 1988) to explore the impact of bargaining outcomes in nearby districts on an individual district’s contract. Specifically, we assess the extent to which the restrictiveness of a district’s contract is influenced by spillovers from contracts in geographically proximate districts, or from contracts in other districts that share common institutional bargaining structures.

Our analysis of spatial relationships of CBAs is motivated by three possibilities. One is that districts could have similar CBAs because they are similar in terms of their structure (e.g. number of students) or student demographics (Strunk, 2012). A second is that districts compete for the same teachers in highly localized labor markets (Boyd et al. 2005; Reinnerger 2012).

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2 For instance, one might also code provisions from the perspective of a teacher and evaluate each contract’s ability to offer protections or security. And there are “restrictions,” such as class size caps or minimum requirements for teacher preparation, that may be seen as having beneficial effects for students. We opted to code for restrictiveness to be consistent with prior studies (e.g. Strunk and Reardon, 2010; Strunk and Grissom, 2010).

3 As we describe below, the restrictiveness of each contract is estimated using Partial Independence Item Response (PIIR) models (Strunk and Reardon 2010; Reardon and Raudenbush 2006). By institutional bargaining structures we are referring to either Education Service Districts (ESDs), regional education units designed to support local school districts, or Uniserv councils, regional union collaboratives that supply bargaining support for local teacher unions. These are discussed in more detail below.
Finally, district contracts may resemble one another because the districts belong to the same institutional bargaining structures and employ similar bargaining tactics, approaches, and goals (Kochan and Wheeler 1975). There are two bargaining structures in Washington, each representing one side of the bargaining table, which might be expected to influence a district’s bargaining approach. Educational Service Districts (ESDs) are regionally-based district cooperatives designed to assist member districts with services ranging from curricular development to transportation, and bargaining support. Similarly, Uniservs are union collaboratives formed to supply bargaining-related support for local affiliates. Additional details on both institutional bargaining structures are provided in Section III.

Our results corroborate findings from previous work on CBAs that some district features, such as the number of students in a district, influence CBA restrictiveness. They also suggest that bargaining outcomes in one district do have a spillover effect on outcomes in nearby surrounding districts. Importantly however, models that consider both geographic proximity and institutional bargaining structures demonstrate that the primary sources of spatial dependence in contract restrictiveness are the regional bargaining structures, not geographic proximity in and of itself. This relationship is robust across different specifications and for various subsets of CBA provisions. We therefore argue that spatial correlations in bargaining outcomes are driven not by competition for teacher labor, but rather by the influence of shared bargaining structures.

In the next section we provide a review of theories from a variety of disciplines that suggest why we might observe spatial correlations in bargaining outcomes. We follow in Section III with a description of our data on contract restrictiveness, district characteristics, and measures

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4 This is consistent with findings that focus specifically on teacher salaries (e.g. Babcock et al 2004; Winters 2011). Teacher salaries in Washington are determined at the state level and are not subject to collective bargaining. Given this, this study can be viewed as a companion to earlier work that focuses on the effect of spatial or social relationships on teacher salaries.
of proximity. We describe our analytic approach in Section IV, while Sections V and VI detail empirical results and robustness/falsification tests, respectively. Finally, we conclude in Section VII with a discussion of implications for policy.

II. **Background**

One reason to expect a spatial relationship among teacher CBAs is because closely clustered school districts are likely to share similar demographic, social, political and economic environments—district size and student composition, for example—that may play an important role in the bargaining process (Dolowitz and Marsh, 1996; Grossback et al, 2004; Karch, 2007; Strunk, 2012; Volden, 2006). For our purposes, though, the more interesting possibility is that, once we account for similarities in district characteristics, the bargain struck in one district actually has a causal impact on the negotiations and subsequent contracts in nearby districts.

There are at least two possible explanations for this “policy spillover”: competition between districts for teacher labor, and various forms of spatially dependent policy diffusion.

There is clear evidence from the economics literature that teachers care about and respond to working conditions (Clotfelter et al 2010; Goldhaber et al. 2011; Hanushek et al. 2004; Player 2010; Scadifi et al 2007). And several recent studies show that teacher labor markets are quite localized; that is, teachers often choose to stay and teach in the districts they themselves attended as students (Boyd et al. 2005; Reininger 2012). Since CBAs codify working conditions and nearby districts compete for teachers in the same teacher labor market, it might not be surprising for proximate districts to have relatively similar contracts. This possibility is analogous to recent findings from the tax literature (Brueckner and Saavedra 2001) that local governments respond to changes in the property tax rates of nearby communities, since these
communities compete for residents and tax revenue. The competition between school districts can be viewed as part of a larger political process, described by Summers (1974), in which the “terms and conditions of employment for public employees are governmental decisions made through the political process.”

Sociologists DiMaggio and Powell (1983) provide another oft-cited theory for how competition can lead to similarities across contracts. They define “institutional isomorphism” as the result of organizations competing for resources and legitimacy. In their framework, proximate districts could have similar collective bargaining agreements because of coercive isomorphism (if nearby districts and unions exert external pressure on a district to adopt similar provisions) or mimetic isomorphism (if districts and unions purposely model their contract on those of nearby districts). Either way, the theory suggests that firms (districts) actively respond to the actions of their neighbors. Winters (2011) mentions “union threat effects”\(^5\) (similar to the idea of coercive isomorphism) as a possible explanation for “union spillovers,” which he defines as the effect of union activity in nearby districts on teacher salaries in a given district.

While competition seems like a reasonable explanation for spatial dependence between CBAs in different districts, policy scholars suggest that learning or shared knowledge between proximate districts may also be an important factor. Social learning theory, for example, suggests that a unit (in this case a district) will examine peers with similar ideological, political, demographic, cultural, racial or ethnic profiles and needs to introduce reforms best suited to specific contexts (Bennett 1991). This type of knowledge sharing reduces the cost of the bargaining process for both sides of the table, and may come through informal routes or more directly through formalized bargaining structures, such as shared associations between district

\(^5\) See Leicht (1989).
leaders or teacher representatives. Finally, policy diffusion—a derivative of social learning theory—suggests that policy spread results from political decision-makers’ efforts to solve public policy problems. Leaders actively search for successful solutions and engage in a form of “satisficing” to simplify the process, emulating solutions posed by other municipalities, states or countries rather than incurring the cost of independently evaluating all possible alternatives and hedging political risks (Boemke 2004, Bennett 1991).

Policy diffusion is a particularly important possibility in the context of collective bargaining, because we might imagine that a “bargaining shock”—a departure from standard contract design which may arise from external factors like federal and state incentive-based initiatives or changes in personnel influential in the bargaining process (union or district contract negotiation team leaders, superintendents, etc)—in one district changes the focus and scope of local bargaining and negotiations in neighboring districts. In fact, pattern bargaining theory posits that an agreement reached by a firm (district) sets the pattern for subsequent or nearby firms (districts) (Marshall and Merlo 2004). And anecdotal evidence that NEA affiliates use pattern bargaining within local union associations—if one union can get language into one

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6 Another form of social learning may occur when teachers switch school districts from year to year. However, the rate of cross-district teacher transfers in Washington state is quite low—there are fewer than two cross-district transfers per district per year, on average—so we do not explore this possibility empirically.

7 Note that both the theory of institutional isomorphism and social learning theory contain a time element; that is, they predict that collective bargaining agreements should look more similar over time, and specific provisions should spread geographically over time. Our data is a snapshot in time of every collective bargaining agreement operating in Washington State, so we do not address the time element of this process. Rather, we measure the extent to which the provisions in CBAs are spatially dependent at a specific moment in time.

8 There have been relatively few teacher strikes in Washington State (four since 2003), and Seattle is the only district in the state receiving TIF funding, so we do not explicitly model these bargaining shocks in our analysis. For an example of policy diffusion across school districts—in this case, in the adoption of charter schools—see Rincke (2007).

9 A strike in one district, for instance, is likely to play up union power in that district and in neighboring locations if the strike is met with broad community support.
contract, then a concerted effort is made to get the same language into all contracts negotiated by associated unions—provides concrete support of this theory.  

Some empirical work has tested these theories. Research on teacher contracts has tended to focus on spatial relationships for specific contract provisions. For example, recent studies of the teacher labor force find “wage spillovers” between districts in states that allow teachers’ salaries to be collectively bargained (Babcock et al 2004, Winters 2011). Babcock et al (2004) focus on spillovers between districts that identify each other as “referent districts” in an informal survey, while Winters (2011) focuses on spatial relationships between districts within 50 miles of each other.

But research has generally overlooked the influence of spatial relationships on other aspects of teacher labor contracts – association rights, hiring and transfers, workload, evaluation, grievance, benefits and leave, layoff and recall. This is surprising given 1) concerns that CBAs may have a significant impact on teacher quality, teacher distribution, and ultimately student achievement (Hoxby 1996; Leven and Quinn 2003; Moe 2009) and 2) existing conceptual frameworks that suggest districts and unions alike may learn from and contribute to their neighbors’ bargaining decisions. Moreover, while previous studies attribute spatial dependence to geographic proximity, geographically proximate districts often share institutional bargaining structures that may also be important in the bargaining process (Kochan and Wheeler (1975) argue that bargaining agreements are a function of environmental characteristics and the organizational characteristics of union and management). We explore spatial dependence across the full spectrum of teacher contract provisions, and investigate the extent to which the dependence should be attributed to geographic proximity or institutional bargaining structures.

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10 We thank Ron Wilson, Executive Director of the North American Association of Educational Negotiators, for this information (personal communication, March 2013.)
III. Data

This paper utilizes a unique new dataset derived from the collective bargaining agreements (CBAs) of all 270 public school districts in Washington State that are governed by collective bargaining.\textsuperscript{11} We obtained the CBAs for all of these districts and coded each CBA across 633 different provisions using a rubric developed in Strunk and Reardon (2010).\textsuperscript{12} Following this paper, we transform all CBA data to estimate Partial Independence Item Response (PIIR) models that treat each provision in a CBA as a binary “response” to a survey that includes all contract provisions covered in collective bargaining agreements.\textsuperscript{13} The analytic dataset we use includes measures of contract restrictiveness for each CBA, linked to indicators of geographic proximity and other spatial and demographic variables for each district. We next describe our measures of contract restrictiveness and other district-level control variables, and then conclude this section with a description of our indicators of geographic proximity.

\textit{Contract restrictiveness}

There are several challenges in calculating a single measure of contract restrictiveness across hundreds of contract provisions. First, provisions of interest may be qualitative (“How is seniority considered in teacher transfers?”) or quantitative (“How much preparation time are teachers guaranteed per week?”). Second, language in different contracts may place different

\textsuperscript{11} 25 districts in the state do not have a collective bargaining agreement and are therefore not included in this analysis. Districts without CBAs tend to be extremely small (the average enrollment of the 25 districts is 100 students) and located in eastern Washington. We are indebted to Dylan D’Entremont for his tireless work collecting the other 270 CBAs.

\textsuperscript{12} We are very grateful to Katharine Strunk for sharing the rubric she used to code teacher CBAs in California (see Strunk and Reardon 2010 and Strunk 2011).

\textsuperscript{13} Reardon and Raudenbush (2006) introduce an item response model designed to account for partial independence in surveys with a conditional structure. Strunk and Reardon (2010) utilize this Partial Independence Item Response (PIIR) model to obtain valid, reliability, replicable measures of union strength calculated from CBAs.
levels of restriction on the same provision; for example, if we are interested in the role of seniority in teacher transfer policies, seniority could play no role, be a tiebreaker, be one of several determinants, or be the sole determinant of which teachers are able to transfer between jobs. Finally, and perhaps most importantly, not all provisions apply to all CBAs. That is, some provisions (such as whether seniority is the deciding factor in transfer decisions) can only appear if other provisions (such as whether seniority plays any role in transfer decisions) also appear in the contract.

All of these challenges can be addressed using a coding strategy introduced by Strunk and Reardon (2010) that builds on methodology developed by Reardon and Raudenbush (2006). Strunk and Reardon treat each provision in a CBA as the “response” to a conditionally-structured survey that includes binary questions about all provisions covered in collective bargaining agreements. This conditional structure allows them to address quantitative provisions (e.g., “Is preparation time guaranteed in the CBA? If so, are teachers guaranteed at least 225 minutes per week?”) and provisions that can only appear if other provisions appear as well (“Does seniority play a role in transfer provisions? If so, is seniority the sole determinant of which teachers can transfer jobs?”). We follow Strunk and Reardon’s method to code the 270 CBAs in effect in Washington in the 2010-11 school year; the details of this coding process are described in Goldhaber et al (2013). This process results in a final binary dataset of 633 different restrictions. We refer to the final items in our dataset as “restrictions” because all provisions are coded so that each binary response represents an additional restriction to district management.15

14 For an in-depth analysis of similar provisions in California, see Koski and Horng (2007) and Anzia and Moe (2011)
15 For example, unions generally try to negotiate for smaller class sizes. We code negotiated class sizes for each grade level, using the following binary questions for grade 4, for example: “Is there a negotiated class size in grade 4?”; “If so, is the negotiated class size 29 students or less?”; “If so, is the negotiated class size 27 students or less?”; “If so, is the negotiated class size 26 students or less?” We determine the cutoffs using quartiles of negotiated class size in grade 4 across the state, and our coding indicates that contracts become more restrictive as class sizes
By coding each CBA in this fashion, we are able to employ a Partial Independence Item Response (PIIR) model (Strunk and Reardon 2010) to calculate the latent restrictiveness of each contract in the state.\(^\text{16}\) The PIIR model exploits the conditional structure of the data by only considering restriction \(k\) in CBA \(i\) if it is in the “risk set” of that CBA (i.e. the item in question could have appeared in the CBA given responses to previous questions). Specifically, let \(Y_{ik}\) be the outcome of restriction \(k\) in contract \(i\). We code restrictions so that \(Y_{ik} = 1\) if restriction \(k\) appears in contract \(i\). We further let \(h_{ik}\) be an indicator for whether restriction \(k\) is in the risk set of CBA \(i\), and define \(q_{ik} = \Pr(Y_{ik} = 1 | h_{ik} = 1)\). The model is then:

\[
\log \left( \frac{q_{ik}}{1 - q_{ik}} \right) = \theta_i + \gamma_k + \varepsilon_{ik} \quad (1)
\]

In equation 1, \(\theta_i\) represents the latent level of restrictiveness for CBA \(i\), while \(\gamma_k\) represents the relative frequency of restriction \(k\).\(^\text{17}\) Although the model allows simultaneous calculation of the restrictiveness of each CBA as a whole and the relative frequency of each individual restriction, we only use the estimates of the restrictiveness of each CBA (\(\hat{\theta}_i\)). Once we center the restrictiveness estimates, each \(\hat{\theta}_i\) can be interpreted as the estimated difference between the log odds of a restriction appearing in contract \(i\) relative to the log odds of the same restriction appearing in the average contract in the state, holding the relative frequency of the restriction decrease. For example, a district with a negotiated class size of 25 students in grade 4 (which is very small by Washington standards) has a “1” for all four questions, meaning that the contract is quite “restrictive” in this area. On the other hand, a district with a negotiated class size in grade 4 of 28 students has a “1” for only two questions, while a district with no negotiated class size has a “0” for all questions. This coding reflects no value judgment about the relative importance or consequences of smaller class sizes, but reflects the fact that guaranteeing smaller class sizes is a restriction to district management.

\(^{16}\) For more detail on these restrictiveness estimates and how they are related to specific CBA provisions, see Goldhaber et al (2013).

\(^{17}\) As detailed in Reardon and Raudenbush (2006), this model can be estimated either as a fixed effect model or a random effect model. We choose to estimate a fixed-effect specification—with fixed effects for each district and provision—because we believe that a CBA’s overall restrictiveness is likely to be correlated with the provisions that CBA addresses, and the fixed effect specification directly models this correlation. The correlation between estimates from the two specifications is over .99.
constant. Contracts with larger restrictiveness estimates contain more restrictions that unions tend to bargain for, and thus can be interpreted as being more “union friendly” than contracts with smaller restrictiveness estimates.\footnote{Importantly, by using the relative frequencies of restrictions to inform the restrictiveness estimates, we make no value judgments about the relative importance of various contract provisions.}

Under this model of contract restrictiveness, adding an additional restriction to a contract always increases the restrictiveness of the contract, but the provision that is added matters. Specifically, adding a relatively uncommon restriction increases restrictiveness more than a restriction that appears in most contracts. For example, almost every CBA in the state (264 of the 270) guarantees bereavement leave for teachers, but only 13 districts guarantee paid sabbatical or study leave. Thus, the second restriction receives more weight in the calculation of contract restrictiveness.\footnote{As a concrete example, suppose Districts A, B, and C have identical contracts, except that District A offers sabbatical leave and no bereavement leave, District B offers bereavement leave and no sabbatical leave, and District C offers neither type of leave. District A has the most restrictive contract because sabbatical leave is more rare than bereavement leave, and District B has a more restrictive contract than District C because it contains an additional restriction.}

Figure 1 demonstrates that while contract restrictiveness is highly correlated with the number of restrictions in a contract ($r = 0.95$), there is considerable variability due to the specific restrictions that appear or do not appear in each contract. In particular, two contracts with an equal number of provisions may be categorized as differentially restrictive given how rare the particular provisions in the contracts are relative to other districts in the state.

To ease in the interpretation of our models, we standardize our restrictiveness estimates to have a standard deviation of 1. Since standardized contract restrictiveness is the dependent variable in each of our models (see Table 1), marginal effects in these models are in units of standard deviations of contract restrictiveness.
We link our CBA data to district-level data from Washington’s Office of the Superintendent of Public Instruction, and also add indicators for whether each district borders Oregon, Idaho, or Canada, is west of the Cascades Mountains, or is located in an urban area. Column 1 of Panel 1 of Table 1 presents summary statistics for each of these variables across the 270 districts in our sample. Approximately half of all school districts in the sample are on either side of the Cascades, a small percentage of districts are on each border, and fewer than 5% of the districts in the sample are classified as “urban.” We also consider the log enrollment of each district, the district unemployment rate in the year the district’s CBA was bargained, and the percent of students in each district who are eligible to receive free/reduced priced meals (FRPM), and standardize these variables so coefficients in future models are on comparable scales.

We include these variables because we believe they may be predictive of contract restrictiveness. To explore the relationship between these variables and contract restrictiveness, Columns 2 and 3 in Panel 1 of Table 1 present summary statistics for districts with CBAs estimated to be in the top (Column 2) and bottom (Column 3) quartiles of restrictiveness. Districts with highly restrictive CBAs (and thus more union-friendly contracts) are much larger on average, have lower unemployment rates, and have fewer students who qualify for free/reduced priced meals than districts with the least restrictive CBAs. Districts with highly restrictive CBAs are also more likely to be located west of the Cascades and in urban areas, while districts with the least restrictive CBAs are more likely to be located on the Oregon border. The finding that urban districts in Washington are more likely to have restrictive CBAs is consistent with findings about CBA restrictiveness based on California school districts (Strunk 2012).

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20 We use district student demographic data from the year that each contract was bargained, accessed from http://reportcard.ospi.k12.wa.us/DataDownload.aspx?schoolId=1&OrgTypeId=1&reportLevel=State&orgLinkId=
Measures of proximity

The first step in a spatial analysis is to specify the structure of spatial dependence. This is typically done by specifying a spatial weighting matrix $W$, which in our case is a 270 by 270 matrix in which each entry $W_{ij}$ is a measure of the proximity of districts $i$ and $j$.\footnote{We set $W_{ii} = 0$ for each district $i$ by convention, and also row-standardize each weighting matrix $W$ so each row sums to one. We explain how this standardization influences interpretation of the results in the next section.} As we discussed in the literature review above, the role of proximity in collective bargaining could be geographical or institutional or both, so we experiment with a number of spatial weighting matrices in our analysis. As a measure of continuous geographical proximity, we first let $W_{ij}$ equal the reciprocal of the driving distance between the headquarters of districts $i$ and $j$ (so larger values of $W_{ij}$ indicate that the districts are closer).\footnote{We use the driving distance between the headquarters of each pair of districts, calculated using the package ggmap (Kahle and Wickham 2013) in R (R core team 2012), as we believe it is the most meaningful measure for teachers and administrators of the distance between two districts. We thank Erica Greenberg for this suggestion.} Following Winters (2011), we make three different weighting matrices from these inverse distance measures (“within 25 miles”, “within 50 miles”, and “within 100 miles”) that set $W_{ij} = 0$ for districts greater than 25 miles, 50 miles, or 100 miles apart, since contracts are unlikely to influence negotiations on the other side of the state. Figure 2 highlights the districts within 25, 50, and 100 miles of two school districts on opposite sides of the state—Tacoma and Spokane—to give the reader a sense of scale.

Treating distance as continuous may be problematic given that school systems in western Washington are significantly smaller than those in the eastern part of the state; for example, there are 24 districts within a 25-mile drive of the Seattle School District, while there are no other districts within 25 driving miles of the Methow Valley School District. So, we also create two other weighting matrices that use non-continuous measures of geographic proximity: $W_{ij} = 1$ if
districts $i$ and $j$ share a common district boundary ("neighbors")\textsuperscript{23}; and $W_{ij} = 1$ if districts $i$ and $j$ fall into the same metropolitan statistical area or micropolitan statistical area as defined by the U.S. census ("MSA").\textsuperscript{24}

Institutional proximity may also be important. Specifically, school districts in Washington are organized into two types of institutional bargaining structures: nine Education Service Districts (ESDs) and 21 local Uniserv councils. Each type of organization is affiliated with one side of the bargaining table. ESDs, or structures like them, exist in a number of states.\textsuperscript{25} These within-state regional entities cooperate to develop curriculum and instructional support and assessment, provide transportation and financial advice and discounting, process data, payroll, and fingerprinting, develop preschool programs and youth initiatives and better serve special education populations (Oregon Transparency, 2013).

In many parts of the country, ESDs also provide negotiating services for member districts. These regional alliances of district leaders may prepare and utilize a common set of wage and fringe benefit comparisons for their member districts, solicit agreement among school boards and districts not to relinquish key management rights, or establish regional negotiations trainings. Uniserv councils supply bargaining support for those at the other end of the bargaining table - local teacher unions. Often the same set of negotiators work on behalf of all unions in a given Uniserv to develop a bargaining strategy that shares goals, proposals, timetables, and support activities. For example, unions may collude to ensure that all local contracts expire in a

\textsuperscript{23} Census shape files in ArcGIS provide district boundaries that extend into water, meaning that we can code for neighbors of island school districts as well.

\textsuperscript{24} Neither of these measures makes it into our final analysis since we do not find evidence of spatial correlation in CBA restrictiveness across either measure.

\textsuperscript{25} School districts in Washington, Oregon, Michigan, Pennsylvania, Ohio, Nebraska, New York, Texas, Arkansas, North Dakota, Maine, New Mexico, Colorado, Utah, and West Virginia form regional cooperatives variously referred to as intermediate school districts, intermediate units, educational service centers, educational service units, boards of cooperative educational services, education service cooperatives, regional education associations, regional education cooperatives, regional service areas, regional service centers, and regional education service agencies.
given year or increase the threat of strike, establish minimum bargaining goals, or encourage members to delay bargaining to the start of the school year to increase pressure on negotiations.  

We create two final weighting matrices for these measures of institutional proximity: $W_{ij} = 1$ if districts $i$ and $j$ are in the same ESD; and $W_{ij} = 1$ if districts $i$ and $j$ are in the same Uniserv council. Figures 3 and 4 are maps of the nine ESDs and 21 Uniserv councils in the state. Importantly, while ESDs and Uniservs often share borders, there are many pairs of districts that share an ESD and not a Uniserv (1621 total), and vice versa (561 total). This identifying variation allows us to include both measures in the models described in the next section.

Institutional distance is potentially different than geographic distance because the determination of which districts are included in ESDs and Uniservs may be endogenous whereas geographic proximity is less likely to be so. That is, to the extent that districts and unions can choose which other districts or unions are in the same ESD or Uniserv, we might worry that any similarities within these structures are due to this “self-selection” rather than the influence of the structures themselves. Having said this, we are not terribly concerned about this type of self-selection in either case given that both ESDs and Uniservs were formed over thirty years ago via state legislature and regional collaboration, respectively, and they have remained stable since then (Kink and Cahill, 2004). We argue that the stability of institutional structures on both sides of the bargaining table suggests that any remaining similarities in the contracts that share an institutional structure are likely due to the structure itself rather than remnants of shared bargaining goals from the 1970s. Nonetheless, we acknowledge the possibility that if unions

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26 We thank Ron Wilson, Executive Director of the North American Association of Educational Negotiators, for information about both ESDs and Uniserv councils (personal communication, March 2013), and Andy Coons, former president of the Tacoma (WA) teachers’ union, for additional information about Uniserv councils (personal communication, March 2013.)

27 District boundaries themselves may be endogenously determined (see, for instance, Hoxby 2000), but we do not explore this possibility.

28 We thank the editor and an anonymous reviewer for their input on this topic.
chose to form Uniserv councils and ESDs with like-minded districts in the 1970s, and if those districts continue to share bargaining goals for reasons other than shared membership in the same Uniserv council, ESD, or our other control variables, then we may misattribute the impact of this self-selection to the influence of the Uniservs or ESDs themselves. Moreover, if individual teachers self-select into districts because they belong to a particular Uniserv, then our results could be likewise affected by this additional source of endogeneity.

Panel 2 of Table 1 explores the extent to which districts with highly restrictive (unrestrictive) contracts tend to be in geographic proximity to other districts with highly restrictive (unrestrictive) contracts. Districts with highly-restrictive contracts have more highly-restrictive contracts within 50 miles, in the same ESD, and in the same Uniserv than districts with unrestricted contracts. Likewise, districts with unrestricted contracts tend to have many nearby districts with unrestricted contracts. This is preliminary evidence that there is a geographic clustering of contract restrictiveness, an issue we explore more thoroughly in the next section.

IV. Analytic Approach

Our primary goal is to explain the mechanism through which collective bargaining provisions are adopted, and, in particular, the degree to which there are spatial relationships between districts.\textsuperscript{29} As preliminary evidence of spatial dependence in contract restrictiveness, we calculate Moran’s I statistic of spatial correlation (Moran 1950) for each measure of proximity outlined in the previous section:

\textsuperscript{29} A natural first step to explore spatial relationships is to model the similarity between CBAs as a function of the proximity of the districts. We omit these models from this version of the paper.
\[ I = \frac{N \left( \sum_i \sum_j W_{ij} \theta_i \theta_j \right)}{\left( \sum_i \sum_j W_{ij} \right) \left( \sum_i \theta_i^2 \right)} \tag{2} \]

In equation 2, \( N \) is the number of districts (\( N = 270 \)), \( W_{ij} \) are the entries of the weighting matrix \( W \) for each measure of proximity, and \( \theta_i \) is the restrictiveness of the contract in district \( i \).\(^{30}\) This statistic gives an estimate of the degree of spatial correlation in contract restrictiveness, but does not account for the fact that nearby districts are likely to be similar in other ways that also influence contract restrictiveness.

Thus, as the next step in our analysis, we estimate an OLS regression to control for the observable district characteristics described in the previous section. By examining the residuals from this regression, we can determine whether there is still spatial correlation in contract restrictiveness even after we have controlled for observable district characteristics. The OLS model is as follows:

\[ \theta = X\beta + \varepsilon \tag{3} \]

In equation 3, \( \theta \) is a vector in which each entry \( \theta_i \) is the restrictiveness of the CBA in district \( i \), while \( X\beta \) controls for the year the CBA was bargained, geographic indicators (whether the district is west of the Cascades or borders another state or Canada)\(^ {31} \), and district covariates (log enrollment, unemployment rate, the percent of students receiving free/reduced priced meals, and whether the district is in an urbanized area).\(^ {32} \) We test the OLS residuals from the OLS model for

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\(^{30}\) Note that the sample mean contract restrictiveness is zero (Table 1), so this is not included in equation 2.

\(^{31}\) If two nearby districts \( X \) and \( Y \) are both on the same state border, we cannot distinguish whether any similarity between the CBAs of the two districts is due to their proximity or because of the \textit{shared influence} of a district \( Z \) on the other side of the border. The border indicators control for this potentially confounding effect.

\(^{32}\) Specifically, \( X_{ij} \) is the value of the \( j^{th} \) covariate for district \( i \)
spatial correlation within various measures of proximity using Lagrange Multiplier tests introduced by Anselin et al (1996).\textsuperscript{33}

If the Lagrange Multiplier test rejects the null hypothesis of no spatial correlation in the residuals of the OLS model for a given measure of proximity, then the next step in our analysis is to use that measure of proximity to directly model the correlation between contract restrictiveness in a district and the restrictiveness of contracts in proximate districts. Following prior papers focusing on wage spillovers (Babcock et al 2004; Winters 2011), we estimate variants of the following “spatial lag model” (Anselin 1988)\textsuperscript{34}:

\[ \theta = \rho W\theta + X\beta + \varepsilon \quad (4) \]

Equation 4 simply adds a spatial lag term to equation 3: \( \rho \) is the spatial lag coefficient (the parameter of interest) describing the direction and magnitude of spatial correlation, while \( W \) is one of the weighting matrices discussed in the previous section. The intuition behind this model is that the restrictiveness of each CBA may be a function of the district’s location and observable district covariates, but may also be a function of the restrictiveness of CBAs in proximate districts. For inverse distance within 50 miles, for example, the \( i^{th} \) entry of \( W\theta \) is simply a weighted average of the restrictiveness of all the other CBAs within 50 miles, with nearby districts receiving more weight.\textsuperscript{35} For the ESD and Uniserv measures, the \( i^{th} \) entry of \( W\theta \) is simply the average restrictiveness of the other contracts within the same ESD or same Uniserv.\textsuperscript{36} In the base model, \( \rho = 0 \) means that the restrictiveness of nearby CBAs are not correlated with

\textsuperscript{33} We use the user-written STATA module ANKETEST (Jeanty 2010a) for this and other diagnostic tests of our spatial models.

\textsuperscript{34} For district \( i \), this equation 4 can be written as \( \theta_i = \rho \sum_{j=1}^{n} W_{ij}\theta_j + X_i\beta + \varepsilon_i \)

\textsuperscript{35} This interpretation is due to the fact that we have row-standardized each weighting matrix \( W \).

\textsuperscript{36} We also experiment with weighting matrices for ESDs and Uniservs that give more weight to districts that are closer geographically, and discuss these results in the next section.
the restrictiveness of a district’s CBA, all else equal, while $\rho > 0$ and $\rho < 0$ mean that this correlation is positive or negative, respectively. This coefficient has a different interpretation than the marginal effects of the control variables.\footnote{The marginal effect with respect to any variable $k$ is $\beta_k[1 - \rho W]^{-1}$. For a derivation, see the appendix in Winters (2011).} The marginal effect of district enrollment, for example, describes the correlation between district enrollment and contract restrictiveness across \textit{all districts in the state}. The spatial lag coefficient, on the other hand, describes spatial correlation in contract restrictiveness \textit{within the measure of proximity used in the weighting matrix} $W$.

We begin by estimating the parameters in the spatial lag model with OLS, but it should be clear that the spatial lag term $\rho W \theta$ is endogenous, since $\theta$ is also the dependent variable. This issue is referred to by Manski (1993) as the “reflection problem,” and arises in many scenarios in which units are potentially influencing each other simultaneously. The consequence is simultaneity bias in the OLS estimates of the spatial lag coefficient $\rho$. One method to account for this simultaneity bias is to estimate the spatial lag model via maximum likelihood (Ord 1975). Solving equation 4 for $\varepsilon$ gives the following reduced form:

$$\varepsilon = (I - \rho W)\theta - X\beta$$

(5)

As in Ord (1975), we assume that $\varepsilon \sim N(0, \sigma^2 I)$, which allows us to derive the joint likelihood for $(\rho, \sigma^2, \beta)$ and calculate the MLE for each parameter.\footnote{The likelihood is derived in equations 4.3-4.5 of Ord (1975). We estimate the ML model using the user-written STATA module SPMLREG (Jeanty 2010b), and use the user-written STATA module SPSEUDOR2 (Jeanty 2010c) to calculate goodness-of-fit measures for the ML models.}

The ML model accounts for simultaneity bias in equation 4, but does not account for the possibility that there is an omitted variable in the error term of equation 4.\footnote{We thank Dick Startz for his insight on this topic (Personal communication, March 2013).} Two-stage least squares (2SLS) can account for both potential sources of bias, so we also estimate the spatial lag
model as a 2SLS regression, using $WX$ and $W^2X$ as instruments. $WX$ is the weighted average of the characteristics of nearby districts, while $W^2X$ is the weighted average of the characteristics of the neighbors’ neighbors. The identifying assumption is that the average characteristics of nearby districts do not affect the restrictiveness of a district’s contract except through the average restrictiveness of those nearby districts’ contracts. This assumption makes conceptual sense, and we have little concern about the strength of these instruments, as the $R^2$ from the first-stage regression is typically greater than 0.9. 2SLS is the estimation method used by Babcock et al (2004) and Winters (2011), and is recommended in Franzese and Hays (2007).

Estimates of the spatial lag coefficient in the spatial lag model indicate the extent of spatial dependence along each individual measure of proximity. We can then try to establish the primary source of this dependence. This involves adding multiple spatial lag terms to equation 4, with each spatial lag term capturing the influence of a different measure of proximity. A multi-spatial lag model has the following form:

$$\theta = \rho_1 W_1 \theta + ... + \rho_k W_k \theta + X\beta + \epsilon$$

(6)

We can estimate the multi-spatial lag model with maximum likelihood (after re-writing the likelihoods in Ord (1975) with multiple spatial lag terms) or with 2SLS (using $W_1X, ..., W_kX$ as instruments) but report estimates from the 2SLS model for reasons explained in the results section.

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40 See Kelejian et al (2004) for more information about IV estimation of spatial autoregressive models. These authors recommend using at least a linearly independent subset of the columns of $WX$ and $W^2X$ as instruments. For the spatial lag models for ESDs and Uniservs, we instrument only with $WX$ since $WX$ and $W^2X$ are highly collinear (ESDs and Uniservs are self-contained, so a district’s neighbors are the same as the district’s neighbor’s neighbors.)

41 We test the robustness of this assumption in Section VI.

42 The very high $R^2$ in the first-stage regression is in fact preliminary evidence of a spatial relationship between district CBAs.

43 We also experiment with a model with both a spatial lag and spatial error term (see Anselin 1988, p. 34.) The estimates of the spatial lag coefficients are similar to the estimates from the 2SLS model, so we omit results here, though results are available from the authors upon request.
One reason that we are interested in establishing the primary source of spatial
dependence is because spatial correlation along different measures of proximity are associated
with different explanations for spatial dependence, outlined in Section II. If the spatial
dependence is due to competition for teacher labor, we might expect to see that the primary
source of spatial dependence is geographic proximity. On the other hand, if the spatial
dependence is due to the relationships between districts and unions—either because of
institutional isomorphism, social learning, or pattern bargaining—then we might expect
institutional structures to be more important in determining bargaining outcomes.

*Categories of Provisions*

Our base models use as the dependent variable the restrictiveness measured over all
provisions in each contract. However, it is also of empirical interest whether spatial relationships
can be detected for subsets of provisions. Unions may have different levels of power over
different issues addressed by CBAs (Manning 1987), and policymakers could have differing
concerns about different aspects these agreements. Are spatial relationships more important for
some types of provisions than others? To investigate this, we divide all contract provisions into
one of seven categories: 1) Association rights, 2) evaluation, 3) grievance, 4) layoff and recall, 5)
benefits and leave, 6) hiring and transfer, and 7) teacher workload. We also consider an
additional category of “provisions” that concern the accessibility of the contract to teachers and
administrators (such as the length of the contract, the number of provisions, and the number of
contacts necessary to acquire the CBA.) We then estimate variants of the spatial lag models that
use restrictiveness estimates calculated only considering the provisions in each of the eight
categories above.
Finally, to get an idea of whether or not districts imitate and borrow high-profile provisions from one another, we subjectively “cherry picked” a set of 40 provisions that have received a lot attention in the press and teacher labor literature; they include provisions addressing seniority-based transfer and layoff policies, evaluation procedures, class size restrictions, and teacher workday agreements, among others (these provisions are reported in Table 2).\textsuperscript{44} As with the subsets above, we estimate variants of the spatial lag models that use restrictiveness estimates calculated only considering the provisions in the cherry-picked data.

V. Results

Is There Spatial Dependence in Contract Restrictiveness?

We begin by calculating Moran’s I statistic (equation 2) for each measure of proximity discussed in Section III. The values of Moran’s I statistic range from .079 (for Uniserv councils) to .267 (for districts within 25 miles), and all are statistically significant (p < .001). This is preliminary evidence that there is considerable spatial correlation in contract restrictiveness in Washington State.

We proceed by estimating an OLS model (equation 3) that controls for other district characteristics that may be correlated with the restrictiveness of a district’s contract. We do not report the estimates from this model, but as in later estimates from the spatial lag models, two district-level covariates are statistically significant predictors of contract restrictiveness. All else equal, a one standard deviation increase in log enrollment is correlated with an increase of about half a standard deviation of CBA restrictiveness, while districts on the Oregon border have

\textsuperscript{44} The cherry-picked provisions from the transfers section, for example, are the types of provisions that Anzia and Moe (2011) and Koski and Horng (2007) focus on when exploring the relationship between contract provisions and teacher distribution.
contracts that are roughly a third of a standard deviation less restrictive than other districts. It might be surprising that student poverty in the district, proxied by the percent of students eligible for free/reduced priced lunch, is not significantly correlated with contract restrictiveness. One might, for instance, have thought that high poverty districts would have less restrictive – and thus more union-friendly – CBAs in order to attract teachers since it is clear that schools with more disadvantaged students tend to have a harder time recruiting (Jacob, 2007) and retaining (Clotfelter et al 2008; Goldhaber et al. 2011; Hanushek et al., 2004) teachers. However, this corroborates Winters’ (2011) findings that a district’s poverty level is not significantly correlated with salary bargaining outcomes, controlling for other factors. The estimated coefficients for all district characteristics are also remarkably consistent with results from a similar model estimated for districts in California (Strunk 2012).

To determine whether there is still spatial correlation in contract restrictiveness even after we have controlled for observable district characteristics, we test the residuals from the OLS model for spatial correlation using Lagrange Multipliers for each measure of proximity. We find that the null hypothesis of no spatial correlation is rejected at the 10% level for only four of our seven measures of proximity: same ESD (p = .04); inverse distance within 100 miles (p = .07); inverse distance within 50 miles (p = .08); and same Uniserv (p = .10). For these measures of proximity, then, we have established that there is spatial correlation in contract restrictiveness

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45 This second finding is interesting in the context of the competition for teacher labor. School districts compete for teacher labor, so districts facing more competition should be more likely to adopt union friendly (and thus more restrictive) CBAs. We would expect, then, that being on the border with a neighboring state should slightly lower the competition for teacher labor given that there are frictions in the teacher labor market across state boundaries due to licensure laws (Goldhaber 2011). This implies that we might expect less restrictive (i.e. less union friendly) contracts in districts on the state border. The finding for districts on the Oregon border fit with this notion, but the direction of the coefficients for Idaho and Canada do not, although they are not statistically significant.

46 This null hypothesis was not rejected for districts within 25 miles, districts in the same MSA, or districts that are neighbors. We do not discuss these measures of proximity further.
even after controlling for observable district characteristics, so we use these measures of proximity in our spatial lag models (equations 4 and 6).  

*What is the Magnitude of Spatial Dependence for Different Measures of Proximity?*

We begin by estimating the spatial lag model (equation 4) with OLS and maximum likelihood (ML) to directly model the correlation between contract restrictiveness in a district and the restrictiveness of contracts in proximate districts. Columns 1-3 of Table 3 report results from the spatial lag model where the spatial weighting matrix $W$ is formed using the within 50 miles measure, columns 4-6 use the ESD measure, and columns 7-9 use the Uniserv measure. Spatial lag coefficients $\rho$, the coefficients of interest, are reported in one of the first four rows. Each row is based on a different measure of proximity. Recall that these coefficients describe the spatial correlation in contract restrictiveness within each measure of proximity. The coefficients $\beta$ in equation 4 are not interpretable as marginal effects, so we report the marginal effect for each control variable in brackets.

For each measure of proximity, we find that the OLS estimate of the spatial lag coefficient is larger than the ML estimate. This is consistent with derivations and simulations from Franzese and Hays (2007) demonstrating that the OLS estimates of the spatial lag coefficient should be biased up because of the simultaneity bias in equation 4. Given that the OLS estimates are likely to be biased, we focus on the ML estimates. For this model, the spatial lag coefficient for the ESD and Uniserv measures are positive and statistically significant (columns 5 and 8). This is preliminary evidence that the adoption of CBA provisions by one district in an institutional bargaining structure may influence the provisions adopted by others in

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47 We experiment with several cutoffs for the inverse distance measure and conclude that the within 50 cutoff gives the best fit. The results are very similar to the within 100 miles measure, so we only report results from the within 50 miles measure, along with ESDs and Uniservs.
the same institutional structure, because CBAs within the same structure end up with a more similar level of restrictiveness than districts across institutional boundaries.\textsuperscript{48}

As discussed in the previous section, though, we still need to be concerned about spatial correlation in the error term of equation 4. We test the residuals from the ML models using Lagrange Multipliers, and find strong negative correlation for all three proximity measures (p < .001). One potential explanation for this is that there is an omitted variable in the error term. We can account for this second potential type of endogeneity using two-stage least squares (2SLS) approach. Specifically, we estimate the spatial lag model by 2SLS, using $WX$ and $W^2X$ (for the “within 50” measure) as instruments, the assumption being that the average characteristics of nearby districts do not affect the restrictiveness of a district’s contract except through the average restrictiveness of those nearby districts’ contracts.

The results from the 2SLS models (columns 3, 6, and 9) show a positive statistically significant spatial lag coefficient for all three measures of proximity, suggesting that there are direct positive spillovers in contract restrictiveness for districts within 50 miles, within the same ESD, and within the same Uniserv council.\textsuperscript{49} But the estimates of spatial lag coefficient from the 2SLS models are strikingly larger in magnitude than the estimates from the OLS and ML models. Given that 2SLS can account for omitted variable bias while ML and OLS do not, this suggests that there is an omitted variable in the error term of the spatial lag model that is \textit{positively} correlated with the spatial lag term but \textit{negatively} correlated with contract restrictiveness, or vice versa. While we cannot determine with our existing data the precise

\textsuperscript{48} Despite the large differences in the estimates of the spatial lag coefficients in Table 3, the differences in model fit across the various models are negligible: the range in $R^2$ across the various spatial models is only .310 to .316.\textsuperscript{49} IV diagnostic tests indicate that the instruments $WX$ and $W^2X$ satisfy the typical recommendations for 2SLS. The Durbin and Wu-Hausman tests reject the exogeneity of the spatial lag term in all models, and F-tests of the instruments used in the first-stage are greater than 20 for every model, suggesting that weak instruments (Bound et al 1995; Staiger and Stock 1997) are not a significant concern.
nature of the omitted variable, one possibility is that it is related to the distribution of limited resources across proximate districts. For example, Uniserv councils provide bargaining support for local unions, and must decide how to devote their resources (such as bargaining power or money) to each union in the Uniserv. A district whose union receives these resources is likely to have a more restrictive contract (i.e., the marginal effect of the omitted variable is positive), but then other districts in the same Uniserv are likely to have less restrictive contracts because they did not receive these resources (i.e., the omitted variable is negatively correlated with the spatial lag term, or the average restrictiveness of other contracts within the same Uniserv.) We could tell a similar story about the distribution of state-level bargaining support or strong administrators within ESDs and the effect that may have across nearby districts. In each of these scenarios, the 2SLS model would mitigate the bias induced by these omitted variables and produce an estimate of the spatial lag coefficient that is significantly larger than in the OLS and ML models (as we observe). Again, we cannot empirically test this hypothesis, but this explanation is consistent with our finding that once we account for potential negative feedback along unobserved dimensions, the estimates of the “direct spillover” of contract restrictiveness across proximate districts becomes even larger.

_Are Spatial Relationships Driven by Geographic Proximity or Institutional Structure?_

The results from the spatial lag model provide strong evidence that bargaining outcomes in one district are positively influenced by bargaining outcomes in nearby districts, whether we consider districts within 50 miles, within the same ESD, or within the same Uniserv. However, there is a great deal of overlap between these measures of proximity, so we next investigate the _relative_ importance of these three measures of proximity. Columns 10-13 of Table 3 report
estimates from the multi-spatial lag model (equation 6.) When we include spatial lag terms for both within 50 miles and ESDs (column 10) and within 50 miles and Uniserv councils (column 11), we find that the spatial lag coefficient for each institutional bargaining structure is still positive and statistically significant even after controlling for the geographic proximity of the districts. This suggests that institutional bargaining structures are the primary source of spatial dependence in bargaining outcomes. When we add all three spatial lag terms to the same model (column 12), we find that the spatial dependence is driven primarily by spillovers within Uniserv councils. Finally, when we also include a spatial lag term that interacts ESDs and Uniserv councils (column 13), we see an even stronger spillover effect across districts that share the same ESD and Uniserv council. From this, we conclude that institutional bargaining structures are actually more important in the bargaining process than geographic proximity. In fact, we suspect that some of the influence of geographic proximity in studies suggesting spatial relationships (e.g. Babcock et al, 2004; Winters, 2011) may be attributable to the effects of similar institutions.

The finding that institutional bargaining structures appear to be driving the spatial relationships in bargaining outcomes is important in the context of existing theories (discussed in Section II) that explain patterns in contracts. If spatial relationships in bargaining outcomes were due primarily to competition for teachers (Boyd et al. 2005; Reininger 2012), then we would expect to see geographic proximity as the primary source of spatial dependence, since districts compete with nearby districts for teachers regardless of institutional affiliation. The fact that

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50 We experiment with models that relax the assumption that districts more than 50 miles apart cannot influence one another, and find that the results are very similar to the results reported in Tables 3 and 4.
51 We also experiment with models in which districts are only considered to be “proximate” if they are on the same side of the Cascades (a mountain range that runs north to south through the center of the state). We find that this only strengthens the estimates reported in Table 3. For example, the coefficient on the spatial lag interaction term in Column 13 of Table 3—the interaction between ESD and Uniserv councils, controlling for whether districts are within 50 miles of each other—increases from 0.34 to 0.52 when we account for this natural boundary.
geographic proximity matters little once we account for relationships within institutional structures suggests that: 1) competition for teacher labor may be more of a school-level than district-level phenomenon; and, 2) theories describing the relationships between districts and unions – such as social learning, pattern bargaining, or policy diffusion – are better able to explain bargaining outcomes.

*Are These Relationships Consistent Across All Sections of a Contract?*

The measure of restrictiveness that forms the dependent variable in the models in Table 3 is calculated over all 633 contract provisions in our final dataset. It is informative, however, to see whether the spatial relationships we observe in Table 3 are consistent over all subsets of provisions, or are more important for some contract provisions than others. Not only is this an important additional test of the robustness of our findings, but some research (e.g. Anzia and Moe 2011; Moe 2005) suggests that particular aspects of CBAs may have important consequences for districts. So, this disaggregation is useful to understand the extent to which our findings may be generalized to aspects of CBAs that are deemed to be particularly important.

Table 4 reports results from models in which the dependent variable, contract restrictiveness, is calculated only from specific subsets of provisions in each contract. Column 1 repeats the results from all provisions as a reference. The results for this exercise are remarkably consistent across the various subsets of provisions, with two exceptions. Whether we are only considering a subset of high-profile provisions (Column 2) or provisions from a specific area of the contract (Columns 3-10), the average restrictiveness of contracts that share the same ESD and Uniserv council is strongly correlated with the restrictiveness of a district’s contract. The exceptions are the subset of provisions describing hiring and transfer rights, in which the primary
spatial relationship appears to be within Uniserv councils, and the subset of provisions describing grievance rights, in which ESDs appear to be more important. Nonetheless, these results demonstrate that institutional bargaining structures are important in determining the restrictiveness of CBAs across a wide range of contract provisions.\footnote{We also test whether there are spatial correlations in the adoption of specific cherry-picked provisions by estimating variants of the spatial lag model in which the dependent variable is a binary indicator for whether a specific provision (e.g., is seniority the sole determinant of which teachers receive layoff notices?) appears in a contract. In these models, the spatial lag term is the percent of nearby CBAs that contain this provision. Interestingly, while we find little evidence of spatial correlation in seniority layoff provisions, we find strong correlations within ESDs and Uniservs in the adoption of several other specific provisions, including whether the contract contains a no strike/lockout clause, whether seniority is used in teacher transfer decisions, whether the contract specifies maximum class sizes and limits on the length of the school day, and whether teachers can reject an offer of re-employment after receiving a layoff notice.}

VI. Robustness and Falsification Checks

We perform a series of robustness and falsification checks to bolster the credibility of our findings: 1) we assess the robustness of the central finding of the paper, that the primary source of spatial dependence in teacher CBAs is within institutional bargaining structures; 2) we estimate an alternative 2SLS model that utilizes instruments that are more plausibly exogenous; and finally, 3) we exploit the timing of CBA bargaining to perform a falsification exercise to test our findings.

Robustness Check #1: Is it Really About the Bargaining Structures?

The central finding of our paper is that the primary source of spatial dependence in teacher CBAs is within institutional bargaining structures. As a robustness check on whether we are in fact identifying spatial relationships or institutional ones, we create three additional weighting matrices that represent “overlaps” between geographic proximity and institutional bargaining structures: (1) $W_{ij} = 1$ if districts $i$ and $j$ are within 50 miles but not within the same district; (2) $W_{ij} = 1$ if districts $i$ and $j$ are in the same Uniserv council; and (3) $W_{ij} = 1$ if districts $i$ and $j$ are in the same ESD.
ESD or Uniserv; (2) \( W_{ij} = 1 \) if districts \( i \) and \( j \) are not within 50 miles but within the same ESD or Uniserv; and (3) \( W_{ij} = 1 \) if districts \( i \) and \( j \) are within 50 miles and within the same ESD or Uniserv. We estimate variants of the spatial lag model with each of these weighting matrices, and find that while there is no spillover effect for districts within 50 miles that do not share a bargaining structure (measure 1), there are large positive spillover effects for districts that share a bargaining structure (measures 2 and 3), regardless of whether they are within 50 miles. This is further evidence that ESDs and Uniservs, not geographic proximity, is the driving force behind spatial relationships in bargaining outcomes.\(^{53}\)

We perform a second robustness check by including an interaction between an indicator for whether a district is “large” (i.e., has over 10,000 students) and the spatial lag term.\(^{54}\) We might expect \textit{a priori} that large districts are less dependent upon bargaining support from ESDs and Uniserv councils than smaller districts, so the spillover for larger districts within these bargaining structures should be smaller. This is precisely what we find: within both ESDs and Uniserv councils, the spatial lag coefficient for small districts is large (0.598 for ESDs, 0.682 for Uniservs) and statistically significant, while the spatial lag coefficient for large districts is not statistically distinguishable from zero. This also supports our argument that the distribution of resources within ESDs and Uniservs may help explain the discrepancy between our 2SLS and ML estimates.

\textit{Robustness Check #2: Are Our Instruments Exogenous?}

The instruments we use to identify the 2SLS models – the average characteristics of nearby districts – do pass Sargan’s over-identifying restrictions test (Sargan 1958), but this is not

\(^{53}\) Results are available from the authors by request.
\(^{54}\) We thank James Cowan for this suggestion.
a perfect test of instrument validity. Each of our instruments is an average characteristic of
nearby districts, and Sargan’s test is suspect when all instruments share a common rationale
(Murray 2006). Given this, there is still concern that our instruments may not in fact be
exogenous, particularly if the bargain struck in a district is influenced by the characteristics of
nearby districts. For instance, one could imagine that a district with student characteristics that
are seen as favorable by teachers (e.g. low poverty, high achieving students) that is surrounded
by nearby districts with characteristics seen as unfavorable would face less competition for
teacher labor than a district with student demographics seen as unfavorable that is surrounded by
nearby districts with student characteristics seen to be favorable.

To assess whether our 2SLS models are sensitive to the choice of instruments, we test a
specification of the model that does not rely on all the characteristics of nearby districts as
instruments, but instead relies only on using unemployment rates. The assumption we make in
using unemployment rates as instruments is that the unemployment rates in districts whose
contracts are negotiated earlier than other districts should not directly affect the negotiations in
those later district contracts, controlling for the unemployment rates at the time that those
contracts are being negotiated. In other words, assuming that District A’s contract is negotiated
at time t and District B’s contract at time t+1, the unemployment rate in District A at time t
should not directly affect the bargain struck in District B at time t+1, controlling for the
unemployment rate in Districts A and B at time t+1.⁵⁵

In this specification, we exploit the fact that different CBAs in our dataset were bargained
in different years, and for each district, we calculate two lagged terms for unemployment rate for
each District X: the average unemployment rate in districts nearby District X in the year that

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⁵⁵ This test works better for unemployment rates than other district characteristics, such as student demographics, because most district characteristics do not change significantly over the years in our dataset but unemployment rates do vary a good deal from year to year.
those nearby districts bargained their contracts, and the average unemployment rate in nearby districts in the year that District X bargains its own contract. In our alternative specification, we include the second lagged unemployment term as a predictor of contract restrictiveness—to account for the fact that the unemployment rate in nearby districts during a district’s bargaining year may affect a district’s contract—but then use the first lagged unemployment rate as the sole instrument in the 2SLS model. This approach uses variation in economic conditions associated with the timing of the contract negotiation, which are scheduled ahead of time and likely exogenous, and not regional variation in economic conditions, which may be related to other factors influencing district bargaining decisions, to identify the effect of nearby collective bargaining agreements.

We estimate 2SLS spatial lag models for all three measures of proximity, and while the standard errors of the estimates from these models are larger because the instruments are somewhat weaker, the estimates of the spatial lag coefficient are quite similar to those reported in Tables 3 and 4. Given this, we conclude that the exogeneity of the instruments in our primary models is not a significant concern.

*Falsification Test*

For a subset of 69 districts, we collected and coded the CBA that was in effect prior to the CBA that we included in the main analytic dataset. These CBAs are not included in any of the analyses reported above, but we use them to perform a simple falsification test of our results. Specifically, if the estimates reported in Tables 3 and 4 are true causal estimates of spillover, then the restrictiveness of nearby CBAs negotiated *after* a district’s CBA should have no direct effect on that district’s CBA, controlling for the restrictiveness of nearby CBAs negotiated
before a district’s CBA.\textsuperscript{56} We perform this falsification test for one measure of proximity (ESDs) and only include districts for which we have more than one CBA. We estimate a variant of the 2SLS spatial lag model that includes two spatial lag terms: one that is the average restrictiveness of CBAs within the same ESD that were bargained before a district’s CBA, and the other that is the average restrictiveness of CBAs within the same ESD that were bargained in the same year or after a district’s CBA.

In the specification described above we find neither past nor future spatial lag coefficient to be statistically significant, which is not terribly surprising given the much smaller sample of CBAs that we are utilizing. But, the spatial lag coefficient for past CBAs in the same ESD is 0.379 with a standard error of 0.267, compared to 0.080 and a standard error of 0.445 for future CBAs in the same ESD. The fact that the future CBAs appear to have little influence on past bargains, while the past CBAs have a much larger (and closer to statistically significant) impact suggests that we have accounted for endogeneity in the 2SLS models.

\textbf{VII. Policy Implications and Conclusions}

Politicians, policymakers and pundits have recently offered varying opinions on the degree to which collective bargaining agreements inhibit school operations and reforms. Yet as Lewin et al. (2012) suggest, we really know very little about collective bargaining. In this paper we explore how the adoption of specific terms and conditions in one district’s CBA may influence the terms and conditions in other districts’ bargaining agreements. We find that teacher contracts do have a strong geographic relationship to one another, and that this relationship is not solely based on the similarity of district characteristics. Rather there is good evidence of spillovers when it comes to contract negotiation, and these spillovers are driven by

\textsuperscript{56} We thank Thomas Dee for suggesting this falsification test.
geographically based institutional bargaining structures. The finding that institutional relationships are important, while purely geographic ones are not, suggests that political learning and policy diffusion arguments are more compelling in explaining the nature of CBAs than are theories about the economic competition for teacher labor.

Knowing the mechanism through which school district CBAs influence each other provides information about the way in which future contract reforms might spread. Prior research on geographically proximate policy diffusion gives us little insight as to how quickly or widely we might expect contract innovations from a given district may spread (Shipan and Volden, 2008; Karch, 2007). Because our work indicates that institutional structures may serve as information networks for member districts and unions, we imagine that future contract innovations will diffuse quickly within the bounds of these institutional structures and be less likely to cross institutional boundaries, such as across state lines. Thus, our findings indicate that those wishing to understand or influence the nature of CBAs should look to these institutional bargaining structures both as an explanation for existing CBA provisions and as a means for the purposeful dissemination of future policy innovations.
References


Jeanty, P. Wilner (2010b). “SPMLREG: Stata Module to Estimate the Spatial Lag, the Spatial Error, the Spatial Durbin, and the General Spatial Models.”


Figure 1: Contract Restrictiveness vs. Number of Restrictions in District Contracts

$r = 0.95$
Figure 2. Districts Within 25, 50, and 100 Miles of Tacoma (west) and Spokane (east)
Figure 3: Education Service Districts (ESDs) in Washington State

*SOURCE: http://k12.wa.us/Maps/Download.aspx
Figure 4: Uniserv Councils in Washington State

*SOURCE: www.washingtonea.org
## Table 1: Summary Statistics

<table>
<thead>
<tr>
<th>Panel 1: District variables</th>
<th>All districts (N = 270)</th>
<th>Top quartile CBA restrictiveness (N = 67)</th>
<th>Bottom quartile CBA restrictiveness (N = 68)</th>
<th>P-value of difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Standardized PIIR Contract Restrictiveness (dependent variable)</td>
<td>0.00 (1.00)</td>
<td>1.17 (0.33)</td>
<td>-1.32 (0.72)</td>
<td>.000***</td>
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<tr>
<td>West of Cascades</td>
<td>53.33%</td>
<td>64.18%</td>
<td>39.71%</td>
<td>.004***</td>
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<tr>
<td>On Oregon border</td>
<td>10.37%</td>
<td>4.48%</td>
<td>14.71%</td>
<td>.044**</td>
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<tr>
<td>On Idaho border</td>
<td>5.56%</td>
<td>5.97%</td>
<td>2.94%</td>
<td>0.397</td>
</tr>
<tr>
<td>On Canada border</td>
<td>3.70%</td>
<td>4.48%</td>
<td>2.94%</td>
<td>0.639</td>
</tr>
<tr>
<td>Standardized Log enrollment</td>
<td>0.00 (1.00)</td>
<td>0.66 (0.78)</td>
<td>-0.76 (0.87)</td>
<td>.000***</td>
</tr>
<tr>
<td>Standardized District Unemployment Rate</td>
<td>0.00 (1.00)</td>
<td>-0.19 (0.93)</td>
<td>0.11 (1.00)</td>
<td>.071*</td>
</tr>
<tr>
<td>Standardized District % Free/Reduced Priced Meals (FRPM)</td>
<td>0.00 (1.00)</td>
<td>-0.22 (0.84)</td>
<td>0.17 (1.02)</td>
<td>.018**</td>
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<tr>
<td>Urban district</td>
<td>3.70%</td>
<td>11.94%</td>
<td>1.47%</td>
<td>.015**</td>
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<table>
<thead>
<tr>
<th>Panel 2: Proximity variables</th>
<th>Avg. % of districts within 50 miles in top quartile CBA restrictiveness</th>
<th>Avg. % of districts within 50 miles in bottom quartile CBA restrictiveness</th>
<th>Avg. % of districts in same ESD in top quartile CBA restrictiveness</th>
<th>Avg. % of districts in same ESD in bottom quartile CBA restrictiveness</th>
<th>Avg. % of districts in same Uniserv in top quartile CBA restrictiveness</th>
<th>Avg. % of districts in same Uniserv in bottom quartile CBA restrictiveness</th>
</tr>
</thead>
<tbody>
<tr>
<td>Avg. % of districts within 50 miles in top quartile CBA restrictiveness</td>
<td>25.58% (13.31%)</td>
<td>30.27% (12.36%)</td>
<td>20.90% (11.20%)</td>
<td>.000***</td>
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<tr>
<td>Avg. % of districts in same ESD in top quartile CBA restrictiveness</td>
<td>25.19% (14.92%)</td>
<td>31.39% (16.47%)</td>
<td>19.01% (9.42%)</td>
<td>.000***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Avg. % of districts in same Uniserv in top quartile CBA restrictiveness</td>
<td>24.81% (18.64%)</td>
<td>33.86% (24.40%)</td>
<td>19.12% (11.24%)</td>
<td>.000***</td>
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<td></td>
</tr>
<tr>
<td>Avg. % of districts within 50 miles in bottom quartile CBA restrictiveness</td>
<td>25.81% (15.61%)</td>
<td>21.05% (15.41%)</td>
<td>32.09% (13.56%)</td>
<td>.000***</td>
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<tr>
<td>Avg. % of districts in same ESD in bottom quartile CBA restrictiveness</td>
<td>25.19% (14.43%)</td>
<td>19.25% (15.61%)</td>
<td>31.00% (9.60%)</td>
<td>.000***</td>
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<tr>
<td>Avg. % of districts in same Uniserv in bottom quartile CBA restrictiveness</td>
<td>24.43% (13.36%)</td>
<td>18.86% (15.94%)</td>
<td>28.44% (8.27%)</td>
<td>.000***</td>
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</table>

NOTES: Significance levels from two-sided t-test: * p < 0.1; ** p < .05; *** p < .01. Standard deviations of continuous variables given in parentheses.
<table>
<thead>
<tr>
<th>Table 2: Cherry-Picked Contract Provisions</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Accessibility</strong></td>
</tr>
<tr>
<td>How many provisions does the CBA contain?</td>
</tr>
<tr>
<td>How long is the CBA?</td>
</tr>
<tr>
<td>How many times was the district contacted to obtain the CBA?</td>
</tr>
<tr>
<td><strong>Association</strong></td>
</tr>
<tr>
<td>Is there a no strike/lockout clause/concentrated activities/work stoppage?</td>
</tr>
<tr>
<td>Does the district pay for release time for negotiations for union members?</td>
</tr>
<tr>
<td><strong>Hiring and Transfers</strong></td>
</tr>
<tr>
<td>Is seniority used to decide who is voluntarily transferred?</td>
</tr>
<tr>
<td>Does CBA require that district post all certificated vacancies/make them available to teachers in the district?</td>
</tr>
<tr>
<td>Does CBA specify the order in which district can consider new employees?</td>
</tr>
<tr>
<td>Is seniority used to decide who is involuntarily transferred?</td>
</tr>
<tr>
<td>If position is filled with probationary/temporary teacher, will it be re-opened the following year to members seeking transfer/reassignment?</td>
</tr>
<tr>
<td><strong>Workload</strong></td>
</tr>
<tr>
<td>Is there a maximum class size for 4th grade? 8th grade? 9-12th grades?</td>
</tr>
<tr>
<td>Does the CBA specify a given length of the school day?</td>
</tr>
<tr>
<td>Is collaboration time set aside in CBA for 4th grade? 8th grade? 9-12th grades?</td>
</tr>
<tr>
<td><strong>Evaluations</strong></td>
</tr>
<tr>
<td>Are there consequences for receiving a negative/&quot;unsatisfactory&quot; performance evaluation?</td>
</tr>
<tr>
<td>Does CBA/Evaluation rubric define the final rating categories?</td>
</tr>
<tr>
<td>Are teachers with 4 years or more experience, who meet or exceed standards on previous evaluation, evaluated on a different schedule?</td>
</tr>
<tr>
<td>Does the CBA allow for teachers to rebut or appeal a negative evaluation?</td>
</tr>
<tr>
<td><strong>Grievance</strong></td>
</tr>
<tr>
<td>May the teacher grieve disciplinary action?</td>
</tr>
<tr>
<td>Does the grievance go to mediation?</td>
</tr>
<tr>
<td>Does the grievance go to the board?</td>
</tr>
<tr>
<td>Does the grievance go to arbitration?</td>
</tr>
<tr>
<td><strong>Layoffs</strong></td>
</tr>
<tr>
<td>Is seniority the only primary factor that determines the order of layoffs?</td>
</tr>
<tr>
<td>Does CBA provide for recall rights after layoffs?</td>
</tr>
<tr>
<td>Does CBA specify that reemployment offers are made in reverse seniority order after layoffs?</td>
</tr>
<tr>
<td>Do factors other than seniority determine the order of layoffs?</td>
</tr>
<tr>
<td>Does CBA specify how reemployment offers are made after layoffs?</td>
</tr>
<tr>
<td>Can members reject a reemployment offer after layoff?</td>
</tr>
<tr>
<td><strong>Leaves</strong></td>
</tr>
<tr>
<td>Do members receive LOA for family illness/ family care leave?</td>
</tr>
<tr>
<td>Do members get additional pregnancy/ maternity leave time?</td>
</tr>
<tr>
<td>Do members receive parenting/ child rearing leave?</td>
</tr>
<tr>
<td>Does CBA specify what members' rights of return are from this leave?</td>
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Table 3: Estimates from Spatial Lag Models Calculated From All Provisions

<table>
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<tr>
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<td>OLS</td>
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<td>(0.174)</td>
<td>(0.167)</td>
<td>(0.175)</td>
<td>(0.146)</td>
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<td>Within 50 miles</td>
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<td>0.322*</td>
<td>0.245*</td>
<td>0.561***</td>
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<td>(0.165)</td>
<td>(0.128)</td>
<td>(0.111)</td>
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<td></td>
<td>0.317**</td>
<td>0.205*</td>
<td>0.512***</td>
<td>0.525***</td>
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<td>(0.157)</td>
<td>(0.107)</td>
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<tr>
<td>ESD*Uniserv</td>
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|                |      |      |      |      |      |      |      |      |      |      |      |      |      |      |
| Oregon Border Indicator | -0.338**| -0.351**| -0.235| -0.252| -0.277**| -0.173**| -0.223| -0.252*| -0.172**| -0.182**| -0.174*| -0.142| -0.158* |
|                | (0.155)| (0.176)| (0.179)| (0.178)| (0.143)| (0.069)| (0.176)| (0.136)| (0.071)| (0.090)| (0.094)| (0.089)| (0.083)|
| Standardized Log Enrollment | 0.518***| 0.523***| 0.477***| 0.483***| 0.493***| 0.451***| 0.502***| 0.514***| 0.481***| 0.454***| 0.482***| 0.468***| 0.474***|
|                | (0.063)| (0.061)| (0.063)| (0.063)| (0.061)| (0.093)| (0.062)| (0.061)| (0.087)| (0.100)| (0.097)| (0.099)| (0.103)|

NOTES: Significance levels from two-sided Wald test: * p < 0.1; ** p < .05; *** p < .01. Standard errors are in parentheses: in models for ESD or Uniserv standard errors are clustered at the ESD or Uniserv level, while models with both ESDs and Uniservs are clustered at the ESD level. Marginal effects for district characteristics are in brackets. All models also include a constant term, indicators for west of the Cascades, Idaho border, Canada border, and urban district, as well as the percent of students in the district eligible for free/reduced priced lunch and the unemployment rate in the district (both standardized).
Table 4: Estimates from Spatial Lag Models Calculated From Subsets of Provisions

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<td>Cherry-Picked</td>
<td>Accessibility</td>
<td>Association</td>
<td>Evaluation</td>
<td>Grievance</td>
<td>Layoffs</td>
<td>Benefits/Leave</td>
<td>Hiring/Transfer</td>
<td>Workload</td>
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<td>Within 50 miles</td>
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<td>ESD</td>
<td>-0.027</td>
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<td>0.431*</td>
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<td>0.064</td>
<td>0.939**</td>
<td>0.847*</td>
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<td>(0.235)</td>
<td>(0.303)</td>
<td>(0.245)</td>
<td>(0.186)</td>
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<td>(0.407)</td>
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<tr>
<td>Uniserv</td>
<td>0.193</td>
<td>0.247</td>
<td>-0.410*</td>
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<td>(0.188)</td>
<td>(0.202)</td>
<td>(0.209)</td>
<td>(0.191)</td>
<td>(0.414)</td>
<td>(0.651)</td>
<td>(0.410)</td>
<td>(0.304)</td>
<td>(0.309)</td>
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<tr>
<td>ESD*Uniserv</td>
<td>0.415**</td>
<td>0.256*</td>
<td>0.473***</td>
<td>0.371***</td>
<td>0.877***</td>
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<td>(0.302)</td>
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<td>Oregon Border Indicator</td>
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<tr>
<td>Standardized Log Enrollment</td>
<td>-0.160*</td>
<td>-0.034</td>
<td>-0.259***</td>
<td>-0.211</td>
<td>-0.312***</td>
<td>-0.191*</td>
<td>0.017</td>
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<td>(0.083)</td>
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<td>(0.080)</td>
<td>(0.212)</td>
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<td>Standardized Log Enrollment</td>
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<tr>
<td>Standardized Log Enrollment</td>
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<td>(0.103)</td>
<td>(0.080)</td>
<td>(0.101)</td>
<td>(0.048)</td>
<td>(0.100)</td>
<td>(0.101)</td>
<td>(0.067)</td>
<td>(0.079)</td>
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<tr>
<td>(0.481)</td>
<td>(0.458)</td>
<td>(0.438)</td>
<td>(0.483)</td>
<td>(0.149)</td>
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<td>(-0.014)</td>
<td>(0.274)</td>
<td>(0.524)</td>
<td>(0.370)</td>
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</tr>
</tbody>
</table>

**NOTES:** Significance levels from two-sided Wald test: * p < 0.1; ** p < .05; *** p < .01. Standard errors are in parentheses: in models for ESD or Uniserv standard errors are clustered at the ESD or Uniserv level, while models with both ESDs and Uniservs are clustered at the ESD level. Marginal effects for district characteristics are in brackets. All models also include a constant term, indicators for west of the Cascades, Idaho border, Canada border, and urban district, as well as the percent of students in the district eligible for free/reduced priced lunch and the unemployment rate in the district (both standardized).