Modeling Considerations

Chapter 5

Making the News: Politics, the Media and Agenda Setting

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It is reasonable to expect that the policy topics modeled in Chapter 5 vary in such a way that we might have unit (topic) heterogeneity in the distribution of the dependent variable, potentially leading to omitted variable bias. Two possible approaches could be used to address this potential problem. The first approach is to use a fixed effects model, which assumes and controls for unit heterogeneity by estimating a dummy variable for each of the (N-1) topics. The second approach, and the one I adopt here, is to employ a random effects model in conjunction with a lagged dependent variable. Unlike the fixed effects model, the random effects model assumes that the units (topics) come from a distribution with a common mean and variance. By itself this assumption is problematic, but it can be partially corrected for through a lagged dependent variable if that variable controls for a large portion of whatever heterogeneity might exist. The lagged dependent variable in my model correlates with the dependent variable at $\rho=0.62$, meaning that remaining variance in attention should be due largely to differences in the independent variables as opposed to the dependent variable. Thus, controlling for fixed effects *in addition* to controlling for variance across policy topics via lagged attention leaves relatively little remaining variance for the model to explain, suggesting that the resulting coefficients may be underestimated. From a theoretical level, the random effects approach is also sensible because, without measures of events or issue "type," I have little expectation of being able to explain meaningful variance across topics beyond that explained by cross-issue variance in the dependent variables. Rather, my interest here is in explaining general trends in attention. Additionally, if any measurement error exists in the dependent variable (as surely it does here), then the fixed effects approach risks picking this error up in the form of biased estimates. The random effects model assumes that the dependent variable is drawn from a theoretically larger population, meaning that it accounts for noise, and thus is not susceptible to biased estimates in the same way that the fixed effects model is. Plus, in the fixed effects model those policy topics that have zero-inflated dependent variable series will have a disproportionately small impact on the model's parameter estimates (Beck and Katz 2001). All that said, a Hausman test comparing the estimates from the random effects and fixed effects versions of the model above rejects the null hypothesis that the estimates do not vary systematically (although for discussion of potential bias in the Hausman test, see Plümper and Troeger 2004). When run with fixed effects, all three models show the same significant effects in the same directions, with the exceptions of two variables—***policymaker attention*** (Congressional hearings as well as executive orders) and the ***diversity of discussion***. The significance washes out for these variables, arguably in large part because, again, so much of the variance is soaked up by controlling for fixed effects when the lagged dependent variable is already included.

The ARIMA modeling approach allows us to ensure that the model employed addresses the specific dynamic properties of the dependent variable (on applying ARIMA modeling to media attention see, for example, Hollanders and Vliegenthart (2008)). Because my expectations in the case of these specific issues are directional in the case of each variable, one-tailed significance tests are reported. Before developing these models, each dependent variable (attention to the war, and attention to the death penalty) was tested for stationarity. A glance at each dependent variable series (captured by the bold line in Figures 6.1 and 6.2) suggests a possible trend in each case—downward in the case of the war, upward in the case of the death penalty. However, significant Dickey Fuller tests indicate that we can reject the null hypothesis of a unit root series in each case and assume stationarity. The theory of the news-generation process I have described suggests that news coverage should be a strongly autoregressive (i.e., values today should be influenced by values yesterday) but not necessarily an integrated or a moving average process. A visual inspection of autocorrelation function and partial autocorrelation function graphs indicate that both dependent variables are indeed autoregressive, with no suggestion of moving average behavior. Thus, with the notable exceptions of when I demonstrate the inappropriate fit of models that violate the requirement of white noise residuals, the models in Tables 6.1 and 6.2 are all in ARIMA (1,0,0) format.