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Interest Group Ratings and Regression Inconsistency

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This article uses spatial voting theory to analyze the properties of linear regressions that employ interest group ratings as measures of legislator policy preferences. Such regressions, in general, yield inconsistent results. In particular, least-squares estimation of a bivariate regression which contains an interest group rating as a regressor produces an inflated slope estimate. Instrumenting for the rating with a second rating, as proposed by Brunell et al. (1999), does not fix this problem, and this is because errors in both sets of ratings are correlated. Finally, estimation of a trivariate regression that contains an interest group rating and a party indicator on its right-hand side yields inconsistent slope estimates and, in particular, a party coefficient estimate of unreliable sign. Hence, regressions including both ratings and party indicators are not useful tools in the debate on whether party affiliation has an independent impact on legislator behavior.

1 Introduction

INTEREST GROUP RATINGS are often used to measure the policy preferences or ideal points of Congressional legislators (e.g., Krehbiel 1992; Dion and Huber 1997; Maltzman 1997; Bishin 2000). Nonetheless, surprisingly little has been published about the extent to which measurement error affects interest group ratings and the consequences of rating measurement problems for applied research. Consider, for instance, the treatment of ratings as if they were contaminated by mean zero error that is uncorrelated with legislator policy preferences. In light of standard econometric theory (Greene 1997, pp. 436–437), this treatment leads naturally to the claim that linear regression estimates which depend on ratings as independent variables suffer from attenuation bias.

But are the premises of this claim valid? That is, are ratings contaminated with errors that are uncorrelated with legislator preferences? It is difficult to answer this question based on existing literature because the conditions under which rating errors are uncorrelated in this fashion have not been explored. Notably, the spatial analysis presented here shows that errors in ratings are in general correlated with underlying preferences and, furthermore,

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that regression estimates which depend on ratings as independent variables will suffer from augmentation, as opposed to attenuation, bias.

This augmentation bias result implies, substantively, that researchers who use ratings as right-hand side variables in bivariate regressions will tend to overstate the impact of legislator preferences on the dependent variables they study. Moreover, this is the case even when party indicators are included in such regressions. When so included, estimated slope coefficients for ratings will be inflated. And party coefficient estimates will be inconsistent and can have incorrect signs. Thus, regressions which include both ratings and party indicators are not useful tools in the debate on whether party affiliation has an independent impact on legislator behavior.

It is often the case that biases in regression coefficient estimates caused by measurement error in a single regressor can be ameliorated with instrumental variables. In particular, Brunell et al. (1999) propose that a researcher who wants to estimate a bivariate regression with a rating on its right hand side instrument for the rating with a second rating. However, I show that this suggestion is problematic because errors in both ratings are correlated. This breaks the standard sufficiency condition used to show that instrumental variables estimation can fix measurement error problems in regressions. And, broadly speaking, it implies that one rating should not be used as an instrument for a second.

This article proceeds as follows. In Section 2 I describe the existing literature on interest group ratings and regressions that use ratings, and in Section 3 I present a simple spatial voting framework and derive from it two useful results. I then show in Section 4 how these results impact bivariate regression estimates, the properties of the Brunell et al. instrumental variables procedure, and a trivariate regression that contains an interest group rating and a party indicator as regressors. Finally, concluding comments are in Section 5.

2 Interest Group Ratings as Legislator Preference Measures

Ideally, a large literature on the characteristics of interest group ratings and the properties of regressions that use ratings as legislator preference measures would have developed prior to an applied literature that relies on ratings to make substantive arguments about Congress. Nonetheless, this has not happened. There exists instead a voluminous literature that employs ratings and only a small group of articles which focuses on the utility of ratings as preference measures.

The article which comes closest to addressing the subject of interest group rating accuracy is by Snyder (1992). Using a spatial voting model, Snyder proves that the distribution of ratings for a given Congressional chamber will in many cases have a greater variance than the corresponding distribution of legislator policy preferences or ideal points; ratings that have this property are said to be artificially extreme. Moreover, Snyder argues, based on graphical intuition, that regressions which use ratings as right-hand-side variables yield rating slope estimates that suffer from attenuation bias.[1] Building on Snyder's findings, I have shown in a simulation study that regressions which rely on artificially extreme ratings will usually lead researchers astray when these models contain party indicators (Herron 1999).

Jackson and Kingdon's (1992) study of voting regressions that use interest group ratings as independent variables reaches conclusions similar to those of Snyder. The former two researchers base their conclusions on, among other things, an assertion that such regressions

[1] Krehbiel (1994) claims that Snyder's results depend on irrational interest group behavior. In addition, using Monte Carlo simulations, Krehbiel argues that the results do not pose serious difficulties for difference in means tests used to check whether committees are preference outliers.

often omit important right-hand-side variables and the recognition that, if the votes used to generate a set of ratings correspond to different policy dimensions, resulting ratings contain errors.[2]

In light of the above literature, this article's contributions are twofold. First, I show that augmentation bias, as opposed to attenuation bias, in slope estimates is a primary consequence of using ratings as regressors. Second, and somewhat in contrast to Jackson and Kingdon, this article's results are based on an extremely simple analytical environment. If ratings fail—in the sense of leading to inconsistent regression estimates—in such a simple and sparse environment, a unidimensional environment in which all roll calls are taken sincerely, then it goes without saying that additional critiques leveled by Jackson and Kingdon, e.g., that Congressional politics may be multidimensional, can only make matters worse. Similarly, if legislators defer to committee members when casting roll calls (Hall and Grofman 1990), then inaccuracy problems for interest group ratings are almost certainly worse than those described here.

3 Legislator Preferences and Interest Group Ratings

Let $P_i \in [0, 1]$ denote legislator i's underlying policy preference or ideal point on a unidimensional space, and suppose without loss of generality that relatively large values of P_i are associated with politically right or conservative preferences. I assume, in accordance with standard spatial principles, that a legislator facing a choice between two alternatives votes for the one closest in a Euclidean sense to her ideal point. For purposes of tractability I also assume that $P_i \sim U(0, 1)$, i.e., that preferences are uniformly distributed on the unit interval.[3]

Let r_i^* denote the rating of legislator i by an interest group (later in the article I introduce ratings by a second group). As in the articles by Snyder (1992) and Herron (2000), a set of ratings corresponds to a distribution of roll call cutpoints where each cutpoint divides a chamber into winning and losing coalitions. I assume that the interest group's cutpoint distribution is uniform on the interval $(\mu_r - \alpha, \mu_r + \alpha)$, $0 < \mu_r - \alpha < \mu_r + \alpha < 1$, and $\mu_r \in (0, 1)$. These assumptions imply that $\alpha \in (0, \frac{1}{2})$, and, because legislators vote according to spatial principles,

$$r_i^* = \begin{cases} 0 & \text{if} \quad P_i < \mu_r - \alpha \\ \frac{P_i - \mu_r + \alpha}{2\alpha} & \text{if} \quad P_i \in [\mu_r - \alpha, \mu_r + \alpha] \\ 1 & \text{if} \quad P_i > \mu_r + \alpha \end{cases} \tag{1}$$

For instance, relatively liberal legislators ($P_i < \mu_r - \alpha$) vote identically on all the bills considered by the interest group and receive low ratings ($r_i^* = 0$). A related statement applies to relatively conservative legislators ($P_i > \mu_r + \alpha$) who receive high ratings ($r_i^* = 1$). The interest group, therefore, prefers conservatives to liberals, but none of the results which follow depend on this.[4]

[2] This review does not discuss inflation-adjusted interest group ratings (Groseclose et al. 1999), which are intended to allow comparisons of ratings across years. This is because the inflation-adjustment procedure assumes that ratings, insofar as they are measures of underlying legislator preferences, are not systematically contaminated by errors. In contrast, the present article is intended to explore whether this assumption is warranted and assess the consequences of its being violated.

[3] See Krehbiel (2000) for similar distributional assumptions.

[4] I also assume that the interest group's ideal point is greater than or equal to one, the ideal point of the most politically conservative legislator. This assumption guarantees that the group's ratings are monotonic in the true ideal points of members of Congress (e.g., Poole and Rosenthal 1997).

Equation (1)'s mapping from preferences to ratings has two noteworthy features. First, for nonextreme legislators ($P_i \in [\mu_r - \alpha, \mu_r + \alpha]$), ratings are rescaled ideal points because the cutpoint distribution is uniform. Note the presence of $2\,\alpha$ in the relevant denominator. Second, for relatively extreme legislators ($P_i < \mu_r - \alpha$ or $P_i > \mu_r + \alpha$), ratings are rather noninformative, as they are either zero or one, i.e., they fall at the endpoints of the distribution of ratings for moderate legislators.[5]

The parameter $\alpha \in (0, \frac{1}{2})$ in Eq. (1) determines the variance in the roll calls that the interest group uses to create its ratings. If, for instance, the group relies on roll calls with similar vote margins, then α will be relatively small. In contrast, the parameter μ_r describes the types of roll calls and associated winning coalitions used by the interest group to form its legislator ratings. Suppose that $\mu_r > \frac{1}{2}$ and consider a single roll call cutpoint $c > \mu_r$. This cutpoint is associated with a roll call that has a winning coalition of all legislators i with $P_i < \frac{1}{2}$ (left-leaning moderates and liberals) combined with legislators who have $P_i \in (\frac{1}{2}, c)$ (right-leaning moderates). As μ_r tends to one, c will tend to one as well since $c > \mu_r$. Thus, as μ_r gets large, associated winning coalitions encompass more and more conservative lawmakers. In general, I restrict α and μ_r only insofar as assuming that $0 < \mu_r - \alpha < \mu_r + \alpha < 1$ and $\mu_r \in (0, 1)$ and thus ignore the issue of optimal α and μ_r values from the perspective of interest group 1.[6]

Since legislator preferences have neither a fixed location nor a fixed scale, what is ultimately important regarding rating accuracy is the correlation—namely, whether it is one—between ratings and preferences.

Proposition 1. *The correlation $\rho(\cdot, \cdot)$ between ratings r_i^* and legislator preferences P_i is*

$$\rho(r_i^*, P_i) = \frac{3\,\mu_r - 3\,\mu_r^2 - \alpha^2}{\sqrt{3\,\mu_r - 3\,\mu_r^2 - \alpha}} \tag{2}$$

and this correlation is always less than one.

Proofs for all propositions are given in the Appendix. Proposition 1 shows that ratings are inaccurate insofar as they are used to measure underlying legislator policy preferences. This is because, simply, the correlation between ratings and preferences is strictly less than one. Figure 1 plots the correlation in Eq. (2) and shows that off-center cutpoint distributions lead to relatively inaccurate ratings; this is because such cutpoint distributions assign endpoint ratings (zero or one) asymmetrically, i.e., to most liberals or to most conservatives. Hence, ratings formed from a collection of cutpoints that are, on average, quite politically left or politically right will yield poor measures of legislator preferences.

Expecting perfection in a legislator preference measure is presumably unreasonable, so the fact that the correlation between ratings and underlying legislator preferences is less than one is not necessarily troubling. However, seeing that there are errors in ratings, it is important to understand the properties of these errors and their consequences for applied research. Let rating errors be defined as $\theta_{r,i}^* = P_i - r_i^*$.

[5] The author thanks an anonymous referee for highlighting these points.

[6] Based on Fowler (1982), one might conjecture that a politically right (left) interest group would, *ceteris paribus*, prefer a relatively large (small) value of μ_r.

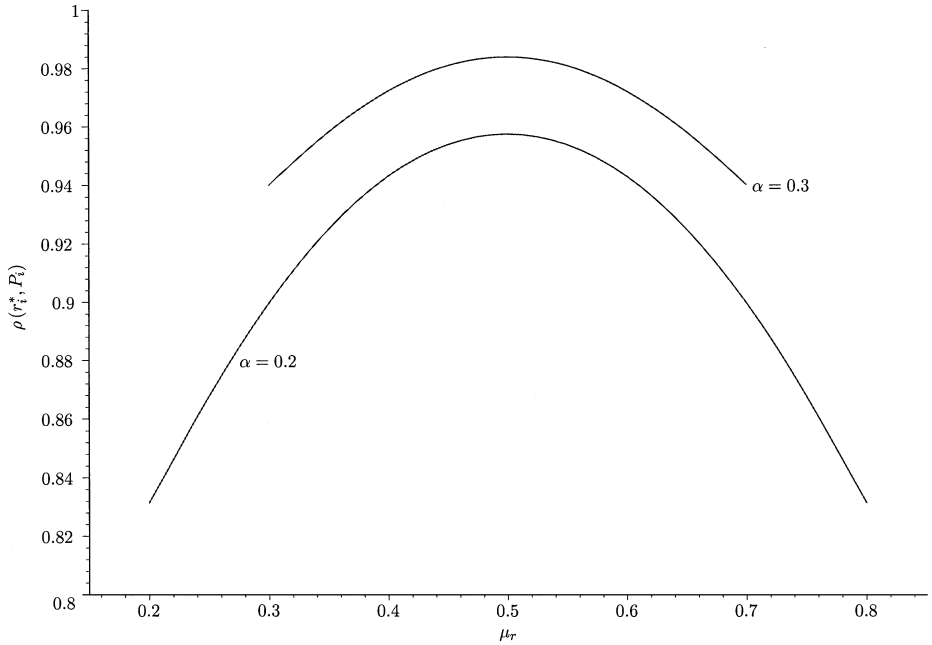

Fig. 1 Correlation between ratings and legislator preferences.

Proposition 2. *The correlation between rating errors* $\theta_{r,i}^*$ *and legislator preferences* P_i *is*

$$\rho(\theta_{r,i}^*, P_i) = \frac{1 + 12\,\mu_r^2\alpha + 4\,\alpha^3 - 12\,\mu_r\,\alpha}{\sqrt{(1 - 2\,\alpha)\left(4\,\alpha^2 - 24\,\mu_r\;\alpha + 24\,\mu_r^2\,\alpha + 2\,\alpha + 1\right)}} \tag{3}$$

and this expression is nonzero.

Proposition 2 shows that errors in ratings are correlated with underlying legislator preferences. At an intuitive level, it is not surprising that this result holds. Consider a group of relatively conservative lawmakers who have P_i close to one. The most conservative legislators of this group will have $r_i^* = 1$ and will be associated with small, i.e., negative, errors $\theta_{r,i}^*$. On the other hand, the most liberal legislators, who have preferences P_i close to zero, will have relatively large, i.e., positive, errors. Thus, large preferences are associated with small errors and small preferences with large errors, and this shows precisely why underlying legislator preferences will in general be correlated with rating errors.

The substantive implication of Proposition 2 is that standard results on regressor measurement error may not apply to regressions that contain interest group ratings as right-hand-side variables. This is because such results usually assume that regressor measurement error is uncorrelated with true regressor values, i.e., underlying legislator preferences.

4 Regressions with Ratings as Independent Variables

In this section I consider the properties of two regression models. The first is a bivariate model where the only (nonconstant) right-hand-side variable is an interest group rating,

and this model is useful insofar as establishing the basic properties of regressions that use ratings as preference measures. After discussing the bivariate model I also derive the properties of the instrumental variables estimator proposed by Brunell et al. (hereafter, BKDGF).

The second model discussed is a trivariate regression that includes a party indicator. This particular model is important in light of the ongoing debate on the role of party affiliation on legislator behavior and the fact that interest group ratings play a role in this debate.

4.1 *Bivariate Regression Results*

Consider a hypothetical researcher who wishes to estimate with ordinary least squares

$$Y_i = \gamma + \beta P_i + \epsilon_i \tag{4}$$

where Y_i is a dependent variable, γ and β are scalar parameters, and ϵ_i is a mean zero disturbance term assumed to be uncorrelated with P_i. Since underlying legislator preferences P_i are not observable, the hypothetical researcher might want to substitute observed ratings for preferences. Before commenting on this, however, I define a rescaled rating,

$$r_i^* = \begin{cases} 0 & \text{if} \quad r_i^* = 0 \\ 2\alpha r_i^* & \text{if} \quad r_i^* \in (0, 1) \\ 2\alpha & \text{if} \quad r_i^* = 1 \end{cases} \tag{5}$$

so that underlying legislator preferences P_i and rescaled ratings r_i lie on the same scale. The correlation between r_i and r_i^* is one and the correlation between r_i and P_i is the same as that between r_i^* and P_i (see Proposition 1).

Then I assume that the hypothetical researcher estimates

$$Y_i = \gamma + \beta r_i + \epsilon_i \tag{6}$$

Let $\hat{\beta}_{\text{OLS}}$ denote the ordinary least-squares estimate of β from Eq. (6), where Eq. (4) represents the true model of Y_i. Because P_i and r_i are on the same scale, one can inquire whether $\hat{\beta}_{\text{OLS}}$ will be close to β.

Proposition 3. *Under standard regularity conditions, the ordinary least-squares estimate* $\hat{\beta}_{\text{OLS}}$ *behaves as follows*:

$$\hat{\beta}_{\text{OLS}} \xrightarrow{\text{P}} \frac{3\mu_r^2 + \alpha^2 - 3\mu_r}{4\alpha\left(-3\mu_r + \alpha + 3\mu_r^2\right)} \times \beta \tag{7}$$

The OLS bias factor, which multiplies β, *is greater than or equal to one.*

Broadly speaking, Proposition 3 shows that $\hat{\beta}_{\text{OLS}}$ is inconsistent for the true preference parameter β when ratings r_i are used in place of legislator preferences P_i. And, because the OLS bias factor is greater than one, $\hat{\beta}_{\text{OLS}}$ suffers from augmentation bias. That is, the estimate $\hat{\beta}_{\text{OLS}}$ will, in the limit, be greater in magnitude than its intended target β.[7] This implies that $\hat{\beta}_{\text{OLS}}$ will tend to overstate the impact of legislator preferences on the dependent variable Y_i. BKDGF's claim that $\hat{\beta}_{\text{OLS}}$ suffers from attenuation bias is, therefore,

[7] Therefore, the estimate of the intercept γ will also be inconsistent and associated standard errors will be incorrect.

not valid under the conditions of the spatial voting model described here. This claim, notably is based on the assumption that ratings are contaminated with errors uncorrelated with true legislator preferences; nonetheless, Proposition 2 shows that, under simple spatial conditions, this does not hold.

4.2 *Instrumenting for Ratings*

BKDGF's concern over inconsistency in $\hat{\beta}_{\text{OLS}}$ is nonetheless appropriate, and they propose instrumenting for the rating r_i in Eq. (6) with a second rating.[8] Suppose that a hypothetical researcher has at her disposal a second set of ratings which measures the same preference values as those measured by the original ratings. Let s_i^* denote the second rating where s_i^* is based on a cutpoint parameter μ_s. For simplicity, I assume that α is the same for both r_i^* and s_i^*. I define s_i as the rescaled version of s_i^* in the sense of Eq. (5) and henceforth assume without loss of generality that $\mu_s < \mu_r$ and that $0 < \mu_r - \alpha < \mu_s + \alpha < 1$.

Let $\hat{\beta}_{\text{IV}}$ denote the instrumental variables (IV) estimator of β based on the procedure advocated by BKDGF (but using the rescaled ratings r_i and s_i as opposed to r_i^* and s_i^*). Before considering whether this estimate will be consistent for the true β in Eq. (4), it is useful to point out a key feature of the relationship between r_i and s_i, the former's instrument. Namely, the measurement errors in these ratings, $\theta_{r,i} = P_i - r_i$ and $\theta_{s,i} = P_i - s_i$, are themselves correlated, and this is because both r_i and s_i (or, without loss of generality, r_i^* and s_i^*) are based on the same set of legislator policy preferences. Figure 2 displays the error correlation $\rho(\theta_{r,i}, \theta_{s,i})$ for $\alpha = 0.3$.

The implication of Fig. 2 (and its tedious and unstated formula) is that the BKDGF instrumental variables approach is one in which the proposed instrument (s_i) is itself measured with an error ($\theta_{s,i}$) that is correlated with the error ($\theta_{r,i}$) the instrument is trying to eliminate. This correlation violates standard sufficiency conditions that would ordinarily be used to prove consistency of the estimator $\hat{\beta}_{\text{IV}}$.

Proposition 4. *The instrumental variables estimator $\hat{\beta}_{\text{IV}}$ behaves as follows:*

$$\hat{\beta}_{\text{IV}} \xrightarrow{\text{P}} -2\alpha\left(3\mu_s^2 + \alpha^2 - 3\mu_s\right) \Big/ \left(12\alpha^2\mu_r - 3\mu_s\mu_r^2 + 12\mu_r\mu_s\alpha + 3\mu_r\mu_s^2 - \mu_s^3 - 6\mu_s^2\alpha + \mu_r^3 - 6\mu_r^2\alpha + 12\mu_s\alpha^2 - 8\alpha^3 - 24\alpha^2\mu_r\mu_s\right) \times \beta \tag{8}$$

The IV bias factor is the fraction that multiplies β.

The expression in Eq. (8) for the bias factor is too tedious to interpret directly, but its implications can be captured graphically. Thus, Fig. 3 plots the bias factor as a function of μ_r and μ_s, where $\alpha = 0.3$ (other values of α lead to very similar results).

Consider the line associated with $\mu_r = 0.7$ (since $\alpha = 0.3$ in Fig. 3, this value of μ_r implies that $\mu_s \in (0.3, 0.7)$ since, by construction, $\mu_s < \mu_r$ and $\mu_r - \alpha < \mu_s + \alpha$). This line shows that, when μ_s is relatively low, the IV bias factor is much greater than one. The comparable OLS bias factor for $\mu_r = 0.7$ and $\alpha = 0.3$ is 1.36, based on Eq. (7). And, importantly, the IV bias factor is greater than or equal to 1.36 for the above values of μ_r and α. In other words, the augmentation bias in the instrumental variables estimator $\hat{\beta}_{\text{IV}}$ is worse than the corresponding bias in the least squares estimator $\hat{\beta}_{\text{OLS}}$. This same pattern

[8] For an application, one which actually precedes the publication of BKDGF's work, see Overby and Cosgrove (1996).

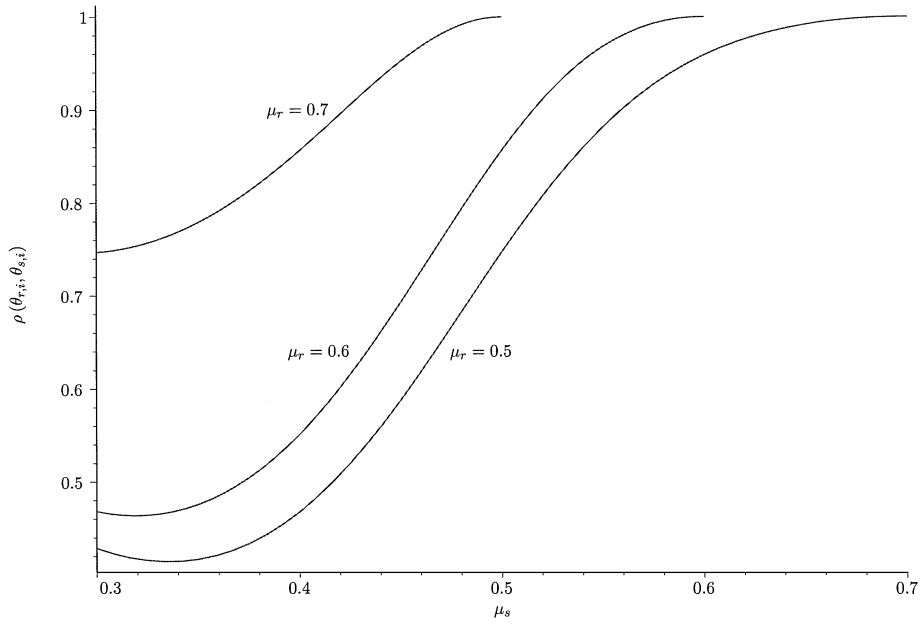

Fig. 2 Correlation between rating errors ($\alpha = 0.3$).

is evident in the lower two lines in Fig. 3; in particular, the OLS bias factor for $\mu_r = 0.6$ is 1.25 and it is 1.22 when $\mu_r = 0.5$. Substantively, these results mean that a researcher who wants to estimate the impact of preferences on the dependent variable Y_i will overstate this impact more if he relies on $\hat{\beta}_{\text{IV}}$ than if he uses $\hat{\beta}_{\text{OLS}}$.

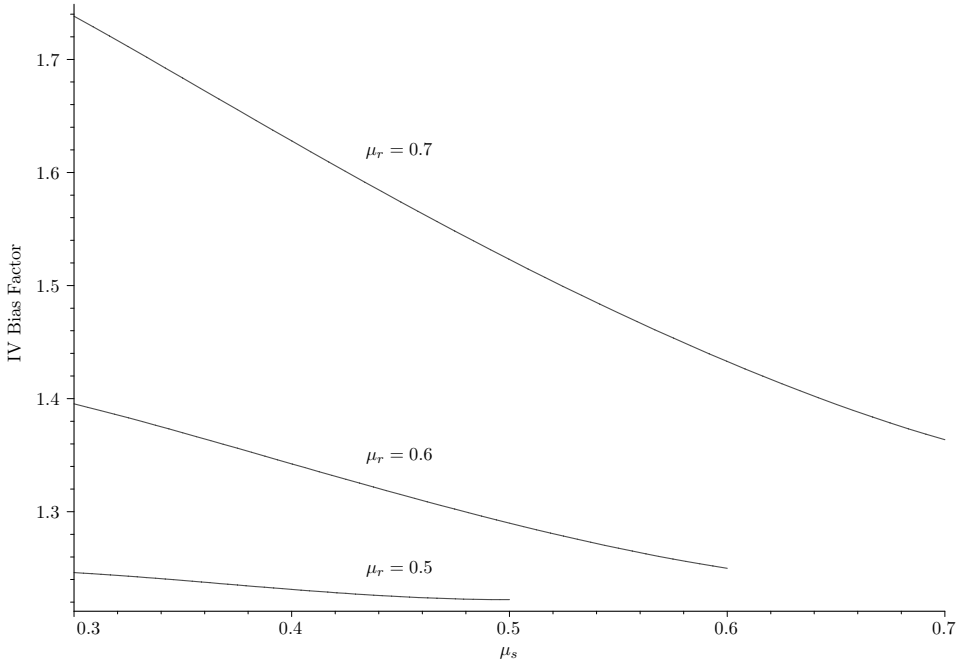

Fig. 3 The IV bias factor as a function of μ_r and μ_s ($\alpha = 0.3$).

Moreover, Fig. 3 shows why BKDGF's ostensible test of their instrumental variables method is in reality not a meaningful test. Namely, using real interest group rating data, BKDGF estimate, using ordinary least squares, a bivariate regression of party loyalty scores on ratings. Then they apply their instrumental variables approach to the same bivariate model and subsequently compare the two resulting slope estimates of the impact of legislator preferences on party loyalty. They find that the instrumental variables slope estimate is larger in magnitude than the corresponding ordinary least-squares estimate, and from this BKDGF conclude that their instrumental variables procedure eliminated some of the attenuation bias in the ordinary least-squares estimate. This conclusion does not follow, however: the BKDGF instrumental variables estimator may be relatively large in magnitude because it is affected by augmentation bias worse than the augmentation bias in the OLS estimate.

4.3 *Regression Results When a Party Indicator Is Included*

I now consider a trivariate regression which contains a constant term, a legislator preferences variable, and a party indicator. In particular, define a Democratic party indicator as $D_i = 1$ if and only if $P_i < \frac{1}{2}$. Since rating errors are in general correlated with underlying legislator policy preferences, then, if preferences are correlated with party membership, it follows that rating errors will be correlated with party membership. This means that a trivariate regression model which uses interest group ratings in place of preferences is one which contains a variable (ratings) that is measured with an error correlated with both the variable (underlying legislator preferences) it contaminates and the other exogenous variable (Democratic party indicator) in the model.

Let the true model of the dependent variable Y_i be

$$Y_i = \gamma + \beta P_i + \kappa D_i + \epsilon_i \tag{9}$$

where κ is the true party parameter and ϵ_i is a mean zero disturbance uncorrelated with both P_i and D_i. As in the previous section, suppose that

$$Y_i = \gamma + \beta r_i + \kappa D_i + \epsilon_i \tag{10}$$

is estimated, and let $\hat{\beta}_{\text{OLS}}$ and $\hat{\kappa}_{\text{OLS}}$ be the least-squares estimates of β and κ, respectively, based on Eq. (10). Proposition 5 describes the consequences of using interest group ratings r_i as proxies for underlying preferences P_i in Eq. (10).

Proposition 5. *The least-squares estimates* $\hat{\beta}_{\text{OLS}}$ *and* $\hat{\kappa}_{\text{OLS}}$ *behave as follows:*

$$\hat{\beta}_{\text{OLS}} \xrightarrow{\text{P}} \hat{\beta}_{\text{OLS}} \text{ Bias Factor} \times \beta \tag{11}$$

$$\hat{\kappa}_{\text{OLS}} \xrightarrow{\text{P}} \kappa + \hat{\kappa}_{\text{OLS}} \text{ Bias Factor} \times \beta \tag{12}$$

Explicit bias factors for Eqs. (*11*) *and* (*12*) *are tedious*; *see the Appendix for required steps.*

Figure 4 plots the $\hat{\beta}_{\text{OLS}}$ bias factor from Eq. (11) as a function of μ_r, where $\alpha = 0.2$ imposes $\mu_r \in (0.2, 0.8)$ and $\alpha = 0.3$ imposes $\mu_r \in (0.3, 0.7)$. The figure's key feature is that the $\hat{\beta}_{\text{OLS}}$ bias factor is greater than one, and thus, as in the previously discussed bivariate regression case, $\hat{\beta}_{\text{OLS}}$ suffers from augmentation bias insofar as it is used to estimate β. Substantively, this result implies that researchers estimating Eq. (10) when Eq. (9) is the

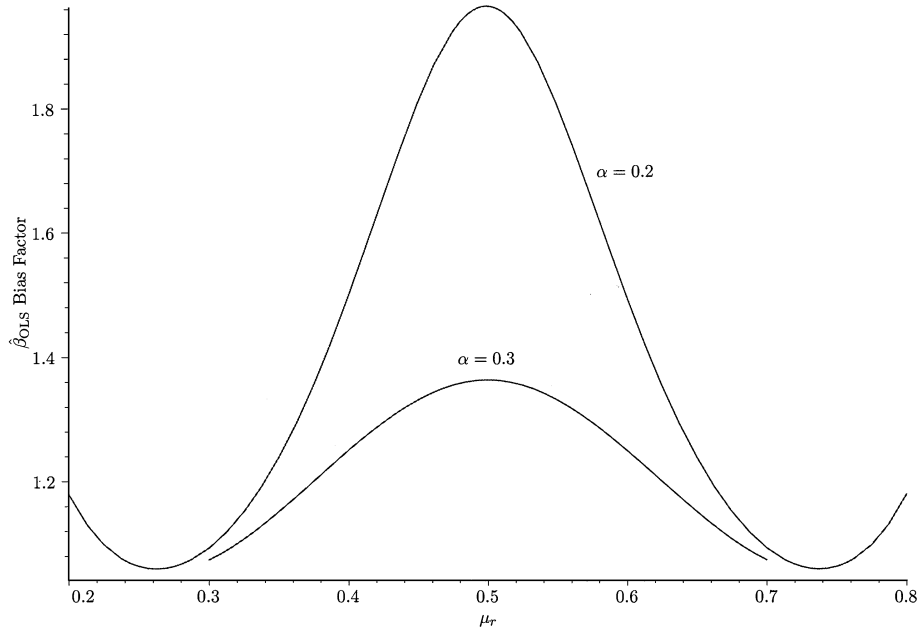

Fig. 4 $\hat{\beta}_{OLS}$ bias factor for the trivariate regression model.

true model will tend to overstate the impact of preferences on the dependent variable Y_i when controlling for legislator party affiliation.

In addition, Eq. (12) implies that substitution of r_i for P_i in Eq. (10) means that the true preference parameter β contaminates the estimate of the party parameter; one can see this through the presence of β in the probability limit of $\hat{\kappa}_{OLS}$, the estimator of κ. Figure 5 plots the $\hat{\kappa}_{OLS}$ bias factor, and it is clear that this factor is qualitatively different from the $\hat{\beta}_{OLS}$ bias factor. Namely, the former can be less than zero.

Suppose, for instance, that both the true preference parameter β and the true party parameter κ are negative; in this case, Eq. (9) implies that politically conservative preferences and Democratic party membership work against the dependent variable Y_i. Then, if μ_r is either large or small with respect to $\frac{1}{2}$, the $\hat{\kappa}_{OLS}$ bias factor will be negative. In such an instance, Eq. (12) implies that the estimate $\hat{\kappa}_{OLS}$ of the party coefficient will be biased upward.

Unlike estimates that suffer from attenuation or augmentation bias, estimates that are biased upward can suffer from sign reversals. That is, if the $\hat{\kappa}_{OLS}$ bias factor is great enough and if the true preference parameter β is sufficiently negative, then $\hat{\kappa}_{OLS}$ can tend to a positive quantity even though the true party parameter κ is negative. Similarly, if the true party parameter κ and the true preference parameter β are positive, then large or small μ_r values can lead to negative values of $\hat{\kappa}_{OLS}$. It goes without saying that estimates which suffer from sign reversals can lead to gross errors in inference.

Equation (12) implies that sign reversals on the party coefficient κ are most likely when β is large in magnitude compared to κ. And a relatively large β implies that underlying legislator policy preferences are important with respect to the dependent variable Y_i. This means, substantively, that estimating the impact of party affiliation becomes difficult when underlying preferences matter to a large extent. In fact, researchers who estimate Eq. (10) when Eq. (9) holds may think, when so-called preference effects are strong, that the impact

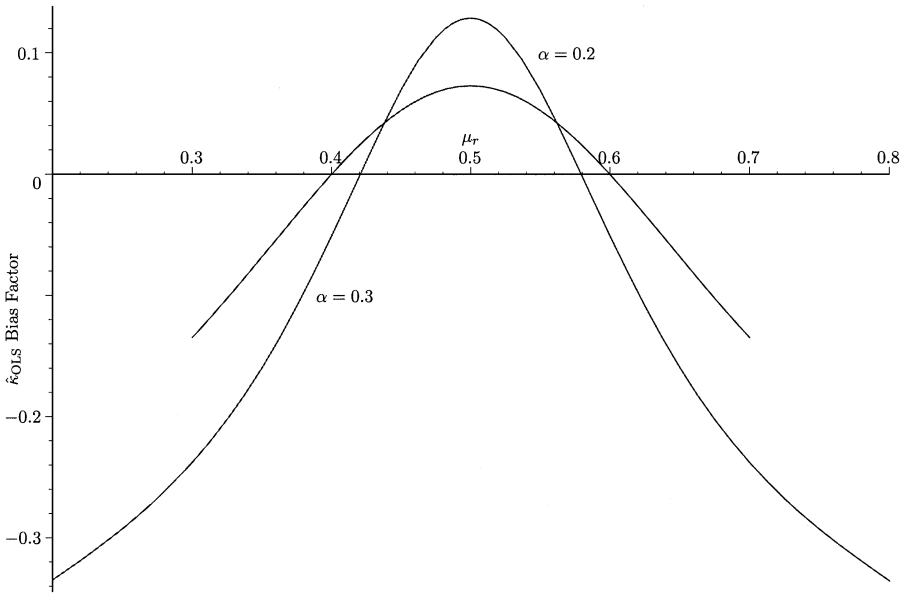

Fig. 5 $\hat{\kappa}_{\text{OLS}}$ bias factor for the trivariate regression model.

of party is the opposite of what it actually is. In contrast, when β is near zero, indicating that underlying legislator preferences matter very little, then $\hat{\kappa}_{\text{OLS}}$ can be a very good estimate of κ despite the fact that r_i is used to proxy for P_i.[9]

These problems with $\hat{\kappa}_{\text{OLS}}$ mean, for example, that the question of whether party membership influenced House members to sign a discharge petition for the "A to Z Spending Plan," a piece of legislation from the 103rd Congress, cannot be resolved using interest group ratings. This is a problem, notably, because both of the analytical entrants in the "A to Z" discharge petition debate are based on interest group ratings. Furthermore, a major part of the quarrel between these two entrants—Krehbiel (1995) and Binder et al. (1999)—is the sign and significance level of a party coefficient. These signs should be given little weight, according to my results, and therefore the extent to which party mattered on the "A to Z" discharge petition should be considered an open question.[10]

Krehbiel (2000) argues that vote score measures like interest group ratings will do a poor job of discriminating between voting that is preference-based (β large in magnitude and κ close to zero) and voting that is party-based (β close to zero and κ large in magnitude). The results here are similar. Moreover, not only will vote score measures be poor discriminators of different types of voting behavior, but also such scores may even lead researchers in the wrong direction as to the role of party membership on legislator behavior.[11]

[9] Ultimately, whether a party coefficient estimate is biased upward or downward is very dependent on party overlap and the underlying distribution of legislator preferences. Here, I have assumed that there is no party overlap since, by definition, $D_i = 1$ if and only if $P_i < \frac{1}{2}$. Yet problematic results for $\hat{\kappa}_{\text{OLS}}$ still obtain.

[10] The "A to Z" papers use regressions with interest group ratings and many other right hand side variables. It is tedious, although technically feasible, to calculate coefficient bias factors such regressions. These bias factors depend on covariances among all independent variables, and there will be many such covariances in a regression with numerous right-hand-side variables. The results presented here should be sufficient to caution researchers who use interest group ratings in regressions with more than three independent variables.

[11] See McCarty et al. (2001) for additional comments on identification of party effects in regression models.

5 Discussion

With a simple spatial framework which assumes that legislators vote sincerely in a unidimensional policy space, I have shown that errors in interest group ratings are correlated with the underlying legislator preferences measured by the ratings. And, in the course of studying a bivariate regression which has an interest group rating as a regressor, I demonstrated that the estimated rating coefficient suffers from augmentation bias insofar as it is interpreted as an estimate of true preference effects. I also showed that a proposal, offered by Brunell et al. (1999), to fix interest group rating problems usually does not work.

Similar, albeit more severe, problems affect coefficient estimates produced by a regression which has an interest group rating and a party indicator on its right-hand-side. In such a trivariate case, the estimated rating coefficient suffers from augmentation bias, and the estimated party coefficient is inconsistent and can suffer from a sign reversal.

I noted in Section 2 that without studying the properties and consequences of rating errors it is not possible to understand how existing empirical results based on ratings might be erroneous. The conclusion posed here regarding estimated party coefficients illustrates this point in a meaningful way. Namely, existing regression-based findings regarding the influence of party membership on legislator behavior should not be trusted if the findings are based on interest group ratings. Estimated party coefficients that depend on ratings can suffer from sign reversals; they are more likely to do so when preferences are relatively important, and this implies that researchers who use ratings as independent variables in regressions risk drawing improper conclusions about the direction of party influence on legislator behavior.

This article's results depend heavily on the use of uniform distributions so that various calculations have closed-form solutions. One feature of uniform cutpoint distributions in particular is that the ratings of nonextreme legislators (those that receive ratings of neither zero nor one) are simply rescaled ideal points. In the analytical framework of this article, then, it follows that consistency of regression estimates that depend on interest group ratings can be attained if legislators with ratings of zero or one are simply dropped from the regression sample.

If the cutpoint distribution were not uniform, though, then this sanguine result would not hold. That is, dropping legislators who have so-called endpoint ratings would not guarantee that regressions using the resulting, truncated sample would return consistent coefficient estimates. Nonetheless, it seems prudent that, when ratings are used in applied research, legislators who receive scores of zero and one are ignored or, at the very least, treated differently than legislators who receive nonextreme scores.

In general, though, interest group ratings lead to serious problems in regression analyses, and whenever possible they should be avoided. When, for instance, a researcher needs a general legislator ideology measure, NOMINATE scores (Poole and Rosenthal 1997) or Heckman–Snyder (1997) scores are preferred over, say, ADA and ACU ratings. Both of the former two preference measurement systems scale many roll call votes from a given legislative session, and because they do not depend explicitly on a cutpoint distribution in the way that interest group ratings do, NOMINATE and Heckman–Snyder scores will not be subject to the same sort of biases that contaminate ratings.[12]

[12] This is not to argue that regressions which depend on NOMINATE scores are faultless. The point here is that some of the biases associated with interest group ratings will not affect NOMINATE ratings because the latter do not depend on an exogenous cutpoint distribution.

A more difficult choice faces the researcher who seeks a jurisdiction-specific measure of legislator preferences, e.g., a measure of preferences on environmental issues. Relying on environmental ratings published by, say, the League of Conservation Votes will lead to the biases and estimator problems described here. Furthermore, scaling environmental votes using the NOMINATE or Heckman–Snyder algorithm is likely to run into small sample size problems since the number of roll calls on environmental issues in a given session of Congress is generally small. In this situation, the estimator in Londregan (1999) might be optimal.

Appendix: Proofs of Propositions

This Appendix outlines proofs of the propositions found in the body of the article. For the sake of brevity many details are omitted.

A1 *Proof of Proposition 1*

For $\rho(r_i^*, P_i)$, $E(P_i) = \frac{1}{2}$ and Var $(P_i) = \frac{1}{12}$, since $P_i \sim U(0, 1)$. Furthermore,

$$\mathrm{E}(r_i^*) = \int_{\mu_r-\alpha}^{\mu_r+\alpha} \frac{x-\mu_r+\alpha}{2\alpha}\mathrm{d}x + \int_{\mu_r+\alpha}^{1} \mathrm{d}x = 1-\mu_r \tag{13}$$

$$\begin{aligned}\mathrm{Var}(r_i^*) &= \int_{\mu_r-\alpha}^{\mu_r+\alpha} \left(\frac{x-\mu_r+\alpha}{2\alpha}\right)^2 \mathrm{d}x + \int_{\mu_r+\alpha}^{1} \mathrm{d}x - (1-\mu_r)^2 \\ &= -\frac{1}{3}\alpha + \mu_r - \mu_r^2 \end{aligned} \tag{14}$$

$$\begin{aligned}\mathrm{Cov}(r_i^*, P_i) &= \mathrm{E}(r_i^* P_i) - \mathrm{E}(r_i^*)\,\mathrm{E}(P_i) \\ &= \int_{\mu_r-\alpha}^{\mu_r+\alpha} x\frac{x-\mu_r+\alpha}{2\alpha}\mathrm{d}x + \int_{\mu_r+\alpha}^{1} x\,\mathrm{d}x - (1-\mu_r)/2 \\ &= -\frac{1}{2}\mu_r^2 - \frac{1}{6}\alpha^2 + \frac{1}{2}\mu_r \end{aligned} \tag{15}$$

The correlation follows from the standard formula. To prove that the correlation is strictly less than one, note that there are two real solutions in α which solve $\rho(r_i^*, P_i) = 1$. These solutions are $\alpha = -\frac{1}{2} - \frac{1}{2}\sqrt{1+12\,\mu_r-12\,\mu_r^2}$, which is negative and hence ruled out, and $\alpha = -\frac{1}{2} + \frac{1}{2}\sqrt{1+12\,\mu_r-12\,\mu_r^2}$. Suppose, that $\alpha = -\frac{1}{2} + \frac{1}{2}\sqrt{1+12\,\mu_r-12\,\mu_r^2}$. By assumption, $\mu_r > \alpha$, which implies that $\mu_r > \frac{1}{2}$; and, by assumption, $\mu_r + \alpha < 1$, which implies that $\mu_r < \frac{1}{2}$, a contradiction. Hence, the correlation is strictly less than one.

A2 *Proof of Proposition 2*

For $\rho(\theta_{r,i}^*, P_i)$, note that

$$\begin{aligned}\rho(\theta_{r,i}^*, P_i) &= \frac{\mathrm{Cov}(P_i - r_i^*, P_i)}{\sqrt{\mathrm{Var}(P_i - r_i^*)}\sqrt{\mathrm{Var}(P_i)}} \\ &= \frac{\mathrm{Var}(P_i) - \mathrm{Cov}(r_i^*, P_i)}{\sqrt{\mathrm{Var}(P_i) + \mathrm{Var}\left(r_i^*\right) - 2\,\mathrm{Cov}(r_i^*, P_i)}\sqrt{\mathrm{Var}\,(P_i)}} \end{aligned} \tag{16}$$

The result follows from substitution based on the expressions in Eqs. (13)–(15) Setting the correlation to zero and solving for μ_r yields two imaginary solutions for α. This implies that the correlation is always nonzero.

A3 *Proof of Proposition 3*

Under standard regularity conditions,

$$\begin{aligned}\hat{\beta}_{\text{OLS}} &\xrightarrow{\text{P}} \frac{\text{Cov}(Y_i, r_i)}{\text{Var}(r_i)} \\ &= \frac{\text{Cov}(\gamma + \beta P_i + \epsilon_i, P_i - \theta_{r,i})}{\text{Var}(P_i - \theta_{r,i})} \\ &= \beta \frac{\text{Var}(P_i) - \text{Cov}(\theta_{r,i}, P_i)}{\text{Var}(P_i) + \text{Var}(\theta_{r,i}) - 2\,\text{Cov}(\theta_{r,i}, P_i)} \end{aligned} \tag{17}$$

Substitutions similar to those found in Propositions 1 and 2 give the result.

To show that the bias factor is greater than one, first suppose that $3\,\mu_r^2 + \alpha - 3\,\mu_r > 0$. Then $1 - \mu_r > \alpha$ implies that $\mu_r < \frac{1}{3}$. Similarly, $\mu_r > \alpha$ implies that $\mu_r > \frac{2}{3}$, a contradiction. Hence $3\,\mu_r^2 + \alpha - 3\,\mu_r < 0$, and it follows that $3\,\mu_r^2 + \alpha^2 - 3\,\mu_r < 0$ since $\alpha < 1$.

Now assume that the bias factor is less than one. This implies that $(3 - 12\,\alpha\,(\mu_r^2 - \mu_r) - 3\,\alpha^2 > 0$. Solving the first-order condition with respect to α of this expression (the second-order condition is negative) and substituting shows that the maximum of the left-hand side is $3\,\mu_r\,(\mu_r - 1)\,(2\,\mu_r - 1)^2 < 0$, a contradiction.

A4 *Proof of Proposition 4*

Under standard regularity conditions,

$$\begin{aligned}\hat{\beta}_{\text{IV}} &\xrightarrow{\text{P}} \frac{\text{Cov}(s_i, Y_i)}{\text{Cov}(r_i, s_i)} \\ &= \frac{\text{Cov}(P_i - \theta_{s,i}, \gamma + \beta P_i + \epsilon_i)}{\text{Cov}(P_i - \theta_{s,i}, P_i - \theta_{r,i})} \\ &= \beta \frac{\text{Var}(P_i) - \text{Cov}(\theta_{s,i}, P_i)}{\text{Var}(P_i) - \text{Cov}(\theta_{s,i}, P_i) - \text{Cov}(\theta_{r,i}, P_i) + \text{Cov}(\theta_{r,i}, \theta_{s,i})} \end{aligned} \tag{18}$$

The result follows from calculations similar to those in the proofs of Propositions 1 and 2.

A5 *Proof of Proposition 5*

Equation (9) implies that $\text{Cov}(Y_i, r_i) = \beta\text{Cov}(P_i, r_i) + \kappa\,\text{Cov}(D_i, r_i)$ and $\text{Cov}(Y_i, D_i) = \beta\,\text{Cov}(P_i, D_i) + \kappa\,\text{Var}(D_i)$. Then, under standard regularity conditions,

$$\begin{aligned}\hat{\beta}_{\text{OLS}} &\xrightarrow{\text{P}} \frac{\text{Cov}(Y_i, r_i)\,\text{Var}(D_i) - \text{Cov}(Y_i, D_i)\,\text{Cov}(D_i, r_i)}{\text{Var}(r_i)\,\text{Var}(D_i) - (\text{Cov}(D_i, r_i))^2} \\ &= \beta \frac{\text{Cov}(P_i, r_i)\,\text{Var}(D_i) - \text{Cov}(P_i, D_i)\,\text{Cov}(D_i, r_i)}{\text{Var}(r_i)\,\text{Var}(D_i) - (\text{Cov}(D_i, r_i))^2} \end{aligned} \tag{19}$$

The $\hat{\beta}_{\text{OLS}}$ bias factor can then be derived using calculations similar to those in the proofs of Propositions 1 and 2.

Finally, and analogous to Eq. (11), Eq. (12) follows from

$$\hat{\kappa}_{\text{OLS}} \xrightarrow{\text{P}} \frac{\text{Cov}(Y_i, D_i)\text{Var}(r_i) - \text{Cov}(Y_i, r_i)\text{Cov}(D_i, r_i)}{\text{Var}(r_i)\text{Var}(D_i) - (\text{Cov}(D_i, r_i))^2} \tag{20}$$

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