Using Graphs Instead of Tables to Improve the Presentation of Empirical Results in Political Science

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Abstract

When political scientists present empirical results, they are much more likely to use tables rather than graphs, despite the fact that the latter greatly increases the clarity of presentation and makes it easier for a reader or listener to draw clear and correct inferences. Using a sample of leading journals, we document this tendency and suggest reasons why researchers prefer tables. We argue the extra work required in producing graphs is rewarded by greatly enhanced presentation and communication of empirical results. We illustrate their benefits by turning several published tables into graphs, including tables that present descriptive data and regression results. We show that regression graphs properly emphasize point estimates and confidence intervals rather than null significance hypothesis testing, and that they can successfully present the results of multiple regression models. A move away from tables and towards graphs would increase the quality of the discipline's communicative output and make empirical findings more accessible to every type of audience.

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1 Introduction

While political science is a diverse field whose practitioners employ a variety of methodologies and tools, a significant portion of the discipline's output includes the study of empirical data and drawing inferences from statistical analyses. As such, the conclusions one draws from political science papers, books and presentations often hinge on the successful communication of the data a researcher is using and the inferences she is drawing from them. Yet, much more often than not, political scientists choose to present empirical results in the form of tables rather than using graphical displays, a tendency that weakens the clarity of presentation and makes it more difficult for a reader or listener to draw clear and correct inferences.

In this paper we seek to highlight the discipline's reliance on tables and to offer suggestions for how to use graphs instead of tables to improve the presentation of empirical results. Six years ago, King, Tomz and Wittenberg's (2000) influential paper urged social scientists to present quantities of interest rather than parameter estimates from statistical analyses. Our paper is a natural follow-up to this effort: we seek to move beyond *what* researchers should communicate to their audience by offering suggestions on *how* they should do so.[1]

Other scholars have made similar recommendations (see e.g Bowers and Drake 2005, Epstein, Martin and Schneider forthcoming, Gelman, Pasarica and Dodhia 2002). But, as we show, political scientists are not heeding the advice to use graphs.[2] Following the

[1]We should note that King, Tomz and Wittenberg (2000) did implicitly urge researches to use graphs by presenting their results mainly in graphical displays; their main focus, however, was on imploring researchers to use quantities of interest rather than on how to communicate these quantities.

[2]This neglect may be due in part to the fact that this work is likely to reach only a small subset of the discipline or is narrow in focus. Epstein, Martin and Schneider (forthcoming), which is aimed at legal researchers, appears in the *Vanderbilt Law Review* and is likely to be seen only by political scientists who study law and courts. Bowers and Drake (2005) does appear in a political science journal (*Political Analysis*) but its focus is on using exploratory graphical displays to improve inferences drawn from multilevel models and not the general use of graphs instead of tables. Finally, the main inspiration for our paper —Gelman, Pasarica and Dodhia (2002)— was written by and for statisticians, and hence is unlikely to have been seen

example of Gelman, Pasarica and Dodhia (2002), we went through every article from five issues of three leading political science journals—the February and May 2006 *American Political Science Review*, the July 2006 *American Journal of Political Science* and the Winter and Spring 2006 issues of *Political Analysis*[3]—and counted the number of tables and graphs presented in each. We also analyzed the basic characteristics and purpose of each table and graph to get a sense of how researchers use tables to communicate empirical results.

This undertaking led to two main conclusions. First, political scientists rely on tables far more than graphs—twice as often, in fact. Second, tables are used mainly to present data summaries and the results of regression models. Indeed, tables presenting parameter estimates and standard errors comprise 50% of the tables in our sample. In addition, we found that political scientists *never* use graphs to present regression results—in our sample, at least.

Our goal in this paper is to demonstrate directly how researchers can use graphs to improve the quality of empirical presentations. Unlike previous attempts to promote the use of graphs, we devote a significant portion of our analysis to showing how graphs can greatly improve the communication of regression results, which are almost always presented in tables whose features can strain even the most seasoned journal reader. Rather than presenting an abstract review of the benefits of graphs, we take a sample of tables from the various journal issues and turn them into graphs, showing that it is possible and desirable to do so for any table that presents numeric information, including data summaries and parameter estimates. We show that graphs better communicate relevant information from both data summaries and regression models, including comparing values across variables or models and the sign and significance of predictors. We argue that while graphs are almost never used to present regression results, the benefits from doing

by many political scientists.

[3]We examined only one issue of the *AJPS* because of the large number of papers in that issue relative to the other two journals.

so are significant. In particular, graphs are superior at displaying confidence intervals for parameter estimates (and thus their uncertainty) and for making comparisons across models. We believe that scholars who follow our advice will both understand their data better and present their empirical results more clearly to their audience, thereby increasing the value and impact of their research.

2 The Use of Tables Versus Graphs in Political Science

Before presenting examples of using graphs instead of tables, it is useful to examine when and how political scientists currently use each. The five issues we examined contained 52 articles, 40 of which presented at least one table or graph. These 40 papers contained 150 tables and 89 graphs, a roughly 2-to-1 ratio.[4] To understand the motivation of political scientists in presenting empirical results, we coded the type of information conveyed by each, such as summary statistics, parameter estimates and uncertainty and predicted values. Figure 1 presents both the frequency with which each type of information appears (in either tabular or graphical form), along with the percentage of tables that are used within each category. (More detailed information on our coding can be found in the caption.)

FIGURE 1 about here

The most striking findings center around the presentation of regression results, the most frequent category. We find that more than half the tables are used to present such results—that is, point estimates and uncertainty, usually accompanied by some combination of stars, bold typeface, and/or letters to indicate statistical significance.[5] In addition,

[4]One point of comparison for this measure can be found in Gelman, Pasarica and Dodhia (2002): the issue of the *Journal of the American Statistical Association* (March 2000) they analyzed contained 72 graphs and 60 tables.

[5]For clarity, we distinguish these results from "quantities of interest" such as changes in predicted probabilities while still recognizing that the latter result from regression analyses.

not a single graph presented in the five issues we studied communicates regression results. Clearly political scientists are of the belief that tables are the most effective way—it seems, in fact, the only way—to present point estimates and uncertainty.

We turn next to summary statistics, which include quantities such as means, standard deviations, and frequency summaries, and which were second only to regression results in frequency. The articles in our sample were far more likely to use tables, although they did utilize graphs about 39% of the time. While this rate far surpasses that of regression tables, it still might be surprising given that the traditional use of statistical graphics focuses on data summaries (e.g du Toit, Steyn and Stumpf 1986, Cleveland 1993, Jacoby 1997).

On the other hand, our results show that political scientists overwhelmingly use graphs to present post-estimation results, such as predicted probabilities. While the reasons for this contrast are unclear, it appears that researchers are comfortable presenting these quantities in graphical form.[6]

Nevertheless, the results are clear: political scientists are far more likely to use tables than graphs, except when presenting post-estimation results. And they never (in our sample, at least) use graphs when presenting regression results.

2.1 Why Tables?

It is not difficult to discern why researchers choose to present empirical results using tables. Compared to graphs, tables are much easier to produce. In fact, it is often possible to convert statistical output automatically into a typeset-quality table using a single command.[7] In addition, tables are standard in teaching, presentation and publishing, thereby providing incentives for scholars to continue producing them. Finally, since tables commu-

[6]One possible reason for this may be the fact that predicted probabilities are continuous, and thus lend themselves more naturally to graphing than discrete variables.

[7]In STATA, for example, the command `outreg` converts output to a Word table, while `est2tex` converts it into a table in LaTeX.

nicate precise numbers, they are valuable for aiding replication studies (a point we return to in our conclusion).

At the same time, it is easy to understand why researchers are reluctant to use graphs. For one, it simply takes more work to produce graphs. With current software, greater knowledge of the nuances of the statistical/graphical packages is needed to produce effective graphs. More importantly, creating informative statistical graphs involves repeated iterations, trial-and-error and much thought about both the deeper issue of what message the researcher is trying to convey and the practical issue of producing a graph that effectively communicates that message. This process can be quite time-consuming; simply put, it takes a much greater amount of effort to produce a quality graph than a table.

Another reason why researchers hesitate to use graphs may be their belief that it is simply infeasible to present certain information graphically. Relatedly, some may believe that graphs take up much more space than tables. Both of these concerns are likely to be paramount particularly with respect to regression tables, which can include multiple models that may involve various combinations of variables, observations and estimation techniques. Researchers may believe it impossible to present results from regressions in a format more convenient than the venerable regression table.

We argue, however, that the costs of producing graphs is outweighed by the benefits, and many of the concerns regarding their production are either overstated or misguided altogether. While producing graphs does require greater effort, the very process of graph creation is one of the main benefits of using graphs instead of tables in that it provides incentives for the researcher to present the results more directly and cleanly. Like Gelman, Pasarica and Dodhia (2002), we struggled with several versions of each graph presented in this paper before settling on the versions that appear. While at times frustrating, the iterative process forced us to carefully consider our communications goals and the means of accomplishing them with each graph. Such iteration, of course, is not needed with tables. Thus, the very strength of tables (their ease of production) can also be seen as a weakness.

Once performed, the extra work put into producing graphs can reap large benefits in communicating empirical results. Extensive research has shown that when the presentation goal is comparison (as opposed to communicating exact values, for which tables are superior), good statistical graphs consistently outperform tables.[8] As we demonstrate below, graphs are simply better devices than tables for making comparisons, which is almost always the goal when presenting data and empirical results.

In addition, concerns about the infeasibility of graphs when presenting certain numeric summaries and about the size of graphs relative to tables are unwarranted. As we show, it is not only possible to present regression results—including multiple specifications—in graphical form, but it is desirable as well. In addition, most of our graphs take up no more room than the tables they replace, including regression tables. And for those that do, we believe the benefit of graphical presentation outweighs the cost of greater size.

3 Using Graphs Instead of Tables: Descriptive Statistics

Our main objective is to convince political scientists that the numerical information currently presented using tables can be more effectively transmitted using graphs. Our first step in this endeavor was to analyze the typical types of information being presented by political scientists in leading journals. In this section we examine specific tables, transform them into graphs, and discuss what is gained (and possibly lost) by the transformation.

We start by analyzing tables with descriptive statistics. Although most of the literature on statistical graphics deals with exploratory data analysis and descriptive statistics, political scientists still choose more often than not to present such information in the form of

[8]See e.g. Cleveland (1993) and the studies cited in Gelman, Pasarica and Dodhia (2002, 121-2).

tables (64% of the time in our sample, as seen in Figure 1).

When assessing the use of graphs or tables, it is useful to consider why researchers might present descriptive statistics. If the goal is to facilitate replication, and hence allow follow-up researchers to be confident that they are using the same data as the original analysis, then tables are indeed superior. But if the goal is to give an audience a sense of the data in order to lay a foundation for subsequent statistical analyses, then we believe that graphing descriptive statistics is a superior choice. For one, graphs allow for easy comparison of variables, which can be important for assessing regression analyses. Graphs, as we demonstrate, also make it much easier to compare variables across two or more settings, such as different time periods, institutions and countries. Finally, graphs of descriptive statistics also provide a better summary of the distribution of variables.

3.1 Using a Barplot to Present Cross Tabulations

We begin with a table presented in Iversen and Soskice (2006), whose study of redistribution in advanced democracies includes nine tables, seven of which present numerical information. Of these, five present descriptive statistics and two present regression results. It is commendable that the authors chose to present in detail much of the data used; notably, however, they chose not to use a single graph in their article.

Figure 2 ABOUT HERE

Their first table (reproduced in Figure 2)[9] presents a cross tabulation of electoral systems and government partisanship for a sample of advanced democracies. The key comparison here is whether majoritarian electoral systems are more likely to feature right

[9]To ease comparison and to prevent confusion between the table numbers in the original papers and the order in which we analyze them here, we present each table and graph in corresponding pairs, labeled as "Figures," except where otherwise noted.

governments and proportional representation systems more likely to feature left governments, a comparison presented in numeric form in the last column. The raw numbers that go into this comparison are presented in the main columns. Although the information in this 2-by-2 table is relatively easy to digest, we think that the same information can be much more clearly and succinctly presented by using the two stacked bar plots presented in Figure 2, with the type of government listed on the y-axis and percentages on the x-axis.

The first thing to note about the graph is that the key comparison the authors are attempting to make immediately stands out, as the graph shows that proportional systems are significantly more likely to produce left governments, and that nearly every country with a proportional system featured center-left governments more than 50% of the time from 1945-1998 (defined as an "overweight" in the paper), while no countries with a majoritarian system featured center-left governments more than 50% of the time. We add the raw counts from each category inside the bars; the use of a bar graph allows us to combine the best feature of a table—its ability to convey exact numbers—with the comparative virtues of a graph. While actual values are frequently not of interest (and hence do not need to be displayed in a graph), the inclusion of counts here alerts the reader that small samples are involved in the calculation of countries with an overweight of left countries without either adding unnecessary clutter to the graph or increasing its size. Finally, the titles above each plot make it clear what is being plotted, while you have to read the actual text in the original article to understand the table.

This example demonstrates that even simple and easy-to-read tables can be improved through graphical presentation. As the complexity of a table grows, the gains from graphical communication will only increase.

3.2 Using Dotplots to Present Central Tendencies and Distributions

Another common type of table is one presenting descriptive statistics about central tendencies (e.g. means) and variation (e.g. standard deviations). When these statistics appear in tables, it can be difficult to make comparison across variables, and to determine the distribution of individual variables. Graphs, on the other hand, accomplish both goals.

Figure 3 ABOUT HERE

As an example, we turn to the top half of Table 1 panel A from McClurg (2006) (reproduced in Figure 3), which presents summary statistics from his study of the relationship between social networks and political participation. We transform the table into a modified dot plot, which is very well suited for presenting descriptive information (Cleveland 1993, Jacoby 2006). We use a single plot, taking advantage of the fact that the scales of all variables are similar. The dots depict the means of each variable, the solid line extends from the mean minus one standard deviation to the mean plus one deviation, and the dashed line extends from the minimum to the maximum of each variable.[10] Because the number of respondents covered under each variable is not a feature of the variables themselves, we note them under the labels on the y-axis (if we were interested in comparing sample sizes across variables, we could of course include a separate graph). The benefits of the graph are apparent: the dots allow for easy lookup and comparison of the means, while the lines visually depict the distribution of each variable. For example, the graph reveals that *political talk* is right-skewed, which is not easily concluded from the table.

As noted, we were able to pursue a single graph because of the similar scaling of the variables. Often, however, scales will differ across variables to the extent that it is not

[10]Another option would be to employ a standard Tukey box plot (Tukey 1977). We believe that the simpler line graph is sufficient to capture the distribution of a variable, and also allows for the clearer presentation of many variables in a single graph. For a contrary view, see Epstein, Martin and Schneider (forthcoming, 25-6).

feasible to present one graph. Such situations will require the analyst to be creative about the best way to present her data. We suggest two options below.

Figure 4 ABOUT HERE

The first is to simply divide variables into groups with similar scales and then present multiple graphs. For example, Table 2 of Kaplan, Park and Ridout (2006) (reproduced in Figure 4) displays summary statistics from their analysis of issue convergence and campaign competitiveness. It is immediately apparent that the mean, variance and maximums differ significantly across variables; the mean *issue convergence* and *percent negative ads*, for example, are much higher than the other variables. Including all the variables in a single graph would result in a severe compression in a majority of the variables, rendering the graph uninformative. Instead, we decided to group similar variables and present separate graphs for each group, allowing for comparisons within each graph. There are three main categories of variables in Table 2: those measured in millions, those measured in percents (including *issue convergence*, which is defined as the percentage of combined attention that Democratic and Republican candidates give to a particular issue (Kaplan, Park and Ridout 2006, 730)), and binary variables. Since *competitiveness* and *issue salience* do not fall into any of these categories, we group them with similarly distributed variables.

The graph is presented in Figure 4. Based on the information we present in the table, we again present means, means plus and minus one standard deviation, and minimums and maximums.[11] Once separated, it is easy to compare the means of the variables within each group and to get a sense of their scales. Again, the graph reveals the skew of several variables, which may help inform both the researcher's empirical analysis and the

[11]Given the nature of the variables, especially the binary and percentage variables, it would probably be more useful and informative to present either the data itself or empirical distributions rather than standard deviations, which are relatively uninformative when variables are not normally distributed. Even with these limitations, however, the graph is an improvement over the table.

reader's understanding of it. As we show below, the use of "small multiples"—several smaller graphs instead of one big graph—can greatly enhance the presentation of data and empirical results in a wide range of situations.

3.3 Using an Advanced Dotplot to Present Multiple Comparisons

The second option for graphing descriptive plots of variables with different scales is to alter the scales themselves. We illustrate this option by converting Table 2 from Schwindt-Bayer's (2006) study of the attitudes and bill initiation behavior of female legislators in Latin America (reproduced in Figure 5) into a graph. Most of the rows of the table are devoted to displaying the number of bills introduced by lawmakers in four Latin American legislative chambers across two time periods (which vary by chamber). While the text of the paper does not explicitly state what comparisons the reader should draw from the table, there are three main comparisons one could make: across issue areas, across countries, and across time periods. The structure of the table, however, only allows for easy comparison of issue areas—for a single country and a single time period. The use of absolute counts for the number of bills introduced in each issue areas instead of percentages hinders cross-column comparison (i.e. across countries and time periods). Using percentages would improve the presentation, but would still place the burden on the reader to find patterns in the data.

Figure 5 ABOUT HERE

Instead, we turn the table into an advanced dotplot, presented in Figure 5. We begin by converting the counts of each bill introduced in each issue area into a percentage, with the total number of bills initiated serving as the denominator. For each chamber and for each issue area, we present the percentages for both the first and second time periods using different symbols: open circles for the first period, "+"s for the second. (Because the "number of legislators who sponsored at least one bill" and the "total number of bills initiated" seem tangential to the table, we include them only as counts under the name of each country or chamber in the panel strips.) One option, of course, would be simply to scale the x-axes on a linear percentage scale, ranging from 0 to 100% (or the maximum percentage); this, however, would mask differences among several issue areas for which relatively few bills were introduced.[12] Instead, we follow the advice of (Cleveland 1985, 4-5) and scale the x-axes on the log 2 scale, and provide for easy lookup by placing tick mark labels at both the top and bottom of the graph. Given this scaling, each tick mark (indicated vertically by the solid gray lines) represents a proportion double that of the tick mark to the left. Looking at the Colombia Senate, for example, we can see the percentage of bills related to health issues declined by half from the 1994-1998 period to the 1998-2002 period. We can also compare easily across issue areas: in Argentina in 1999, for example, it is easy to see that twice as many fiscal affairs bills were introduced as women's issues bills.

The graph thus allows for all three types of comparison. The use of dual symbols allows for easy comparison both across time periods within a given issue area and across issue areas within a single time period. The graph also facilitate cross-legislature comparison by placing each in a single column; by reading vertically down the graph, for example, we can see that more bills pertaining to women's issues were introduced in the Colombia Senate than the Colombia Chamber from 1998-2002.

In summary, we believe that these examples demonstrate the benefits of graphing descriptive statistics. Of course, there are many other types of descriptive data summaries, such as correlation matrices, frequencies and time series, that will require different graph-

[12]For each chamber and time period, "other bills" constitute a majority of all bills. Another option would be to exclude these bills and use the sum of the other seven issue areas as the denominator.

ing strategies. Our purpose is not to exhaust all of these, but to illustrate how descriptive tables can be turned into graphs with great benefit.

4 Using Graphs Instead of Tables: Regression Analyses

4.1 On Regression Tables and Confidence Intervals

Regression tables are meant to communicate two essential quantities: point estimates (coefficients) and uncertainty estimates (usually in the form of standard errors, confidence intervals or t- or z-values). In our sample, 74% of the regression tables presented standard errors, usually supplemented by stars labeling coefficients that have attained conventional levels of statistical significance. Thus, most tables seek to draw attention to coefficients that are significant at the $p < .01$, $p < .05$ or $p < .10$ levels. This tendency is directly related to the discipline's reliance on null hypothesis significance testing in conducting regression analyses.

What are the potential problems and drawbacks from this approach? First, as articles in fields as diverse as wildlife management (Johnson 1999), psychology (Schmidt 1996), statistics (Gelman and Stern 2006) and even political science (Gill 1999) demonstrate, null hypothesis significance testing and reliance on p-values can lead to serious mistakes in statistical inference. These articles suggest substituting confidence intervals for p-values and stars when presenting regression results. Schmidt (1996, 116), for example, argues that "the appropriate statistics [in data analyses] are point estimates of effect sizes and confidence intervals around these point estimates."

A related drawback to standard regression tables is that it is difficult to compare coefficients both within and across models. It is indeed easy to compare the signs of coefficients and their statistical significance. The former, however, is only the starting point in interpreting output, while making comparisons based on the latter is frequently misleading. That is, it is possible for one coefficient to be statistically significant, another to be statistically insignificant, and yet the difference between the two to be insignificant (Gelman and Stern 2006).

Using confidence intervals in regression tables would help mitigate this problem, and theoretically could ease comparison of coefficients. Yet not a single regression table in our sample presented confidence intervals. Given that confidence intervals convey as much information as p-values, and more, their absence is puzzling. Again, part of the reason must be ascribed to the discipline's reliance on null hypothesis significance testing, which in turns leads to tables full of star-accompanied coefficients (that is, assuming the researcher finds at least some significant effects). The source of this reliance is a matter of debate, with some suggesting path dependence in graduate training, pressure from peers and journal editors, and the supposed objectiveness and ease of hypothesis testing, among other reasons.[13] Yet, even if researchers eschewed null hypothesis significance testing, it would still be a tall task to present confidence intervals in regression tables, for reasons of practicality: the presentation of such tables, in particular when multiple specifications or subsamples are compared (as occurred in about 88% of the regression tables in our sample), are simply confusing and unsightly.

Figure 6 ABOUT HERE

Consider, for example, Table 4 of Ansolabehere and Konisky (2006), which we replicate in Figure 6 (we present the graphical version of the table later in this section.) The authors estimate the effect of voter registration laws on county-level turnout in New York and

[13] Nester (1996, 401), for example, argues that "tests of hypotheses are seemingly performed because (a) they appear to be objective and exact, (b) they are readily available and easily invoked in many commercial statistics packages, (c) everyone else seems to use them, (d) students, statisticians and scientists are taught to use them and (e) some journal editors and thesis supervisors demand them."

Ohio, and do robustness checks by presenting six different models, as seen in columns one through six in the table. Note that there are about three dozen coefficients and standard errors pairs to compare. The stars scattered throughout the table focus the attention of the reader to null hypothesis significance testing and how it varies across models. However, since statistical significance conflates effect size, direction and the number of observations into a single quantity, it can lead to mistaken inferences from the table. For example, we see that family income (row four) is statistically significant in all models. Less noticeable is the fact that the third model is statistically significant but has the opposite sign!

Table 1 ABOUT HERE

Would the use of confidence intervals improve interpretation? In Table 1 we present the same table, but instead of standard errors and stars we use confidence intervals. Although inferences are more direct when estimates are presented in this form, it gets confusing quickly when comparing across models. Even a simple question, such as which confidence intervals overlap, demands careful attention to signs and must be done one by one. The table also takes up more space than than the original version.

These difficulties point to a main advantage of the standard regression table: it is less confusing than the alternative. There are others: it is clear from the table which independent variables are present or missing in each model. In addition, information such as model fit statistics and the number of observations can easily be added to the table. In summary, regression tables are able to display a large wealth of information about the models in a very compact, and mostly readable, format. It is no surprise that they are so popular.

Instead of asking how regression tables can be improved, we ask whether graphical displays can do a better job at communicating regression estimates. Given the aforementioned strengths and weaknesses of tables, we look for the following in a good regression graph.

1. It should make it easy to perform significance testing;
2. It should also be able to display several regression models in a parallel fashion (as tables currently do);
3. Relatedly, when models differ by which variables are included, it should be clear to the reader which variables are included in which models;
4. It should be able to show more than one significance level;
5. It should be able to incorporate model information;
6. Finally, the plot should focus on confidence intervals and not (only) on p-values.

4.2 Plotting a Single Regression

We start by plotting a simple regression table. Table 2 from Stevens, Bishin and Barr (2006) (reproduced in Figure 7) displays results from a single least squares regression. Using a survey of elites from six Latin American countries, the authors study the effects of economic perceptions, ideology and demographic variables and a set of country dummies on the survey responder's "individual authoritarianism," measured on a seven-point scale. The table condenses a large wealth of information: regression fit summaries, the number of cases, point estimates, standard errors, significance tests for multiple comparisons among the country dummies, and stars denoting .01, .05 and .10 two-tailed p-values.

Figure 7 ABOUT HERE

In Figure 7 we condense the same information into a simple dot plot, much like those used in the previous section. We take advantage of the similar scaling across the estimates and display the results in a single plot. The dots represent the point estimates, while the horizontal lines depict 95% confidence intervals.[14] We also indicate 90% confidence intervals (i.e. when p $<$ .1) using the vertical tick marks towards the end of each line. We could, of course, indicate any number of confidence intervals, but two is likely to be sufficient in most cases. We place a vertical line at zero for convenience, and make the length of the x-axis symmetric around this reference line for easy comparison of the magnitude of positive and negative coefficients. We also place axis labels indicating the values of the parameter estimates on both the top and bottom axes, while each predictor variable is displayed on the y-axis. Finally, we use the empty space in the plot region to display R^2, adjusted R^2 and the number of observations; this information, however, could just as well be displayed in the caption, if more desirable or if there is not enough room in the plot region.

This figure shows several advantages of using graphs. First, information regarding statistical significance is displayed without any stars, bars or superscripted letters. Instead, the length of the error bars visually signal which variables are significant: those that do not cross the reference line, which is zero in this case. Thus, a vertical scan of the graph allows the reader to quickly assess which variables are significant, including ones (like *Prospective egocentric economic perceptions*) that are significant at $p < .10$ but not $p < .05$.

The visual display of the regression results also focuses the attention of the reader away from plain statistical significance towards the more relevant and perhaps more interesting information revealed by a regression analysis: the estimated effect size and the degree of uncertainty surrounding it. The vertical placement of coefficients makes it easy to compare their relative magnitudes, while the size of the error bars provide information on how precisely each parameter is estimated.

[14] Gill (1999) also recommends that researchers present 'Leamer bounds" (Leamer 1983) for each parameter estimate: the minimum and maximum coefficient estimate across every specification the researcher performs. Our graphical approach could easily incorporate this information using symbols or dotted lines.

The use of confidence intervals also provides much more information, displayed intuitively, than a regression table. For instance, when confidence intervals do not overlap, we can conclude that two estimates are statistically significantly different from each other. Thus, if one goal of a regression analysis is to compare two or more parameter estimates, then this simple type of graph is sufficient.

However, even if confidence intervals of two coefficients overlap, it is quite possible that they are nevertheless significantly different, even if they are independent. With the data at hand, one possibility would be to move beyond this basic graph and plot all contrasts of interest(the estimates of the differences in the country coefficients, for example: $\beta_{Argentina} - \beta_{Chile}; \beta_{Argentina} - \beta_{Colombia}$, etc.)[15] By using graphs similar to the one presented, the presentation will be concise and easy to digest.

4.3 Plotting Multiple Models in a Single Plot

As noted earlier, in our survey of political science tables we found that more often than not researchers present multiple models. Graphing multiple models, of course, presents new challenges, as we must be sure that an audience can distinguish the parameter estimates and confidence intervals from each model, and to be sure that the differences between each model in terms of variables included are visually apparent.

Figure 8 ABOUT HERE

We begin with the case of two regression models. Table 1 of Pekkanen, Nyblade and Krauss (2006) (replicated in Figure 8) displays two logistic regression models that examine the allocation of posts in the LDP party in Japan. In the first model, *PR Only* and *Costa Rican in PR* are included and *Vote share margin* is excluded, while in the second model

[15]Multiple comparisons raise various methodological issues. See Hsu and Peruggia (1994) for a discussion of the Tukey's multiple comparisons method and a novel graphical display.

the reverse is true. We present the two models by plotting parallel lines for each of them grouped by coefficients, as can be seen in Figure 8. We differentiate the models by plotting different symbols for the point estimates: filled (black) circles for the first model and empty (while) circles for the second. The similar scaling of the coefficients again allows us to graph all the estimates in a single plot. Because most of the coefficients fall below zero, to save space we do not make the x-axis symmetric around zero. And in this case we would present model information in the caption.

By plotting the two models, we can now easily compare both the coefficients within each model and across the two models. The fact that only single estimates are plotted for *PR Only*, *Costa Rican in PR* and *Vote share margin* signals that these predictors appear in only one model. Rather than having to compare individual parameter estimates (and the presence or absence of stars) across models in a regression table, a vertical scan of the graph shows that the estimates are mostly robust across models, as the parameter estimates and their respective confidence intervals vary little.

4.4 Using Multiple Plots to Present Multiple Models

As the number of models increase, we suggest a different strategy. Instead of presenting all the models and predictors in a single plot, we use "small multiple" plots to present results separately for each predictor. The main objective when presenting results from multiple models is to explore how inferences change as we modify the specification and/or subsample. Using multiple dotplots with error bars accomplishes this task well. They allow the researcher to communicate the information in a multiple regression table with much greater clarity and also make it much easier to compare parameter estimates across models. This strategy also overcomes any problems that might arise from having predictors with greatly varying scales.

As an example, we return to Table 4 of Ansolabehere and Konisky (2006) (see Figure

6), turning it into the graph presented in Figure 9. Rather than placing all the predictors in a single plot, which would make it difficult to compare individual estimates, we created a separate panel for each of the six predictors, with three panels presented in each of two columns.[16] We also shift strategy and display the parameter estimates on the y-axes, along with vertical 90% and 95% confidence intervals. This maximizes efficiency since we can stack more plots into a single column than into a single row, given the portrait orientation of most journals. The x-axis depicts which model is being displayed. To facilitate comparison across predictors, we center the y-axis at zero, which is the null hypothesis for each of the predictors.

Figure 9 ABOUT HERE

The regression table presents six models, which vary with respect to sample (full sample vs. excluding partisans registration counties) and predictors (with/without state year dummies and with/without law change).[17] On the x-axis we group each type of model: "full sample," "excluding counties with partial registration" and "full sample with state year dummies." Within each of these types, two different regressions are presented: including the dummy variable *law change* and not including it. Thus, for each type, we plot two point estimates and intervals—we differentiate the two models by using solid circles for the models in which *law change* is included and empty circles for the models in which it is not.

This graphing strategy allows us to easily compare point estimates and confidence intervals across models. Although in all the specified models the *percent of county with registration* predictor is statistically significant at the 95% level, it is clear from the graph

[16] To save space we chose not to plot the intercept estimates, which are substantively uninteresting.

[17] Note that not all combinations were included. There is no model where the sample has the partial registration counties excluded and state year dummies included.

that estimates from the full sample with state/year dummies models are significantly different from the other four models. In addition, by putting zero at the center of the graph, it becomes obvious which estimates have opposite signs depending on the specification (*log population* and *log median family income*). Thus, it is easy to visually assess the robustness of each predictor—both in terms of its magnitude and confidence interval—simply by scanning across each panel. In summary, the graph appropriately highlights the instability in the estimates depending on the choice of model.

5 Conclusion

As a largely empirical discipline, the quality of political science depends on how well its practitioners can communicate their findings to audiences professional and public. We believe that a turn towards greater use of graphical methods, particularly for regression results, can only increase our ability to communicate successfully.

A major potential objection to our approach is that the benefits of graphs in terms of aiding comparisons are outweighed by the corresponding loss of precision in presenting data or results. This objection certainly holds with respect to aiding replication studies, as it difficult to measure replication against a graph; greater use of graphs will increase the burden on researchers to aid replication studies in other ways, by publishing corresponding tables and/or replication material on public archives or web sites. Yet with respect to the broader goal of presentation, the choice of precision versus communication is in fact false: given the nature of the phenomenon studied by political scientists, measurement error and other sources of uncertainty renders an illusion the precision implied by tables. Indeed, the inherent ability of graphs to present uncertainty efficiently is one of their major strengths.

Concluding their call for researchers to present quantities of interest, King, Tomz and Wittenberg (2000) acknowledged that the methods they proposed were "more onerous than the methods currently used in political science." The same is true here. As our graphs demonstrate, different empirical quantities require different strategies for presentation, which in turn requires more work. Advances in statistical software will likely lower production costs.[18] But in the meantime, we believe the extra effort undertaken in creating graphs will lead to clearer and more accessible papers, lectures and presentations in political science.

[18]One innovation that we suspect is not long in coming are programs that automatically convert regression output into graphs, as is currently possible with tables.

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6 Figures and Tables

Note: For ease of comparison, figures and tables are not separated into separate sections, but instead appear in the order they are listed in the text. For each table turned into a graph, both the table and graph are presented in a single figure as a pair (except where otherwise noted).

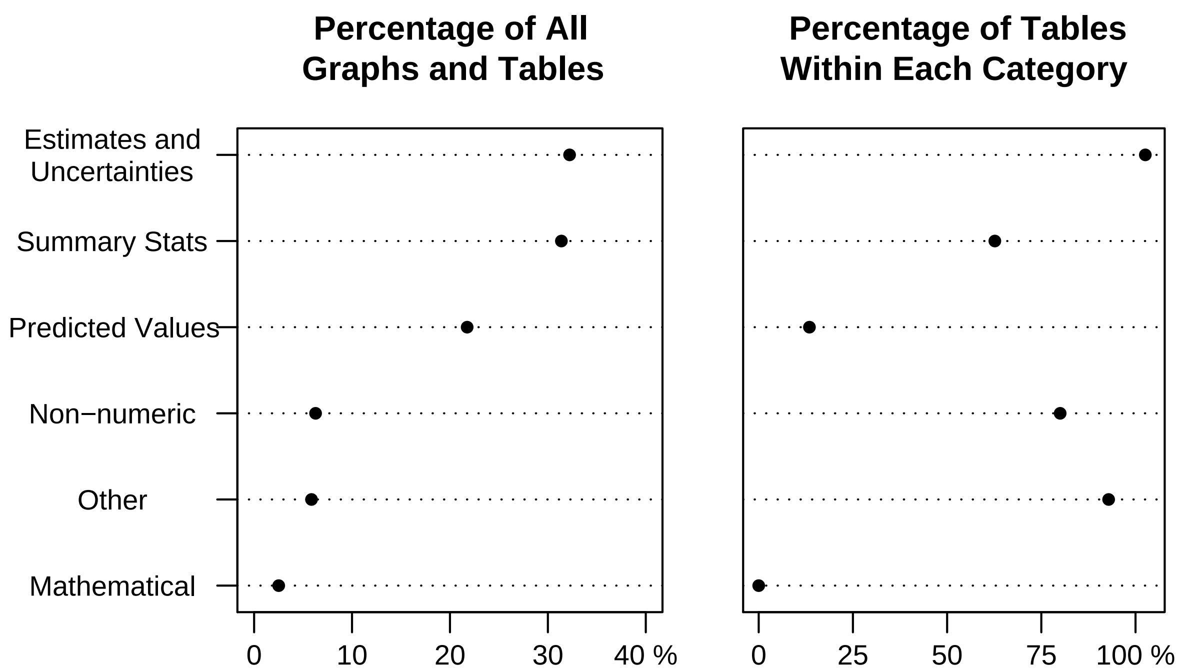

Figure 1: *Tables and Graphs in Political Science Journals. The left graph depicts the percentage of all graphs and tables presented in five political science journals that fall into the categories on the y-axis, while the right graph depicts the percentage of tables within each category. "Estimates and uncertainties" include such quantities as regression coefficients and standard errors; "Summary stats" include descriptive statistics like means and standard deviations; "Predicted values" include post-regression estimations such as changes in predicted probabilities; "Non-numeric" includes any information that is not quantitative; "Mathematical" generally includes figures from formal models; finally, "other" is a residual category. The plots show that estimates and uncertainties and summary stats comprise the majority of graphical and tabular presentation, and that they are much more likely to be presented in table form – indeed, regression coefficients are always presented as tables.*

TABLE 1. Electoral System and the Number of Years With Left and Right Governments (1945–98)

		Government Partisanship		
		Left	Right	Proportion of Right Governments
Electoral system	Proportional	342 (8)	120 (1)	0.26
	Majoritarian	86 (0)	256 (8)	0.75

Note: Excludes centrist governments (see text below for details).

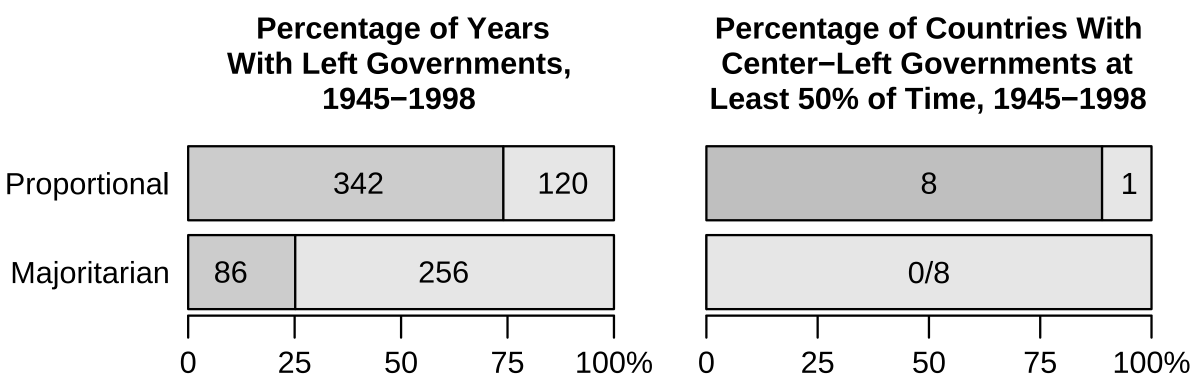

Figure 2: *Using a Barplot to Present Cross Tabulations. Table 1 from Iversen and Soskice (2006) displays a cross-tabulation of electoral systems and government partisanship. The left panel depicts the percentage of years with left governments across proportional and majoritarian systems, while the right panel depicts the percent of countries with center-left governments at least 50% of the time (defined as an "overweight" in the text of the paper), also across proportional and majoritarian systems. Our bar graph clearly displays the key comparisons while retaining the actual counts. Titles above each graph make it clear to the reader what is being compared, unlike the table.*

Table 1 The Political Character of Social Networks This table provides descriptive statistics for the political character of the social networks as perceived by respondents.

	Mean	**Standard Deviation**	**Min**	**Max**	**N**
Panel A: Descriptive Statistics					
Size[a]	3.13	1.49	1	5	1260
Political Talk	1.82	0.61	0	3	1253
Political Agreement	0.43	0.41	0	1	1154
Political Knowledge	1.22	0.42	0	2	1220

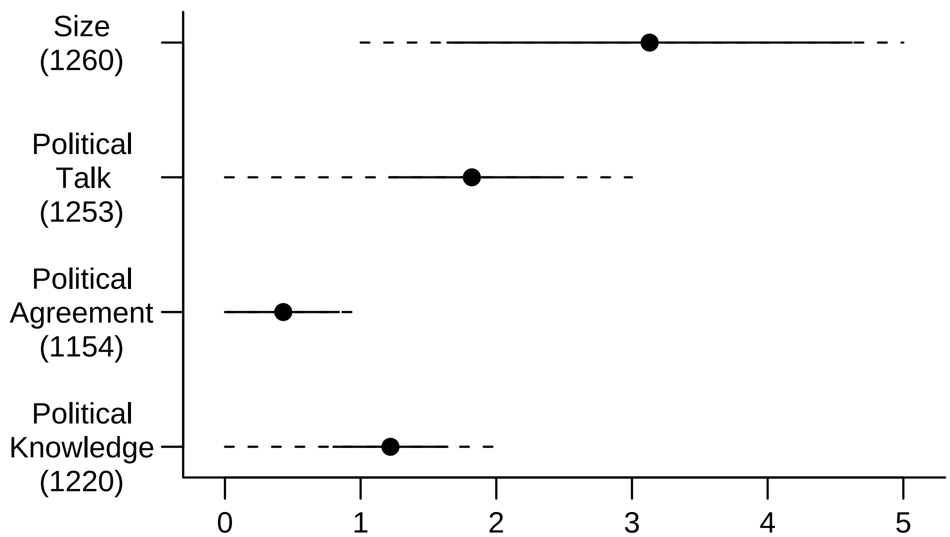

Figure 3: *Using a Single Dotplot to Present Summary Statistics. Table 1 (panel A) from McClurg (2006) presents descriptive statistics from his study of social networks. We use a single dotplot, taking advantage of the fact that the scales of all variables are similar. The dots depict the means of each variable, the solid line extends from the mean minus one standard deviation to the mean plus one deviation, and the dashed line extends from the minimum to the maximum of each variable. The number of respondents covered under each variable is given under the y-label axis labels. The graph allows for easy lookup and comparison of the means, while the lines visually depict the distribution of each variable.*

Table 2 Descriptive Statistics of Campaign and Issue-Level Variables

Variable	N	Mean	SD	Min	Max
Issue Convergence	982	24.85	34.73	0.00	99.98
Competitiveness (CQ Ranking)	65	1.54	1.20	0.00	3.00
Total Spending/Capita (millions)	65	3.47	2.71	0.28	13.39
Difference Spending/Capita (millions)	65	1.12	1.32	0.03	9.26
State Voting Age Pop. (millions-ln)	65	1.20	0.85	–0.65	3.13
Percent Negative Ads	65	21.38	16.84	0.00	54.96
2000 Year (binary)	65	0.38	0.49	0.00	1.00
2002 Year (binary)	65	0.32	0.47	0.00	1.00
Consensual Issue (binary)	43	0.28	0.45	0.00	1.00
Issue Owned (binary)	43	0.49	0.51	0.00	1.00
Issue Salience	43	2.86	6.38	0.00	35.63

Figure 4: *Kaplan, Park and Ridout (2006), Table 2, present summary statistics from their study of issue convergence and campaign competitiveness. (Graph appears on next page.)*

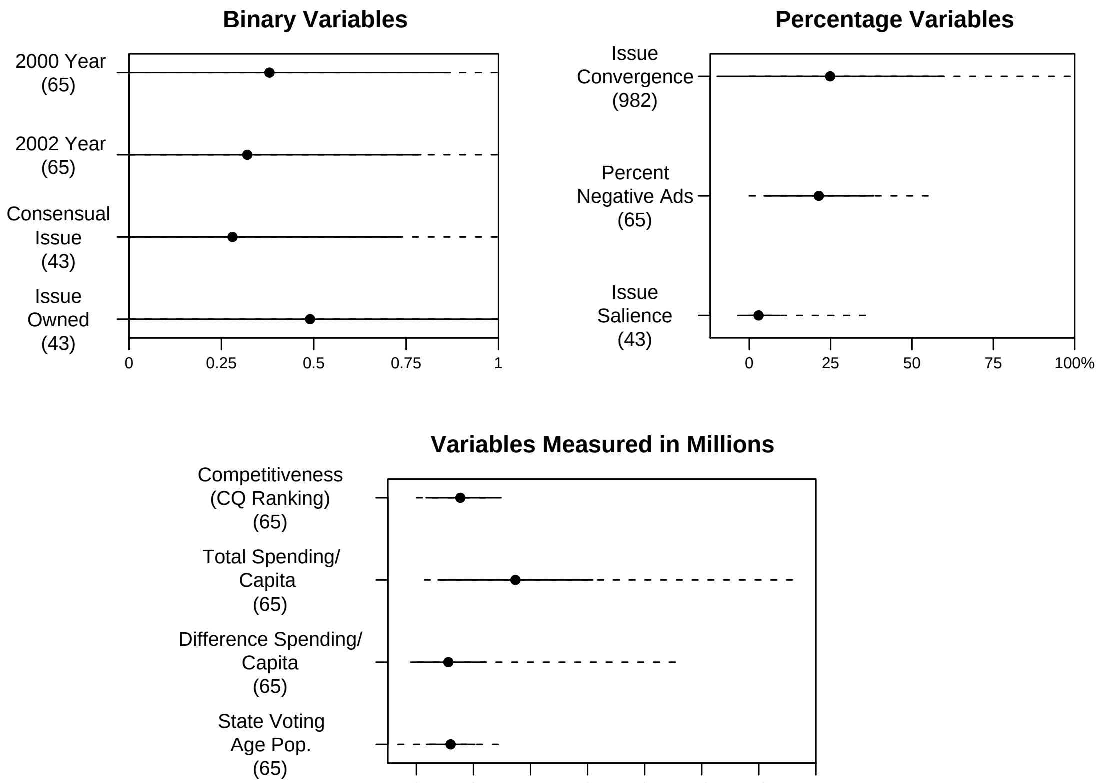

Figure 4: *Using Multiple Dotplots to Present Summary Statistics. Table 2 from Kaplan, Park and Ridout (2006) present summary statistics from their study of issue convergence and campaign competitiveness. We group similar variables and present separate graphs for each group, allowing for comparisons within each graph. The dots depict the means of each variable, the solid line extends from the mean minus one standard deviation to the mean plus one deviation, and the dashed line extends from the minimum to the maximum of each variable. The numbers under the variable labels in parentheses denote the number of observations for each variable. The top-left graph summarizes binary variables, the top-right graph summarizes percentage variables and the bottom graph summarizes variables measured in millions. Separation allows for easy comparison of variables within each group and also provides a more accurate sense of their scales.*

Table 2 Number of Bills Sponsored in Each Thematic Area

	Argentina		Colombia–Chamber		Colombia–Senate		Costa Rica		
	1995	**1999**	**1994–1998**	**1998–2002**	**1994–1998**	**1998–2002**	**1994–1998**	**1998–2002**	**Total**
Number of legislators who sponsored at least one bill	246	257	139	165	87	94	57	57	1102
Women's Issues	33	30	23	9	16	18	23	35	187
Children/Family	28	40	13	7	22	9	25	27	171
Education	44	66	67	72	42	29	56	75	451
Health	27	51	13	14	13	5	16	33	172
Economics	208	305	74	80	113	65	120	160	1125
Agriculture	28	49	23	18	22	19	34	38	231
Fiscal Affairs	45	61	11	17	21	13	27	51	246
Other Bills†	567	901	405	406	371	356	628	764	4398
Total number of bills initiated	980	1503	629	623	620	514	929	1183	6981

†"Other Bills" include all bills that do not fall into the seven thematic areas. This would include bills related to public administration, the environment, foreign affairs, culture, and public welfare, among others.

Figure 5: *Schwindt-Bayer (2006), Table 2, presents counts of the type of bills initiated in four Latin American legislative chambers in two time periods each. (Graph appears on next page.)*

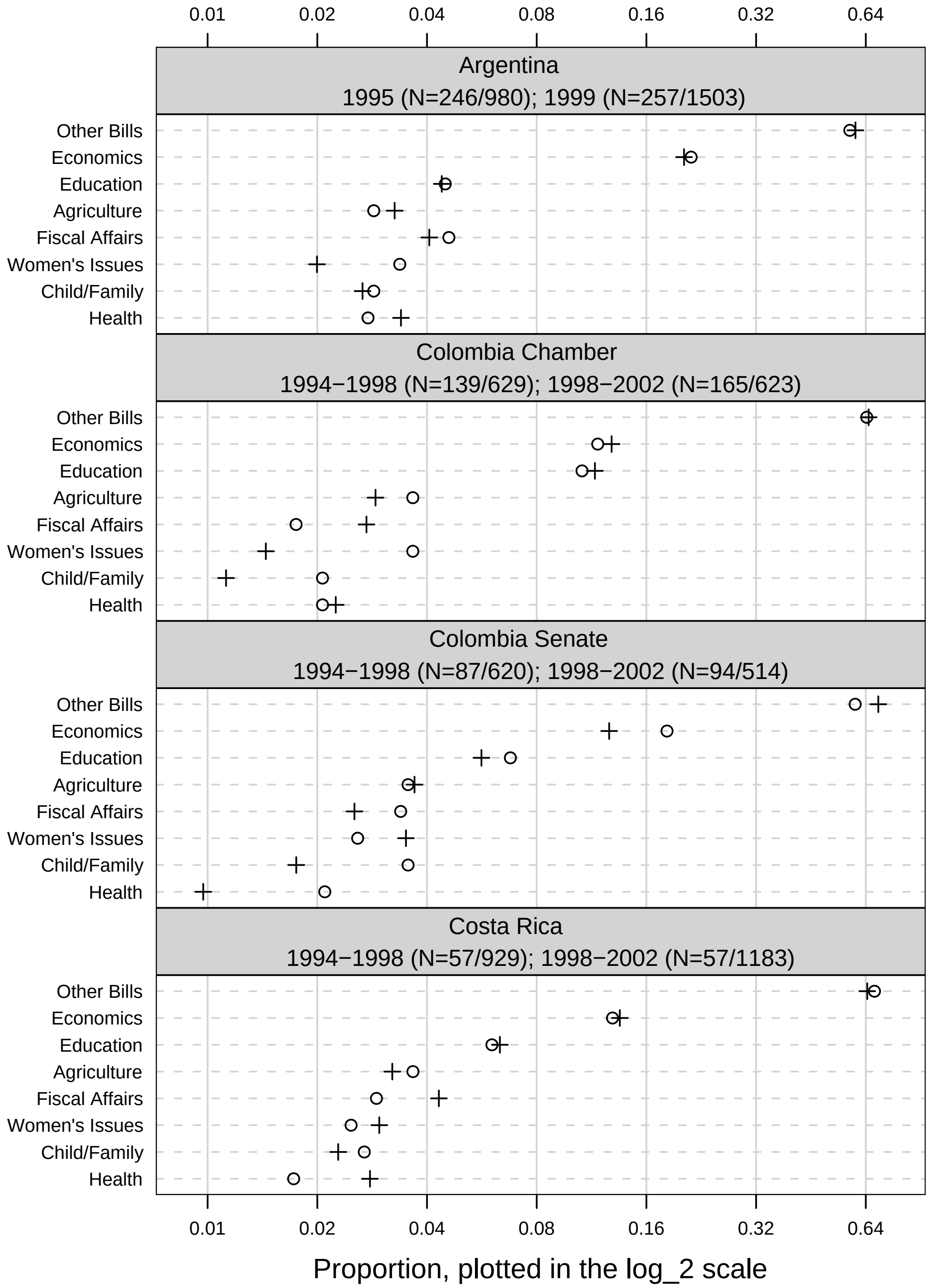

Figure 5: *Using an Advanced Dotplots to Present Proportions. Table 2 from Schwindt-Bayer (2006) presents counts of the type of bills initiated in four Latin American legislative chambers in two time periods each. We turn the table into a graph that allows for comparisons across time periods, chambers and issue areas. For each country or chamber, the "o's" indicate the percentage of all initiated bills pertaining to the issue area listed on the y-axis in the first period, while the "+'s" indicate the percentages from the second period. The grey strips indicate the country or chamber analyzed in the panel immediately below, along with the relevant time periods. For each period, the first count in parentheses gives the number of legislators who sponsored at least one bill, while the second count gives the total number of bills initiated. We scale the x-axis on the log2 scale: each tick mark is double the percentage of the tick mark to its left.*

Table 4 Registration effects on turnout in New York and Ohio counties: Fixed effects model, 1954–2000

	Dependent Variable = County-Level Turnout					
	Full sample (1)	*Excluding counties w/partial registration (2)*	*Full sample w/state-year dummies (3)*	*Full sample (4)*	*Excluding counties w/partial registration (5)*	*Full sample w/state-year dummies (6)*
% of county with registration	−0.039** (0.003)	−0.036** (0.003)	−0.051** (0.003)	−0.037** (0.003)	-0.034** (0.003)	-0.050** (0.003)
Law change				−0.020** (0.005)	−0.018** (0.005)	−0.023** (0.006)
Log population	0.048** (0.011)	0.036** (0.012)	0.017 (0.010)	0.047** (0.011)	−0.035** (0.021)	0.016 (0.010)
Log median family income	−0.133** (0.013)	−0.142** (0.014)	0.050** (0.013)	−0.131** (0.013)	−0.139** (0.014)	−0.049** (0.013)
% population with h.s. education	0.071* (0.028)	0.070* (0.029)	0.011 (0.024)	0.072* (0.028)	0.071* (0.029)	0.013 (0.024)
% population African American	−0.795** (0.056)	−0.834** (0.059)	−0.532** (0.044)	−0.783** (0.055)	−0.822** (0.059)	−0.521** (0.044)
Constant	1.47** (0.152)	1.70** (0.171)	0.775** (0.124)	1.45** (0.152)	1.68** (0.170)	0.819** (0.127)
R^2	0.91	0.91	0.94	0.91	0.91	0.94
N	3572	3153	3572	3572	3153	3572

Note. $^{*}p < .05$, $^{**}p < .01$. Huber-White standard errors in parentheses. Year dummies and state-year dummies are not reported.

Figure 6: *Table 4 from Ansolabehere and Konisky (2006). Our graph version of this table appears in Figure 9.*

	(1)	(2)	(3)	(4)	(5)	(6)
% of county registration	-0.039	-0.036	-0.051	-0.037	-0.034	-0.050
	[-0.045,-0.033]	[-0.042,-0.03]	[-0.057,-0.045]	[-0.043,-0.031]	[-0.04,-0.028]	[-0.056,-0.044]
Law change				-0.020	-0.018	-0.023
				[-0.03,-0.01]	[-0.028,-0.008]	[-0.035,-0.011]
Log population	0.048	0.036	0.017	0.047	-0.035	0.016
	[0.026,0.07]	[0.012,0.06]	[-0.003,0.037]	[0.025,0.069]	[-0.077,0.007]	[-0.004,0.036]
Log median family income	-0.133	-0.142	0.050	-0.131	-0.139	-0.049
	[-0.159,-0.107]	[-0.17,-0.114]	[0.024,0.076]	[-0.157,-0.105]	[-0.167,-0.111]	[-0.075,-0.023]
% population with h.s. education	0.071	0.070	0.011	0.072	0.071	0.013
	[0.015,0.127]	[0.012,0.128]	[-0.037,0.059]	[0.016,0.128]	[0.013,0.129]	[-0.035,0.061]
% population African American	-0.795	-0.834	-0.532	-0.783	-0.822	-0.521
	[-0.907,-0.683]	[-0.952,-0.716]	[-0.62,-0.444]	[-0.893,-0.673]	[-0.94,-0.704]	[-0.609,-0.433]
Constant	1.470	1.700	0.775	1.450	1.680	0.819
	[1.166,1.774]	[1.358,2.042]	[0.527,1.023]	[1.146,1.754]	[1.34,2.02]	[0.565,1.073]

Table 1: *Presenting regression results with confidence intervals. We reproduce Table 4 from Ansolabehere and Konisky (2006) but with confidence intervals instead of standard errors.*

TABLE 2 Determinants of Authoritarian Aggression

Variable	Coefficient (Standard Error)
Constant	.41 (.93)
Countries	
Argentina	1.31 (.33)** B,M
Chile	.93 (.32)** B,M
Colombia	1.46 (.32)** B,M
Mexico	.07 (.32) A,CH,CO,V
Venezuela	.96 (.37)** B,M
Threat	
Retrospective egocentric economic perceptions	.20 (.13)
Prospective egocentric economic perceptions	.22 (.12)#
Retrospective sociotropic economic perceptions	−.21 (.12)#
Prospective sociotropic economic perceptions	−.32 (.12)*
Ideological distance from president	−.27 (.07)**
Ideology	
Ideology	.23 (.07)**
Individual Differences	
Age	.00 (.01)
Female	−.03 (.21)
Education	.13 (.14)
Academic sector	.15 (.29)
Business sector	.31 (.25)
Government sector	−.10 (.27)
R^2	.15
Adjusted R^2	.12
n	500

**p < .01, *p < .05, #p < .10 (two-tailed)
[A]Coefficient is significantly different from Argentina's at p < .05;
[B]Coefficient is significantly different from Brazil's at p < .05;
[CH]Coefficient is significantly different from Chile's at p < .05;
[CO]Coefficient is significantly different from Colombia's at p < .05;
[M]Coefficient is significantly different from Mexico's at p < .05;
[V]Coefficient is significantly different from Venezuela's at p < .05

Figure 7: *Stevens, Bishin and Barr (2006), Table 2. (Graph appears on next page)*

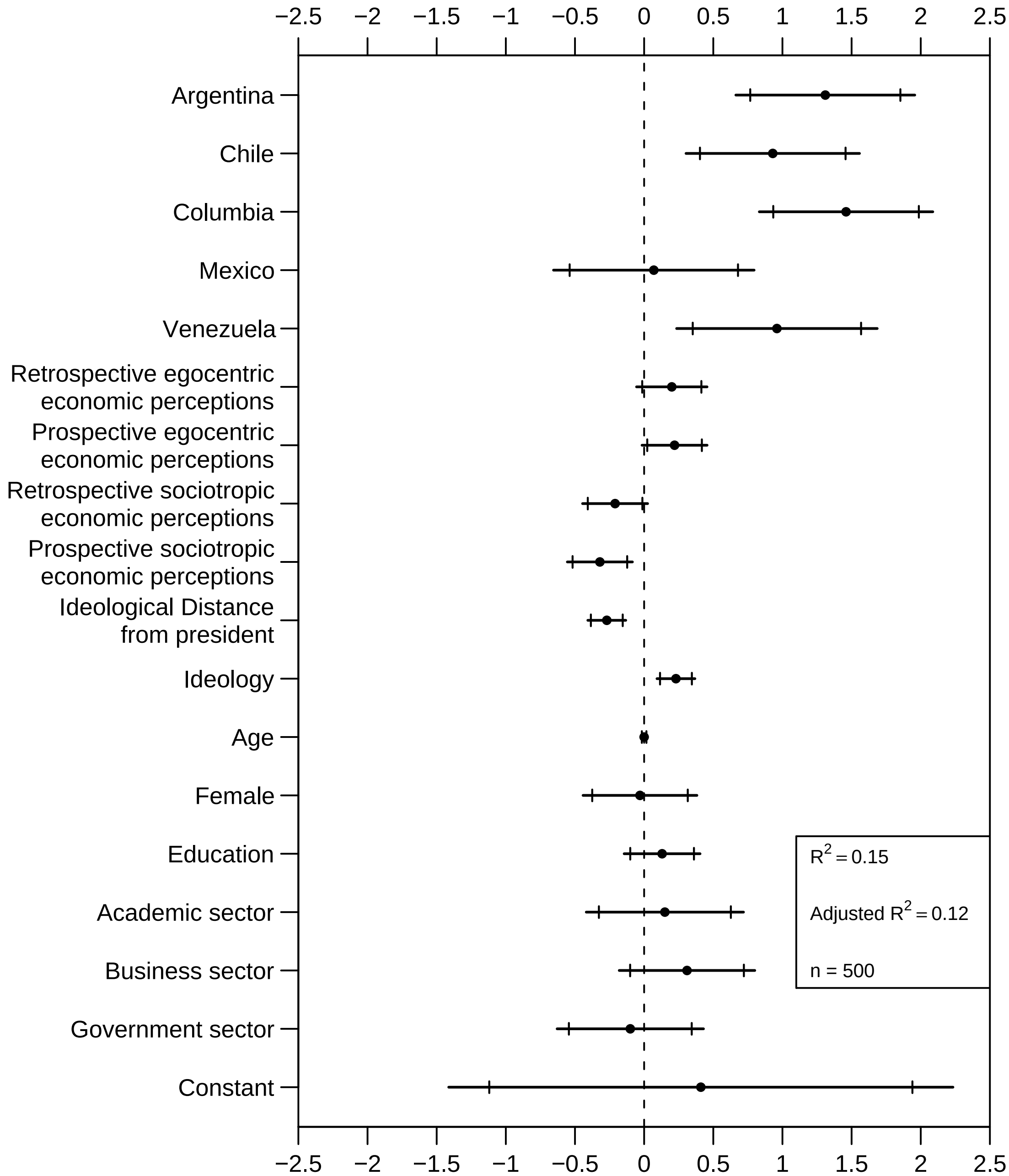

Figure 7: *Presenting a single regression model using a dotplot with error bars. Table 2 from Stevens, Bishin and Barr (2006) displays a single least squares regression model that examines the relationship between individual authoritarianism and economic perceptions, ideology and demographic variables in six Latin American countries. We turn the table into a single regression graph, taking advantage of the similar scaling across the estimates. The dots represent the point estimates, while the horizontal lines depict 95% confidence intervals. We indicate 90% confidence intervals (i.e. when $p < .1$) using the vertical tick marks towards the end of each line. The range of parameter estimates is displayed on the top and bottom axes, while the variable labels are displayed on the y-axis. We place a vertical line at zero for convenience, and make the length of the x-axis symmetric around this reference line for easy comparison of the magnitude of positive and negative coefficients.*

TABLE 1. Logit Analysis of Electoral Incentives and LDP Post Allocation (1996–2003)

Variable	Model 1	Model 2
Block 1: MP Type		
Zombie	0.18 (0.22)	0.27 (0.22)
SMD Only	−0.19 (0.22)	−0.19 (0.24)
PR Only	−0.39 (0.18)**	—
Costa Rican in PR	−0.09 (0.29)	—
Block 2: Electoral Strength		
Vote share margin	—	0.005 (0.004)
Margin squared	—	—
Block 3: Misc Controls		
Urban-Rural Index	0.04 (0.08)	0.04 (0.09)
No factional membership	−0.86 (0.26)***	−0.98 (0.31)***
Legal professional	0.39 (0.29)	−.36 (0.30)
Seniority		
1st Term	−3.76 (0.36)***	−3.66 (0.37)***
2nd Term	−1.61 (0.19)***	−1.59 (0.21)***
4th Term	−0.34 (0.19)**	−0.45 (0.21)**
5th Term	−1.17 (0.22)***	−1.24 (0.24)***
6th Term	−1.15 (0.22)***	−1.04 (0.24)***
7th Term	−1.52 (0.25)***	−1.83 (0.29)***
8th Term	−1.66 (0.28)***	−1.82 (0.32)***
9th Term	−1.34 (0.32)***	−1.21 (0.33)***
10th Term	−2.89 (0.48)***	−2.77 (0.49)***
11th Term	−1.88 (0.43)***	−1.34 (0.46)***
12th Term	−1.08 (0.41)***	−0.94 (0.49)**
Constant	0.20 (0.20)	0.13 (0.26)
Log-likelihood	−917.24	−764.77
N	1895	1574

Notes: Dependent variables: 1 if MP holds a post of minister, vice minister, PARC, or HoR Committee Chair.
Base categories: SMD dual-listed, 3rd term. Excluded observations: senior MPs that held no post (>12 terms), PR-Only MPs in Model 2.
*$p \leq .10$. **$p \leq .05$. ***$p \leq .001$.

Figure 8: *Pekkanen, Nyblade and Krauss (2006), Table 1. (Graph appears on next page)*

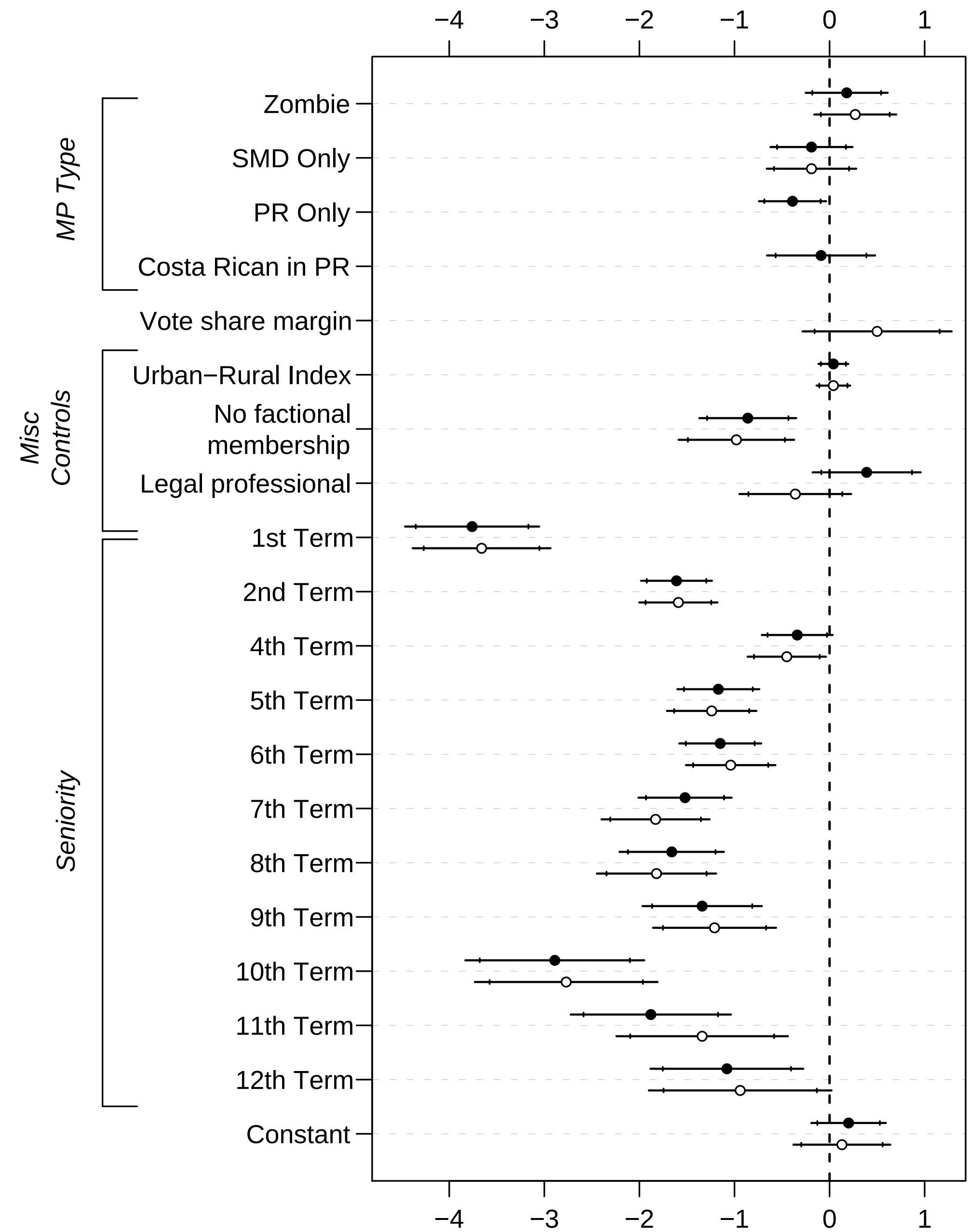

Figure 8: *Using parallel dotplots with error bars to present two regression models. Table 1 from Pekkanen, Nyblade and Krauss (2006) displays two logistic regression models that examine the allocation of posts in the LDP party in Japan. We turn the table into a graph, and present the two models by plotting parallel lines for each of them grouped by coefficients. We differentiate the models by plotting different symbols for the point estimates: filled (black) circles for Model 1 and empty (while) circles for Model 2.*

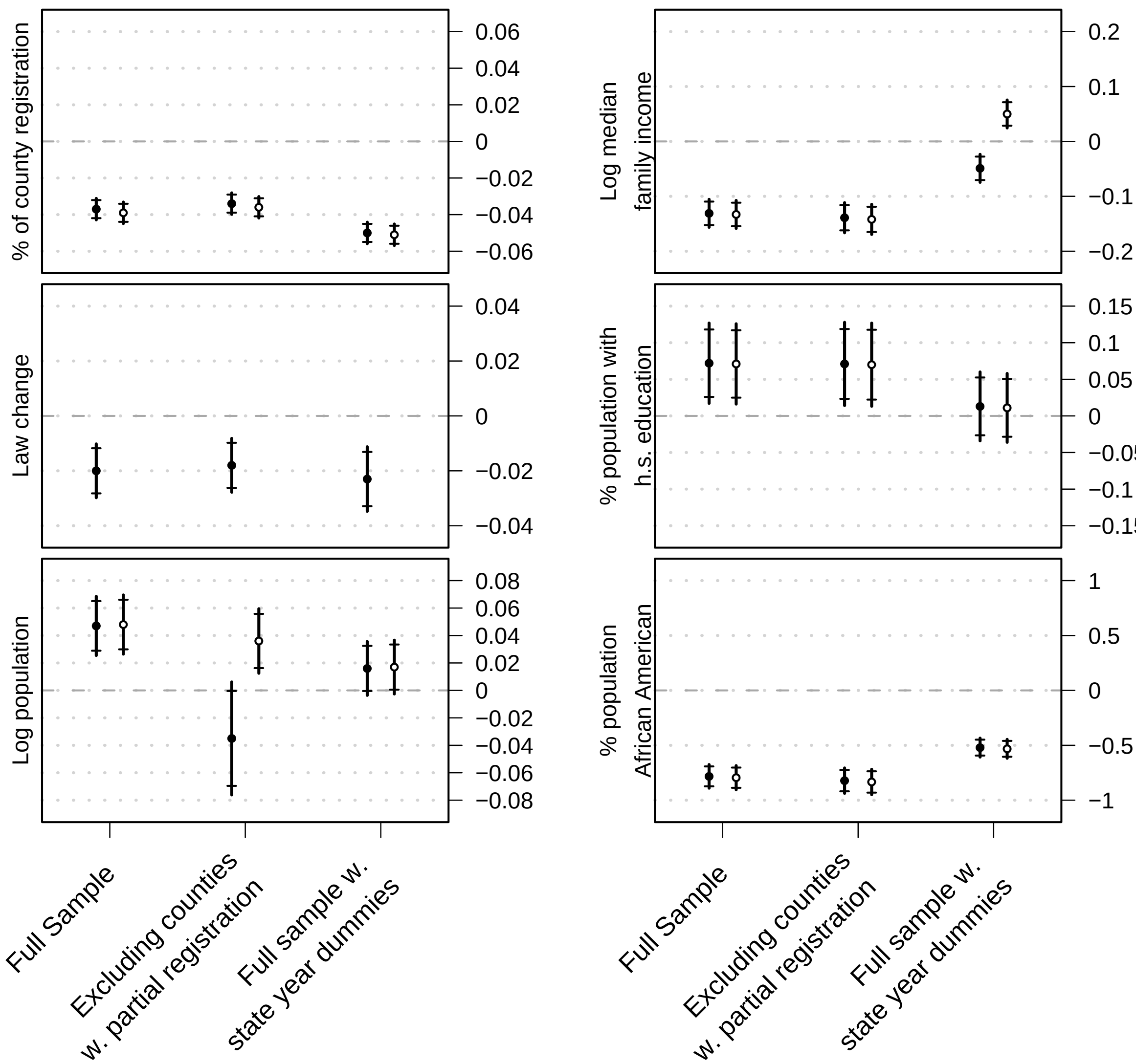

Figure 9: *Using "small multiple" plots to present regression results from several models. Table 4 from Ansolabehere and Konisky (2006) presents regression results from six separate models. We turn the table into a graph that displays a single plot for each predictor, varying across models. The models vary with respect to sample (full sample vs. excluding partisans registration counties) and predictors (with/without state year dummies and with/without law change). On the x-axis we group each type of model: "full sample," "excluding counties with partial registration" and "full sample with state year dummies." Within each of these types, two different regressions are presented: including the dummy variable* law change *and not including it. For each type, we plot two point estimates and intervals, using solid circles for the models in which* law change *is included and empty circles for the models in which it is not.*