# A Day by Day Measure of Legislator Ideology:
## Non-parametric Smoothing of Legislator Ideal Points with Optimal Classification

**Abstract:** This paper adapts Poole's Optimal Classification to smooth ideal points by recovering legislator estimates from localized subsets of the data. Each legislator trend consists of a series of localized kernel estimates, one for each roll call on which the legislator casts a vote. In contrast to the only widely used estimation technique that allows for inter-temporal movement of ideal points, McCarty, Poole, and Rosenthal's DW-NOMINATE, the method measures time by the exact date of the roll call, rather than by a single integer value for each two-year Congress. The method also does not constrain inter-temporal movement to polynomial functions of time. The result is a set of LOESS-like trends that describe legislator movement through time, thus marking the first roll call scaling method capable of summarizing legislator movement within and across legislative periods. I illustrate this method with scalings of the U.S. Senate and the French Fourth Republic.

Adam Bonica

NYU Politics Department

June 2009

## 1. Introduction

There has been a recent resurgence among political scientists interested in estimating legislator ideology from roll call voting records. This is largely in response to the introduction of MCMC IRT ideal point estimation (Londregan 1999; Jackman 2001; Martin and Quinn 2002; Clinton, Jackman, and Rivers 2004). A great deal of attention has been directed at modifying roll call scaling methods to better integrate theory and estimation (Clinton and Mierowitz 2001, 2003; Clinton 2007; Jeong 2007) and incorporating variables of interest other than voting records in the scalings, such as constituent preferences (Clinton 2006) and party influence (Cox and Poole 2002; McCarty, Poole and Rosenthal 2001; Clinton, Jackman, Rivers 2004). Presumably, the increased computational costs associated with MCMC IRT have prevented comparable progress in dynamic estimation. The notable exception is Martin and Quinn's work on the Supreme Court. Despite their contribution, the model has been limited to the courts and other small voting bodies. Dynamic ideal point estimation of legislative bodies has advanced little since the development of DW-NOMINATE (McCarty, Poole, and Rosenthal 1997) over a decade ago. This is unfortunate because properly testing some of the more interesting hypotheses regarding legislative behavior requires better estimates of how legislator ideal points change over time.

There is no straightforward approach to modeling inter-temporal changes in legislator ideology. Existing methods specify time by grouping roll calls into contiguous legislative periods (McCarty, Poole, and Rosenthal, 1997; Poole and Rosenthal, 2007; Martin and Quinn 2002). For example, legislative periods in the U.S. Congress are two years, one for each Congress.[1] This reduces time into a sequence of integer values that take on the familiar form of longitudinal data. To this end, DW-NOMINATE relies on Legendre polynomials to model

[1]A period need not be a two-year Congress. Elections happen to be a natural changing point between periods, but the period can be defined as an arbitrary size.

inter-temporal movement, whereas Martin and Quinn use a dynamic linear model. While dynamic linear models are more versatile than Legrendre polynomials, each assumes that ideal points remain stable during legislative periods and only change after elections. In other words, each method provides a single estimate for each legislative period. Unfortunately, such an approach is unlikely to capture many local features in the data that might be of interest. We can test whether a legislator's ideal point changes over the course of her career by treating time as longitudinal data, however testing whether the legislator adapts to electoral pressures or temporary changes in the political environment is not feasible.

In response to these issues, this paper proposes a dynamic version of Keith Poole's (2000) Optimal Classification (OC) scaling algorithm that utilizes kernel methods (i.e. localized estimates) to smooth legislator positions over time.

This paper contains two contributions to the field of ideal point estimation. The main contribution is the introduction of kernel methods to describe ideological movement of legislators. The proposed scaling method recovers legislator trends from kernels applied to localized subsets of the data. This smoothes legislator estimates within and across periods, which allows us to assess the extent to which legislators' positions change over time with increased "resolution." As opposed to existing roll call scaling methods, which generally estimate a single ideal point per legislative period, this method tracks legislator movement from one day to the next. Naturally, this has broad implications for the types of theories of legislative behavior that can be tested with roll call data.

The second contribution is the development of the first dynamic non-parametric roll call scaling procedure. OC is a non-parametric unfolding procedure built directly on the geometry of voting. The procedure draws cutting lines in a low dimensional space that predict legislators on one side vote "yea" and legislators on the other side vote "nay," and conditional on the cutting lines, finds the maximally classifying ideal point configuration. It only assumes that legislators have single-peaked preferences and that they vote deterministically for the outcome closest to their ideal point. It does not make any assumptions about what leads legislators to make voting errors. It simply minimizes the errors. As a result, non-parametric scaling is preferable in many scenarios, in large part because it is robust to legislatures where party discipline is more prevalent, and is therefore transferable to a greater number of legislatures outside of the U.S. In addition, the localized estimation can be applied to legislatures with a small number of legislative periods, which is typical outside of the U.S., especially for young democracies.

This paper is organized in the following manner. The next section outlines a semi-dynamic version of OC designed to estimate period-specific ideal points on top of a stabilized ideological map. In doing so, it explains the theoretical underpinnings of dynamic estimation—particularly in terms of ensuring that estimates remain identified across time, its importance in conceptualizing dimensionality, and its relationship to the underlying ideological map. Next, the semi-dynamic method is generalized into a fully dynamic version of OC using kernel methods. The following sections report the measures of fit for scalings of the 1st through 110th U.S. Senates and the French Fourth Republic. The final sections illustrate the method using time trends from the U.S. Senate. The paper concludes by outlining a research agenda.

## 2. Recovering Period-Specific Estimates from a Stabilized Ideological Map

The semi-dynamic technique devised to generate a stable ideological map with period-specific legislator estimates is similar to a modified version of DW-NOMINATE developed by Nokken and Poole (2004). They were interested in freeing party switchers from their time trends while keeping the common space intact. Generalizing this technique to OC is relatively straightforward and only requires a slight modification to the static framework. First, OC estimates a single ideal point for each legislator held constant over time. This returns a vector of $n$ ideal points, where $n$ is the total number of legislators who served in at least one period (i.e. Congress), as well as initial estimates for the normal vectors and cutting points for each roll call. After recording the estimates from the static scaling, the ideological map is kept stable by holding the cutting planes and normal vectors parameters constant. This stabilized map is then used to gather period-specific legislator estimates. This is done by treating each period for a given legislator as an independent observation when running the legislator recovery procedure. For example, a legislator that serves in seven legislative periods now has seven independently estimated ideal points plotted onto a stabilized ideological map.

[Insert ***Figure 1*** about here]

While the above procedure can be used to obtain legislator estimates that are comparable across periods, it does not technically constitute a dynamic scaling. The essential feature of a dynamic scaling is the ability to estimate new roll call parameters from dynamic legislator estimates without distorting the common space. DW-NOMINATE relies on time trends to sufficiently constrain legislator movement so that any resulting adjustment to the basic space between periods should be orderly and small, similar to the time trends themselves. This allows the roll call parameters to be re-estimated in each iteration of the loop, which in turn updates the policy space with respect to dynamic legislator positions.[2]

An ideological space that adjusts in response to changes in legislator positions is an essential property of dynamic scaling. It is not difficult to see why the period-specific version of OC lacks this property. If the roll call parameters are updated conditional on the period-specific estimates, they will eventually converge to ten separate scalings, one for each period. On the other hand, holding the basic space constant constricts the scaling to a single estimate of the primary dimension of conflict. Hence, if a scaling spans ten time periods with the ideological map held stable, the first dimension represents an estimate of the primary dimension of conflict for the entire time span. In contrast, a dynamic scaling estimates more than just how legislators and roll calls adjust over time; it also produces time-specific estimates of how individual issues are bundled into the latent ideological dimensions. It registers changes in the ideological axes as issues form, dissolve or shift over time. In a sense, a dynamic scaling provides period-specific estimates of how issues align, which in turn, provide period-

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[2] A loop in DW-NOMINATE consists of successive estimation of the legislator coordinates, including time trends, roll call coordinates, and the error variance and dimension weights.

specific estimates of the primary dimensions of ideological conflict, i.e. what it means to be liberal or conservative. From this perspective, the quantities of interest are actually how legislators move *in relation to the changes in the primary ideological dimensions*.

[Insert **Figure 2** about here]

As an illustration, consider a hypothetical legislature with two orthogonal ideological dimensions—for example, economic and social issues—that, from time to time, trade places as the primary dimension of conflict. This might occur during periods of party or issue realignment. Suppose that a long-serving legislator who has highly consistent positions on individual issues begins her career at a time when social issues are the primary dimension of conflict and remains in office long after economic issues have recaptured dominance. Suppose further that the legislator's position on each dimension remains perfectly stable, holding at .0 on the social dimension and -0.5 on the economic dimension. Despite her consistency on the issues, we should still expect her to move from (0.0, -0.5) to (±0.5, 0.0), corresponding to the change in axes. Consequently, a legislator who moves from a moderate to a more extreme position on the primary dimension of conflict may not have changed her stance on the issues at all. Perhaps the legislator was simply ahead of the curve on important issues. This, of course, would not be observable in the semi-dynamic procedure outlined above.

## 3. Smoothing Legislator Time Trends with Localized Kernel Estimates

Let $\theta_{ist}$ be the ideal point estimate for legislator $i$ for dimension $s$ in period $t$. Each $\theta_{ist}$ is estimated independently of values of $\theta_{is-t}$, where $-t$ denotes all periods other than $t$. As a result, a legislator estimate, $\theta_{ist}$, depends only on the roll calls in period $t$, and $t$ can be defined in a variety of ways. The trick is to constrain legislator estimates across periods such that estimates in periods are sufficiently related to estimates in nearby periods. This can be accomplished by estimating $\theta$ as a function of time using Legendre polynomials (McCarty, Poole, and Rosenthal, 1997) or a Dynamic Linear Models (Martin and Quinn 2001), hence making $\theta_{ist}$ dependent on $\theta_{ist-1}$. However, this is only one possible approach. Modeling $\theta$ globally as a function of time is not theoretically mandated. Again, the primary objective is to make sure that a legislator's estimate in period $t$ is sufficiently constrained to his estimate in other periods, which permits considerable versatility in terms of how each period is defined.

Rather than organizing votes into distinct legislative periods, thereby inevitably grouping them into large, mutually exclusive chunks, this method recovers a legislator estimate for each roll call as though it were a single period. As a result, time is modeled as a function of the frequency of observed events rather than the linear passage of time.[3] This is accomplished by using the data in a way that is conceptually similar to LOESS and other smoothing methods. In brief, after obtaining a stabilized ideological map of the legislature from OC, the method fits a series of ideal points to localized subsets of the data for each legislator. That is, for each roll call, the method recovers a local legislator estimates from the set of the $h$ temporally adjacent data points, where $h$ is the window-width. For instance, assuming a window-width of $h$= 200, the method recovers one ideal point estimate for roll calls 1 through 200, then another estimate for roll calls 2 through 201, then another for roll calls 3 through 202 and so on. This is analogous to taking snapshots of a legislator's voting record from a "moving window." These snapshots summarize the legislator's movement through time without specifying a global function.

The procedure first recovers starting estimates with OC holding legislator ideal points constant over time. It then estimates a smoothed trend using kernel estimators for every legislator who votes on at least $h$ roll calls. This is done by applying a moving window to Poole's legislator recovery algorithm $L(.)$, which is a sophisticated dimension by dimension grid search that locates the point along a line that minimizes voting errors

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[3]An alternative approach is to treat each day as a period. This reduces the total number of parameters to be estimated by grouping together all votes cast by a legislator on a given day.

for each legislator. For a complete treatment of this algorithm see Poole (2005). For our purposes here, it suffices to think of $L(.)$ as no different from any other optimization algorithm that uses a grid search. It may be helpful to think of $L(.)$ as a non-parametric estimator that, rather than computes the sample mean, instead identifies an optimal point, such that maximum number of vote outcomes are on the correct side of their respective cutting lines.

A more formal description of how to fit $L(.)$ with non-parametric kernel estimators is as follows. For legislator $i$ on roll call $j$, let $\theta_{isj} = \hat{L}(\boldsymbol{y}_{\boldsymbol{i}[j-h/2,j+h/2]}; \boldsymbol{\delta}_{[j-h/2,j+h/2]})$, where $\theta_{isj}$ is the estimate for legislator $i$ at roll call; $\boldsymbol{y}_{i[j-h/2,j+h/2]}$ is a vector of vote outcomes for legislator $i$ within the fixed window-width $h$; and $\boldsymbol{\delta}_{[j-h/2,j+h/2]}$ is a matrix of roll call parameters (normal vectors, cutting lines, roll call directions).

Although the legislator estimates are optimally classifying for each window, the localized maxima do not always correspond with the global maxima, which in turn can increase total error rate for the entire legislature. Consequently, in order to guarantee strict convergence, a rejection criterion must be imposed on newly estimated legislator trends such that any legislator trend that fails to pass the rejection criterion reverts to the estimates from the previous round. This will ensure that each legislator trend climbs uphill in each iteration. I have experimented with two criteria. The first simply requires that newly estimated trends reduce the total number of classification errors. The second criterion requires that the new trends reduce the "signal-to-noise" ratio, which is defined as the ratio of classification rate to total movement. Total movement is defined as the total absolute change in legislator trends, summing across all legislators and roll calls. It is calculated using the equation, $\nabla = \sum_{s=1}^{S} \sum_{i=1}^{I} \sum_{j=1}^{J} |\theta_{sij} - \theta_{si(j-1)}|$. In most cases, a trend that is substantially more erratic and only slightly increases classification will be rejected. In practice, the best approach is to force newly estimated trends to satisfy both criteria, because it decreases the number of iterations needed to achieve convergence without meaningfully affecting results. After rejecting the trends that fail to meet the rejection criterion, cutting plane procedure is run conditional on the new legislator trends.

**Algorithm for dynamic OC:**

1. Get starting values from the eigenvectors of the double-centered legislator agreement score matrix.
2. Run OC until convergence with legislator estimates held constant across periods.
3. Recover legislator trends with kernel estimators for all individuals with at least $h$ votes.
4. Replace newly estimated trends that do not meet the rejection criterion with the trends from the previous round.
5. Rerun the cutting plane procedure conditional on legislator trends estimated in step 4.
6. Go to step 3. Repeat until convergence.

Section 7 of this paper includes plots of legislator time trends for four well-known senators that illustrate the results. The trends can be noticeably "rough" in areas. The step-wise movement is partially an artifact that is specific to OC, because of how it utilizes information about errors. Unlike parametric scalings, non-parametric classification does not use data from correctly predicted votes, which constitute the vast majority of the votes cast; it only records errors, and does so with a dichotomous measure. Another reason for the step-wise movement is the use of uniform kernel estimates. Increasing smoothing with a distance-weighted kernel or adding a secondary layer of smoothing with LOESS or a spline, for instance, eliminates much of the roughness that results from the uniform kernels.

Another issue with specifying $\hat{L}(.)$ with a uniform kernel is that it provides poor estimates at the tails, because there are fewer than $h$ votes available to fit the local estimates. Rather than break uniformity of window-width, I set the estimates for $j < h/2$ to $\theta_{is(h/2)}$ and the estimates for $j > J - h/2$ to $\theta_{is(J-h/2)}$. This means that the legislator's trend is held constant for the first $h/2$ votes and again for the final $h/2$ votes. As long as the number of legislators is reasonably large, any effect caused by a few legislator trends that are under or over smoothed at the tails tends to be hedged out in aggregate level legislature trends. Hence, using uniform kernels tends to be less problematic when aggregate trends are the quantities of interest. However, tests that focus on the movement of individual legislators often requires better estimates at the tails—i.e., testing for last period shirking effects. One way to improve estimates at the tails is to distance-weight errors. Tri-Cube Weighted kernel estimators use the same set of observations per window as the uniform kernel but penalize errors such that temporally distant votes receive less weight. The tri-cube weight function is the standard for LOESS. Modified for $\hat{L}(.)$,

$$w(v_x) = \begin{cases} \left(1 - \left|\frac{v_x - v_j}{\mathrm{m}}\right|^3\right)^3 I(x) & \text{for } \left|\frac{x-j}{m}\right| < 1 \\ 0 & \text{for } \left|\frac{x-j}{m}\right| \geq 1 \end{cases},$$

where $v_j$ is the date of the vote at the center of the window; $v_x$ is the date of the vote being weighted; $I(x)$ is an indicator function that takes on the value 1 if $x$ is a voting error and 0 otherwise; and $m$ is the maximum distance of votes included in the window, such that $m = max\left(\left|v_j - v_{(j-h/2)}\right|, \left|v_j - v_{(j+h/2)}\right|\right)$. An error that occurs on the date of the roll call receives full weight, an error on the furthest date in the window receives no weight, and errors on all other dates receive weights in the range (0, 1). Although tri-cube weighted kernels produce better estimates at the tails, the downside is that legislator trends become much more dynamic, roughly tripling values of $\nabla$ over uniform kernels with the same window-width.

Although I designed the statistical software to accommodate a variety of smoothing parameters and specifications, I opted to present results in their rawest form possible[4]. At its core, the method proposed here

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[4]Hardwiring the scaling method with a single specification would be counterproductive, in that it could restrict researchers from employing their best judgment in modeling legislator movement. Instead, I have written and complied a freely available R statistical package that allows users to specify a range of smoothing options—or if they prefer, configure a new smoothing scheme by writing a minimal amount of code. The R package can be downloaded from http://homepages.nyu.edu/~ajb454/files/rcscale.zip. The specific R scripts used to replicate all results and analyses in this article are available on request.

combines two existing technologies, roll call scaling and non-parametric smoothing techniques, each of which has an extensive literature. I present results from the sparsest model specification possible not only because it streamlines exposition, but also because it performs reasonably well against alternative specifications.

In the following section, I present classification results from a dynamic scaling of the 1st through 110th U.S. Senates with a range of smoothing configurations. The next section does the same for the French Fourth Republic as a brief demonstration of the benefit of dynamic roll call analysis for legislatures outside the U.S.

## 4. Classification Results from the U.S. Senate

Table 1 lists the correct classification rate, total errors and total movement of the legislators for DW-NOMINATE, Constant OC, and dynamic OC for four values of $h$. The initial increase in classification of OC over NOMINATE is already well documented.[5] The appropriate comparison between DW-NOMINATE and OC is the increase in aggregate proportional reduction in error (APRE)[6] moving from a constant model to a

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[5] The increase in correct classification when moving to OC from DW-NOMINATE results from the fact that as a random utility model, DW-NOMINATE pursues a different objective than that of non-parametric estimation—DW-NOMINATE minimizes each legislator's total sum of distances from the roll call parameters for votes predicted as errors and weights distances geometrically so that severe errors are granted more weight; OC estimates legislator ideal points with the purpose of minimizing voting errors and treats all errors equally regardless of severity.

[6] The APRE is the total sum of PRE over the total number of roll calls included in the scaling. The equation for proportional reduction in error (PRE) for each roll calls is, $\frac{\text{votes in the minorty} - \text{errors}}{(\text{vote in the minority})}$. It reports the marginal increase in the number of votes correctly predicted by the cutting plane over the null prediction of assuming everyone votes in the majority.

dynamic model—an increase of 1.5 percent for DW-NOMINATE compared to an increase in APRE of 4.3 percent for dynamic OC ($h = 250$). To provide another point of comparison, an unconstrained period-specific OC scaling (scaling each Congress separately and aggregating results) increases the APRE by 2.7 percent over the pooled static OC scaling, about half of the increase associated with dynamic OC. This is evidence that senators shift positions within, not just across, periods.

[Insert **Figure 1** about here]

The fourth and fifth columns provide a general measure of how constrained legislator estimates are from one roll call to the next. Selecting a value of $h$ comes with an inherent tradeoff between correct classification and trend stability. The larger the window size, the more confident we are that the trends reflect actual changes in voting behavior, as estimates become increasingly robust to the data generating process. On the other hand, larger window-widths decrease the sensitivity of the results. Reducing the window-width relaxes the level of constraint—i.e. the "glue" that holds the ideological space together. As a result, the estimates become more localized, in turn causing legislator trends to become more dynamic. Smaller window sizes can be useful in detecting temporary changes in voting patterns but tend to decrease the signal-to-noise ratio.

[Insert **Table 2** about here]

Table 2 displays the correlation coefficients of legislator estimates from scalings specified with different window-widths. To calculate the coefficients, I construct a vector $\theta_{ij}$ for each scaling, such that each legislator estimate on each roll call is matched. The directly off-diagonal cells are the most informative. The correlations are increasing with $h$, indicating that trends become more consistent with larger window-widths. For any two values of $h \geq 200$, the two sets of converged estimates should correlate at or above .98 on the first dimension and .935 on the second dimension. Although not included in Table 2, the correlation between the uniform and weighted kernel estimates each with a window-width of 250 is 0.976 for the first dimension and 0.930 for the second dimension.

For the Senate results presented below, the window-width is set to $h = 250$. This choice is not arbitrary. A window-width of 250 performs the best in cross-validation testing, the results of which are included in the Appendix.

## 5. Legislatures Outside of the U.S.

Although the results in this paper focus on the U.S. Senate, a main selling point of OC is its robustness to the data generating processes of legislatures outside of the U.S. The various parametric models assume that voting errors are independent and identically distributed across both legislator and roll calls. As dubious as the i.i.d. assumptions are for the U.S. Congress, in legislatures where there is across-legislator variation in the magnitude of errors—which may arise, for instance, when parties vary in their degrees of discipline—the assumptions begin to lack face validity. This is particularly apparent in legislatures where the errors are small. In such cases, NOMINATE tends to force a large portion of the legislators to the rim of the unit hyper-sphere (Rosenthal and Voeten 2004).

Smoothing legislator trends with kernels may have the most to offer scholars of comparative legislative behavior. Legislatures outside the U.S. have been the subject of a great deal of research that employs roll call analysis. Supranational legislatures such as the European Parliament (Hix 2001; Noury 2002; Hix, Noury, and Roland 2006, 2007) and emerging democracies in Eastern Europe (Noury and Mielcova 2005, Kiewiet and Myagkov 1996, Carey 2008) and Latin America (Carey 2003a, 2003b, 2008; Desposato 2003; Londregan 2000; Morgenstern 2003) have attracted the most interest. However, none of these studies employs dynamic estimates. The U.S. Congress is distinct in its longevity as well as its frequent elections, held every two years. Legislatures outside of the U.S. typically originated after the Second World War and hold elections roughly every four or five years. This means a legislator in a typical legislature would have to serve for 20 to 25 years before meeting DW-NOMINATE's requirement to be estimated with a time-trend. In contrast, a legislator only needs to serve 10 years in the U.S. Congress. As a result, even in legislatures where the various assumptions made by NOMINATE are less problematic, there are often far too few legislative periods to scale with DW-NOMINATE.

Localized estimation bypasses these time limitations by shifting focus from the number of periods to the number of votes. The technique can be applied to legislatures with fewer than a thousand recorded roll calls. The results from a dynamic scaling of the French Fourth Republic are used to demonstrate.

[Insert Table 3 about here]

The modest increase in APRE over the legislature-specific model seems to suggest that the benefit of dynamic scaling is slight. The two dimensional static scaling already performs exceptionally well, correctly classifying 96.2 percent of votes. A two dimensional legislature-specific scaling increases the correct classification rate to 97.0 percent. The dynamic scaling slightly improves correct classification to 97.2 percent with a window-width of 150 and 97.4 percent with a window-width of 100.[7] However, the seemingly small improvement in fit is deceptive. A chaotic legislature in constant motion, the National Assembly is well known for its dynamism and instability. A major contributing factor was the prevalence of party switchers. In fact, almost 20 percent of legislators switched parties one or more times (Rosenthal and Voeten 2004).

[7]Smaller window sizes are in order for a few reasons. The National Assembly has over 800 members, which makes the issue space less granular and the estimates more precise. The larger legislature also means that each roll call provides eight times as many data-points per roll call as is the case in the U.S. Senate. In addition, the dataset has been reduced from its original size to fewer than a thousand roll calls hand-selected for their significance (MacRae 1967). As a result, a window-width of 250 would be nearly the size of each legislative period.

A valuable feature of the localized estimates is the creation of detailed animations. I include a link to an animation of the dynamic scaling with a window size of 100.[8] The animation makes possible visual analysis of the flow of members from one party or coalition to another and the movements of parties over time. Despite the modest increase in correct classification, the benefit of a dynamic scaling becomes strikingly apparent when the legislator trends are viewed in motion. Phenomena of interest include early party positioning and legislator sorting in the first legislature and the rise and collapse of the Gaullists during the second legislature.

## 6. Senate Trends

Roll call analysis has been applied in analyzing legislature level phenomena, including dimensional analysis (Poole and Rosenthal 2007), polarization (McCarty, Poole and Rosenthal 2006; Brady and Han 2004), party discipline (Hager and Talbot 2000; Snyder and Groseclose 2000; Cox and Poole 2002; McCarty, Poole and Rosenthal 2001), institutional analysis (Krehbiel 1998; Cox and McCubbins 2005; Jenkins 1998), and historical analysis (Jenkins and Stewart 1998, 2003; Jenkins 2000). Localized roll call analysis stands to advance our understanding of any of the above topics that track movement over time. In this section, the implications for two of the above topics, polarization and dimensional analysis, are presented and briefly discussed. The time trends reveal that much can change between elections, and period-specific estimates cannot adequately account for these dynamics.

**Example 1: Polarization**

[Insert **Figure 3** about here]

[Insert **Figure 4** about here]

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[8]The animation includes a secondary layer of smoothing so that the legislator trends are easier to follow: http://homepages.nyu.edu/~ajb454/files/france4th.mov .

The dynamic OC polarization trend closely tracks the corresponding DW-NOMINATE trend. Both trends tell a similar story in the long run: polarization reaches a low-point around the 90th Senate (1967-1968) and steadily increases in the following decades. At the same time, the dynamic OC trend reveals that political polarization varies considerably between elections. Figure 4 magnifies the trend for the period between the 103th and 109th Senates so that it is possible to view how Senate polarization responds to political events. There are three notable events that affect the polarization trend. The first event occurs during the 104th Congress and corresponds perfectly with the federal government shutdowns that resulted after the Republican controlled Congress failed to pass a budget bill. The second event is Senator Jeffords' decision to switch parties during the 107th Senate, which was immediately followed by a sharp decline in polarization. The third notable event is the rapid rise in polarization during the run up to and through the early months of the Iraq War. In December 2003, this trend abruptly ceases and then falls, corresponding with the capture of Saddam Hussein.

Figure 4 contrasts the standard account that member replacement is the driving force behind congressional polarization (Theriault 2004; Brady and Han 2004; Kiewiet and Zeng 1993; Price 2002; Poole and Rosenthal 2007). It tells a story in which political events provide much of the inertia that moves the parties apart in the Senate. Interestingly, some of the events appear to have lasting influence. This is best exemplified by the jump in polarization corresponding with the 1995 government shutdown. Rather than observing a spike in polarization that quickly returns to its previous level, the trend remains at its heightened level, perhaps because increased animosity weakened bipartisan goodwill or reinforced partisan identities.

This is potentially a strong counterpoint to Poole's bold claim regarding ideological constancy. Poole (2007) claims that "based on the roll call voting record, once elected to Congress, members adopt a consistent ideological position and maintain it over time. There may be changing minds, but they are not in Congress." Jacobson (2007) notes that "if Poole is right, then not only have the bitter partisan fights within Congress contributed nothing (at least directly) to partisan polarization but the changing electoral environment is reflected only in the replacement of moderates by more extreme partisans, not by continuing members that adapt to new electoral realities." Figure 5 provides cursory evidence that senators adjust their voting behavior in response to events and that this has contributed to the recent rise in polarization. Moreover, member replacement appears to have made a minimal contribution to polarization during a period marked by its momentous rise—in fact, the initial replacement effect of the 104th Senate actually slightly *decreases* the distance between parties.

**Example 2: Dimensional Analysis**

OC, like NOMINATE, is an alternating procedure in which the roll call parameters are estimated as a function of the legislator estimates, which are in turn estimated as a function of the roll call parameters, creating a loop that can be iterated to explore the parameter space. The ideological space—i.e. the roll call estimates—adjusts in response to movement by legislators from one round to the next. Since the kernel estimates produce ideal points specific to each vote, the ideological space adjusts almost instantaneously with changes in voting patterns, which can be induced by changes in the legislative agenda. The ability to detect these changes provides for richer and far more robust dimensional analyses.

[Insert **Figure 5** about here]

Scaling the Senate with a single dimension and again with two dimensions demonstrates the added value smoothing legislator trends to dimensional analysis. Figure 5 plots the trends of the means for Republicans, Northern Democrats, and Southern Democrats, first from a single dimensional scaling and then from two dimensional scaling. The party trends for the two scalings are largely similar from the 1980's on. Yet during the Civil Rights Era the party trends are considerably different, particularly with respect to Southern Democrats. In the summer of 1964, which was dominated by civil rights legislation, the single dimensional scaling shows the mean Southern Democrat moving to the right of the mean Republican. For this brief period in 1964, civil rights replaced economic issues as the primary dimension of conflict. In later periods, during which civil rights legislation briefly dominates the agenda, Southern Democrats again move temporarily away from Northern Democrats. This is registered in the one-dimensional scaling. In contrast, the two dimensional scaling registers little movement in the position of the mean Southern Democrat during periods of civil rights legislation, an indication that the civil rights conflict scales almost exclusively to the second dimension. Observing that the single dimensional scaling is sensitive enough to register this temporary disruption in dimensionality is an impressive finding. The fact that civil rights legislation scales entirely to the second dimension, leaving the first dimension stable throughout the Civil Rights Era, is a testament to OC's ability to sort between dimensional conflicts.

## 7. Individual Senator Trends

The previous section demonstrates that improved analysis of aggregate legislature trends justifies the added complexity in estimation. Nevertheless, each legislator trend tells a story about a legislative career. Ideological constancy is a defining characteristic of most legislative careers. Time trends accurately track ideological movement—or lack thereof—of ideologically stable legislators but are for the most part uninteresting. In this section, a few of the more telling legislator trends are displayed, along with their corresponding DW-NOMINATE trend lines as reference points. Most time trends correspond closely with their DW-NOMINATE trends and are stable over long periods. In this respect, the four senators displayed below are outliers. With that in mind, even particularly dynamic legislators usually remain stable for periods of hundreds or thousands of votes between jumps. The alternative would be observing frequent shifts between locations every few votes, which would suggest high levels of uncertainty in the estimates. As such, we can be quite confident that legislators belong where they are for those stretches of time and belong elsewhere after observing a jump.

[Insert **Figure 6** about here]

Senator Schweiker's trend is fascinating for two reasons. First, as a first-term Republican Senator he was reelected with 53 percent of the vote against a strong challenger in the 1974 election, a landslide year for Democrats. His trend helps explain what seems like an improbable outcome. In the run-up to the election, he moves to the left of many Democrats and subsequently returns to a moderate-to-conservative position before leaving the Senate to accept a position as Secretary of Health and Human Services in the Reagan Administration. The second reason that Schweiker's trend is fascinating is that during Ronald Reagan's first presidential bid in 1976, Reagan broke precedent by announcing that if he received the party's nomination he would select Schweiker as his running mate to balance out the ticket. Schweiker's trend puts Reagan's electoral promise in context. Schweiker was likely more conservative than his voting record suggested at the time. The fact that he began his Senate career as a moderate and ended it as a moderate-conservative suggests that his liberal period was largely an electoral strategy and that his "conversion" to conservatism was hardly that.

Senator Proxmire, of Golden-Fleece fame, is perhaps the best example of a maverick senator. Given the amount of variation in his trend between elections, period-specific estimates could not adequately describe Proxmire's voting behavior. His ideological movement becomes highly erratic during the late 1970's and remains that way until his retirement in 1989. It appears his maverick streak did not become prominent until late in his career.

Senator Jeffords' trend largely speaks for itself. His ideological position as a moderate Republican remains stable for over a decade. Shortly after he switches parties his trend takes a sharp turn to the left, rebounds to a more moderate position, and then moves to the extreme of the Democratic Party before his retirement. Jeffords' move to the left after switching parties should not be much of a surprise, but it does suggest that party matters. This is consistent with McCarty, Poole, and Rosenthal (2001, 2007) who similarly find that party affiliation strongly influences the position of ideal points. His trend also suggests that he was constrained as a Republican, to a much greater extent than he was as an Independent caucusing with the Democrats, as the final years of his trend describe a senator with strong liberal leanings.

Lastly, Senator Lieberman's trend is noteworthy because his move to the right occurred after he won reelection as an Independent. In fact, prior to being challenged by Ned Lamont in the Democratic primary, Lieberman's position was no more conservative than it had been in the past. In contrast to the other three plots, Lieberman's trend looks more typical of the rest of the sample. Meaningful variation is present, but stability is the norm.

**President Trends**

Time trends for presidents since Eisenhower can be estimated by constructing voting records from *Congressional Quarterly* presidential support scores. Presumably, if a president could vote on these bills, he would vote in the direction indicated by the support scores (McCarty and Poole 1995). Poole has scaled ideal points for presidents using OC and DW-NOMINATE. DW-NOMINATE estimates static ideal points because presidents serve a maximum of four Congresses, one fewer than the five required to estimate a time trend. Hence, the trends presented below are the first dynamic estimates of presidential ideal points.

The relatively sparse voting records of presidents make estimating trends with a window-width of $h = 250$ problematic. Presidents accumulate fewer observations per Congress than the typical legislator does. Legislators vote on most roll calls, revealing their position with each vote. In contrast, presidents only reveal their positions on a select subset of roll calls—ones that they choose to publicize, either because the bills are closely related to their policy agenda or believe they have some strategic influence. The U.S. Congress, where the average size of voting records is in the thousands, accommodates larger window sizes without difficulty. However, if the individuals of interest often cast fewer than a thousand observations, a different approach is needed. One possible approach is to specify tri-cube weighted kernels with $h = 150$. However, when possible, increasing the number of observations is usually the preferred approach. Fortunately, a joint scaling of the House and Senate roughly triples the number of observations for each president.

[Insert ***Figure 7*** about here]

Figure 7 plots the trends for every president since Eisenhower from a joint scaling of the $80^{th}$-$110^{th}$ U.S. House and Senate. The most notable feature of the trends is that the voting behavior of presidents is relatively dynamic.

Table 4 displays the classification rates from static and dynamic OC scalings for each president. With the exception of Gerald Ford, presidents have average or above correct classification percentages. Jimmy Carter and Reagan have the greatest increases in classification when moving from the static to dynamic models—2.1 percent and 2.9 percent, respectively. It is important to note that although a few presidents do not increase correct classification when moving from the static to dynamic model, this does not mean the estimates from the static scaling are superior. It merely entails that for those presidents the static ideal points in a static model perform as well as dynamic ideal points do in a dynamic model. For example, estimating a static ideal point for George W. Bush, conditional on roll call parameters estimated from a dynamic scaling, increases his recorded voting errors to 46. This provides perspective as to why his trend is so dynamic. In comparison, the other two presidents whose dynamic estimates do not improve classification over the static model, John F. Kennedy and Ford, have trends that remain essentially stable throughout their presidencies.

[Insert **Table 4** about here]

## 8. Conclusion

This new method of dynamic ideal point estimation carries with it a research agenda. The first task is to apply localized estimation to parametric roll call scaling methods. Each scaling method has its advantages and disadvantages and ought to be selected on a per legislature basis. Fortunately, generalizing localized estimation to parametric models can be done using either non-parametric kernel smoothers or local log-likelihood methods (Loader 1996), which generally outperform kernel methods when estimating tails of time trends and in multidimensional settings. An advantageous feature of probabilistic models of voting is that every vote, error or otherwise, provides a scalar distance measure that can be used to fit localized estimates. The expectation is that legislator trends will be much smoother. In addition, a parametric model can provide estimates of standard errors.

The second task is to begin testing theories of legislative and judicial politics that are difficult or impractical to test with period-level analysis. A preliminary list of potential empirical applications of this nature might include the following:

1) Testing whether legislators adapt to the changing demands of their constituents;
2) dimensionality analysis, and testing whether exogenous shocks (e.g., September 11th) upset the dimensions upon which legislators are typically aligned;
3) testing whether the increase in polarization in the U.S. Congress in recent decades is the result of member replacement or existing legislators trending towards the ideological extremes;
4) testing whether party cohesiveness and/or party discipline responds to the competitiveness of upcoming elections;
5) testing for legislative learning—do most legislators come into Congress with hardwired ideological positions, or is there a period of learning?

Many empirical tests that have relied on DW-NOMINATE stand to be improved as well. For instance, the date-specific trends allow for a more robust test of Cox and McCubbins' cartel theory (2005). In *Setting the Agenda*, Cox and McCubbins report results regarding a test from their gate-keeping hypothesis, which involved regressing the minority party roll-rates for legislative periods on the distance between the party means as estimated by DW-NOMINATE. Due to the limitations of DW-NOMINATE, they used roll-rates as a measure instead of individual rolls, and as a result were restricted to a very small sample size ($n < 60$). A more appropriate research design would be treating party rolls as a binary dependent variable modeled as a function of the distance between the median legislator and median members of the minority party on the date of the vote, perhaps including control variables for party polarization, party standard deviations and preference shifts. Such a test is now possible.

Period-level analysis is often inadequate for testing questions about whether legislators change their voting behavior across time or how they adjust in response to events and electoral pressures. A scaling method capable of measuring local features of ideological movement is essential to these endeavors. The basic analyses included in this paper hope to demonstrate the benefits of localized estimation over extant methods. This is particularly true with respect to the study of legislature trends. Overall, the empirical traction gained by local estimation should become increasingly apparent as tests are designed with substantive questions in mind.

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## Appendix A: Cross-validation

Cross-validation is a method of estimating generalization errors based on re-sampling that is similar to bootstrapping. I utilize a holdout validation scheme to determine the optimal bandwidth parameter (window-width) for the scaling procedure.[9] Scaling the 1st through 110th Senate is computationally intensive. Lacking sufficient computing resources, I reduced the sample size to the 100th through 106th Senates.

I perform ten training runs for each window size from 100 to 400, moving by increments of 10. On each training run I hold out 1/5 of the roll calls sampled at random from the dataset. I then run the scaling on the training set with the specified window-width. With the recovered estimates, I interpolate values for the held out sample for each of the legislator trends based on the nearest roll calls included in the training set. Given the interpolated legislator trends, I then run the cutting plane procedure on the entire dataset, which reports correct classification rates and APRE for the training set and test set. Averaging the APRE over training runs provides a generalized measure of error. I display the results from the cross-validation in Figure 8.

[Insert **Figure 8** about here]

The out of sample APRE peaks around a window-width of $h$=250. The curve would presumably have been smoother had I increased the number of training runs. Regardless, the relationship between APRE and window size clearly arcs around 250.

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[9] Note that the holdout method is not technically cross-validation because the data is never "crossed."

| | Correct Classification | APRE | Errors | $\nabla_1$ | $\nabla_2$ |
|---|---|---|---|---|---|
| WNOMINATE(constant) | 85.2 | 56.3 | 435429 | | |
| DW-NOMINATE | 85.7 | 57.8 | 420622 | | |
| | | | | | |
| Constant OC | 88.4 | 65.7 | 330691 | | |
| Constrained period-Specific OC | 89.0 | 67.6 | 312942 | | |
| Unconstrained period-Specific OC | 89.3 | 68.4 | 304905 | | |
| Dynamic OC | | | | | |
| *Uniform Kernel* | | | | | |
| *h = 100* | 90.9 | 73.1 | 259120 | 3364 | 6200 |
| *h = 150* | 90.4 | 71.5 | 274489 | 1713 | 3379 |
| *h = 200* | 90.0 | 70.1 | 284031 | 993 | 2007 |
| *h = 250* | 89.9 | 70.0 | 289104 | 644 | 1300 |
| *h = 300* | 89.6 | 69.3 | 296282 | 459 | 921 |
| *h = 350* | 89.5 | 68.8 | 301034 | 326 | 688 |
| *Tri-Cube Weighted Kernel* | | | | | |
| *h = 100* | 91.7 | 75.6 | 235499 | 8606 | 15623 |
| *h = 150* | 91.1 | 73.6 | 254455 | 4599 | 9130 |
| *h = 200* | 90.6 | 72.3 | 266854 | 2769 | 5740 |
| *h = 250* | 90.3 | 71.4 | 276301 | 1873 | 3855 |
| *h = 300* | 90.1 | 70.6 | 283240 | 1306 | 2752 |
| *h = 350* | 89.9 | 70.1 | 288142 | 949 | 2055 |

***Table 1: 1st through 110th US Senates*** The Constant-OC model pools all roll calls and legislators by estimating a single ideal point for the entirety of a legislator's career. The Constrained period-specific OC model uses the roll call estimates from the Constant-OC scaling to estimate Congress-specific estimates for each legislator, as discussed in Section 2. In contrast, the Unconstrained Congress-specific model estimates each Congress individually and does not produce estimates that can be compared over time. All results are from two-dimensional scalings. The congressional voting records are taken from Poole and Rosenthal's voteview.com.

| | $h = 100$ | $h = 150$ | $h = 200$ | $h = 250$ | $h = 300$ | $h = 350$ |
|---|---|---|---|---|---|---|
| Dimension 1 | | | | | | |
| $h = 100$ | 1.000 | | | | | |
| $h = 150$ | 0.964 | 1.000 | | | | |
| $h = 200$ | 0.960 | 0.975 | 1.000 | | | |
| $h = 250$ | 0.957 | 0.973 | 0.983 | 1.000 | | |
| $h = 300$ | 0.955 | 0.971 | 0.981 | 0.987 | 1.000 | |
| $h = 350$ | 0.954 | 0.969 | 0.980 | 0.986 | 0.989 | 1.000 |
| Dimension 2 | | | | | | |
| $h = 100$ | 1.000 | | | | | |
| $h = 150$ | 0.895 | 1.000 | | | | |
| $h = 200$ | 0.883 | 0.929 | 1.000 | | | |
| $h = 250$ | 0.876 | 0.922 | 0.949 | 1.000 | | |
| $h = 300$ | 0.870 | 0.915 | 0.945 | 0.958 | 1.000 | |
| $h = 350$ | 0.862 | 0.907 | 0.939 | 0.955 | 0.965 | 1.000 |

***Table 2:*** Correlations of legislators estimates from two-dimensional scalings of the 1st -110th U.S. Senates with uniform kernels across varying window-widths.

| | 1 Dimension<br>Correct Classification | APRE | Errors | $\nabla_1$ | 2 Dimensions<br>Correct Classification | APRE | Errors | $\nabla_1$ | $\nabla_2$ |
|---|---|---|---|---|---|---|---|---|---|
| Constant-OC | 92.4 | 78.8 | 35520 | | 96.2 | 89.3 | 17725 | | |
| Legislature-Specific | 93.5 | 82.0 | 30149 | | 97.0 | 91.6 | 14128 | | |
| Dynamic OC | | | | | | | | | |
| *h = 100* | 94.3 | 84.0 | 26731 | 448 | 97.4 | 92.8 | 12035 | 303 | 244 |
| *h = 150* | 93.8 | 82.8 | 28767 | 238 | 97.2 | 92.1 | 13211 | 156 | 142 |
| *h = 200* | 93.7 | 82.3 | 29697 | 131 | 97.0 | 91.5 | 14126 | 94 | 80 |
| *h = 250* | 93.4 | 81.6 | 30865 | 82 | 96.8 | 91.1 | 14980 | 55 | 58 |

***Table 3:*** Classification results for the French Fourth Republic (1946-1958). Roll call records are from Rosenthal and Voeten.

| | Static OC | | Dynamic OC | | | |
|---|---|---|---|---|---|---|
| | Errors | CC | Errors | CC | Diff CC | N Votes |
| Eisenhower | 63 | 0.909 | 58 | 0.916 | 0.007 | 694 |
| Kennedy | 25 | 0.953 | 25 | 0.953 | 0.000 | 527 |
| Johnson | 104 | 0.908 | 88 | 0.922 | 0.014 | 1125 |
| Nixon | 113 | 0.862 | 96 | 0.883 | 0.021 | 818 |
| Ford | 75 | 0.798 | 75 | 0.798 | 0.000 | 372 |
| Carter | 120 | 0.867 | 101 | 0.888 | 0.021 | 903 |
| Reagan | 158 | 0.877 | 121 | 0.906 | 0.029 | 1286 |
| Bush | 74 | 0.868 | 64 | 0.886 | 0.018 | 560 |
| Clinton | 95 | 0.902 | 79 | 0.918 | 0.017 | 968 |
| Bush | 35 | 0.947 | 35 | 0.947 | 0.000 | 658 |

***Table 4:*** Comparison of error rates for presidents in static and dynamic scalings.

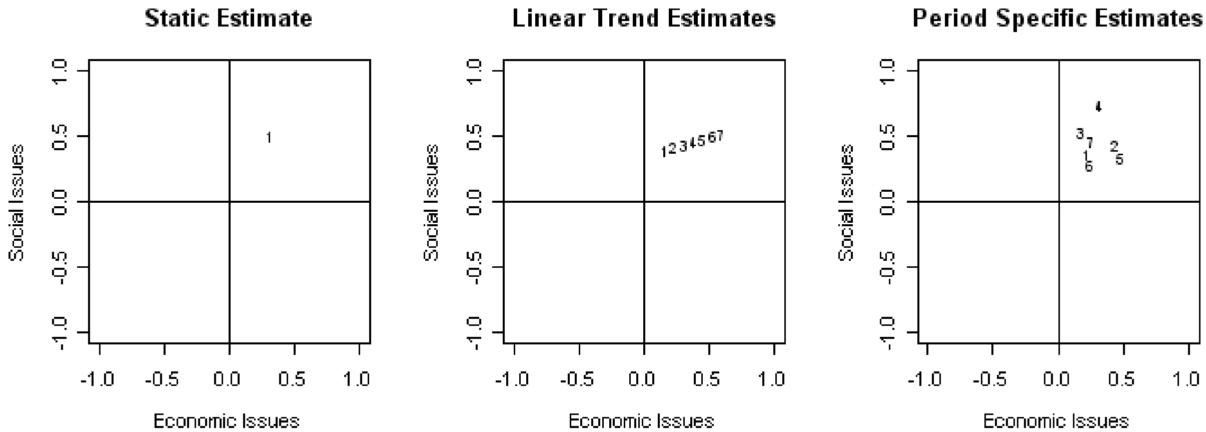


***Figure 1:*** An example of a static estimate, a linear trend estimate, and a vector of period-specific estimates for a hypothetical legislator who serves in seven legislative periods.

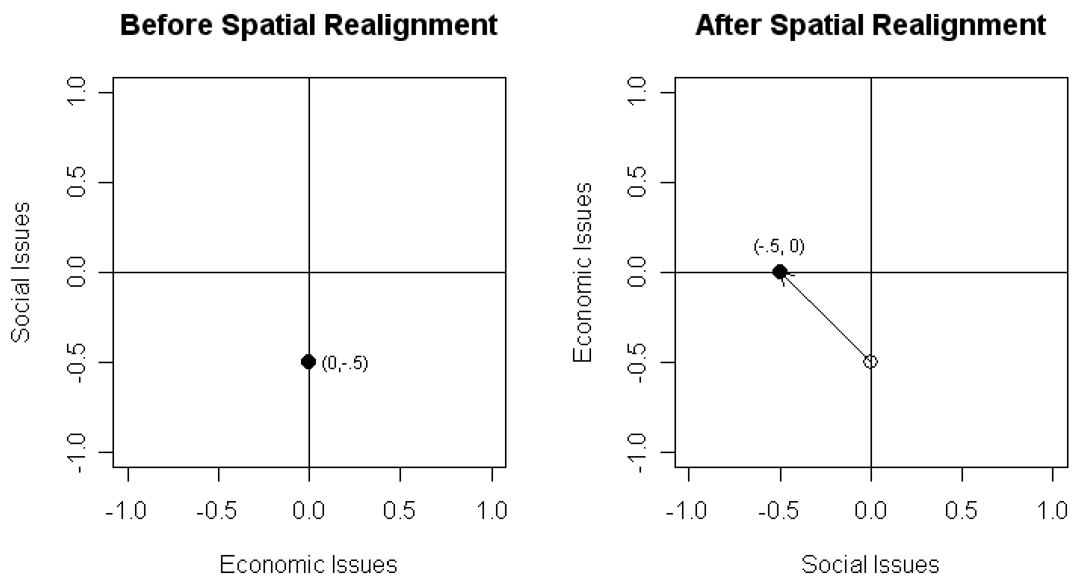


***Figure 2:*** Illustration of a legislator before and after periods of Spatial Realignment.

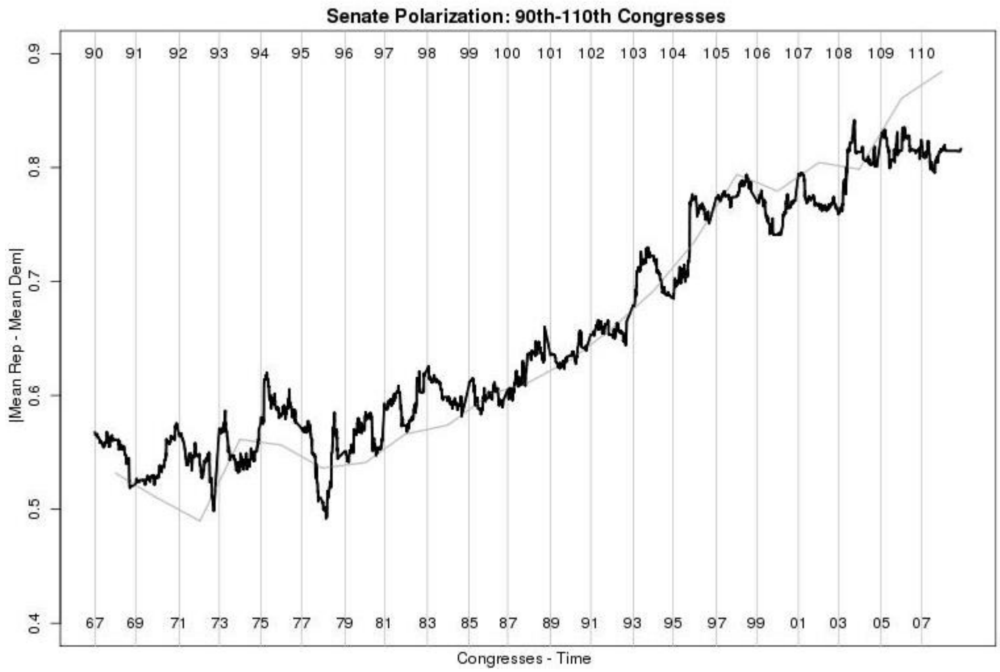


***Figure 3:*** Political polarization measured by the distance between party means. The grey line is the DW-NOMINATE MPR measure. The black line is the measure from the dynamic OC scaling.

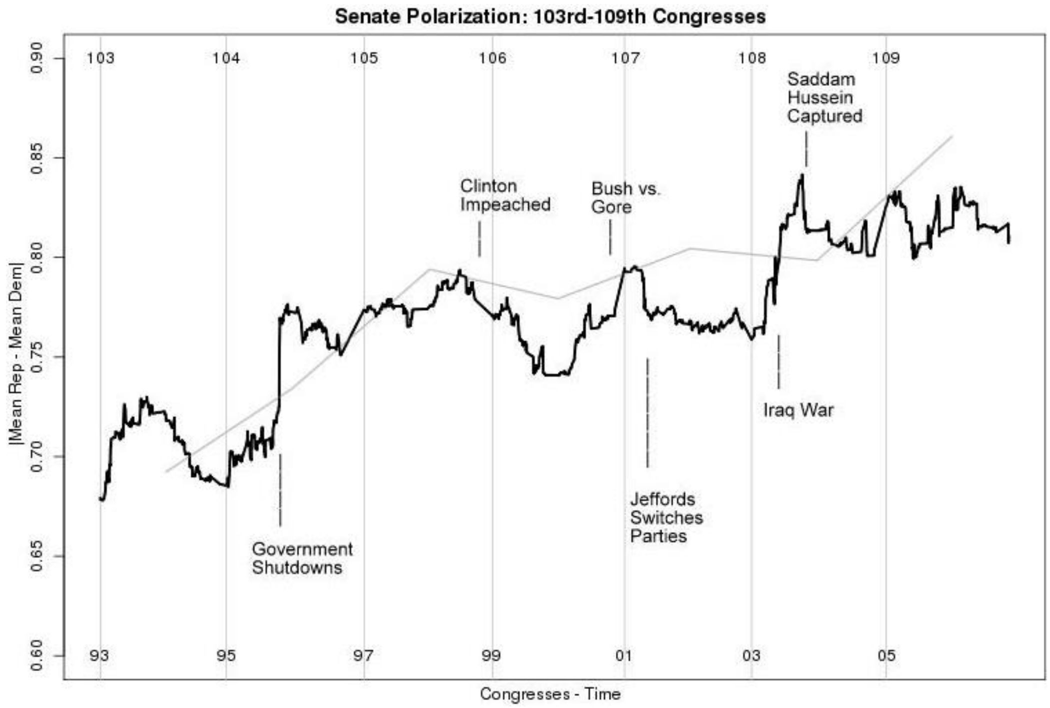


***Figure 4:*** The effects of selected events on the polarization trend for the 103rd through 109th Senates.

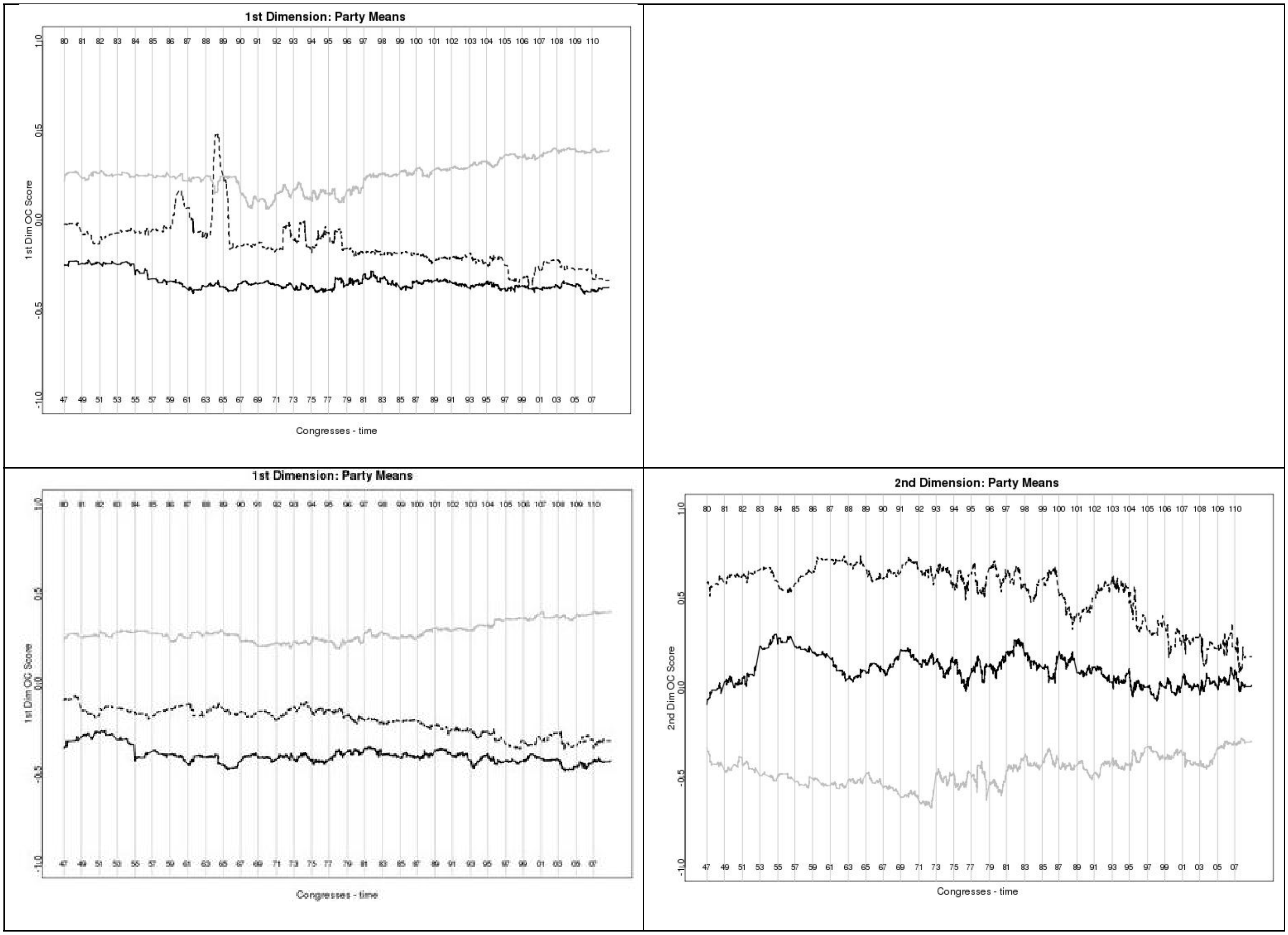


***Figure 5*****:** The first row displays party means for Republicans (gray) and Northern (black) and Southern (black dotted) Democrats from a single dimensional scaling. The second row displays party means on each dimension of a two-dimensional scaling. The rank orderings are normalized to the interval [-1.0, 1.0].

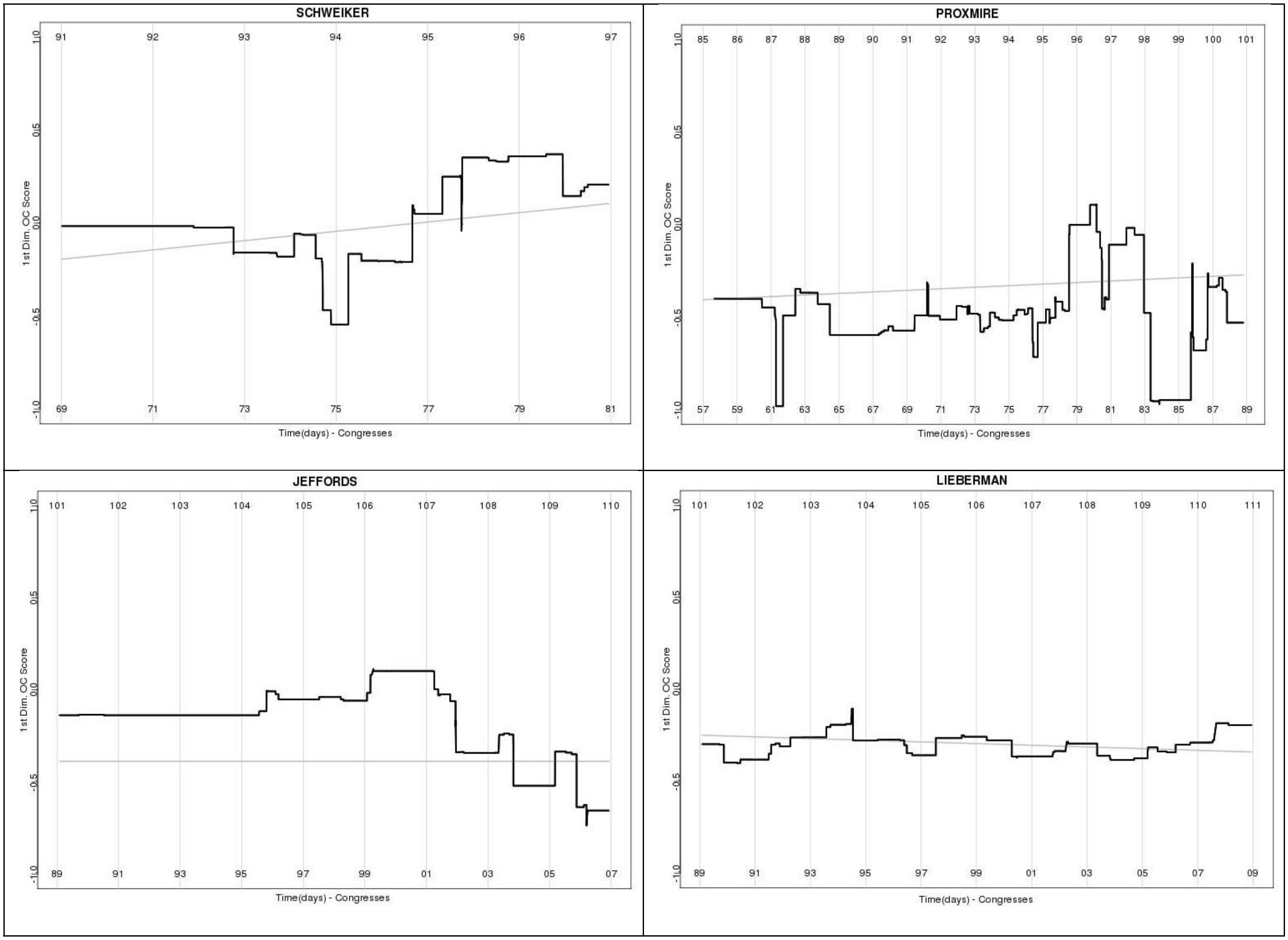


***Figure 6:*** Four legislator time trends from a scaling of the $1^{st}$-$110^{th}$ US Senates, with corresponding DW-NOMINATE trends (gray).

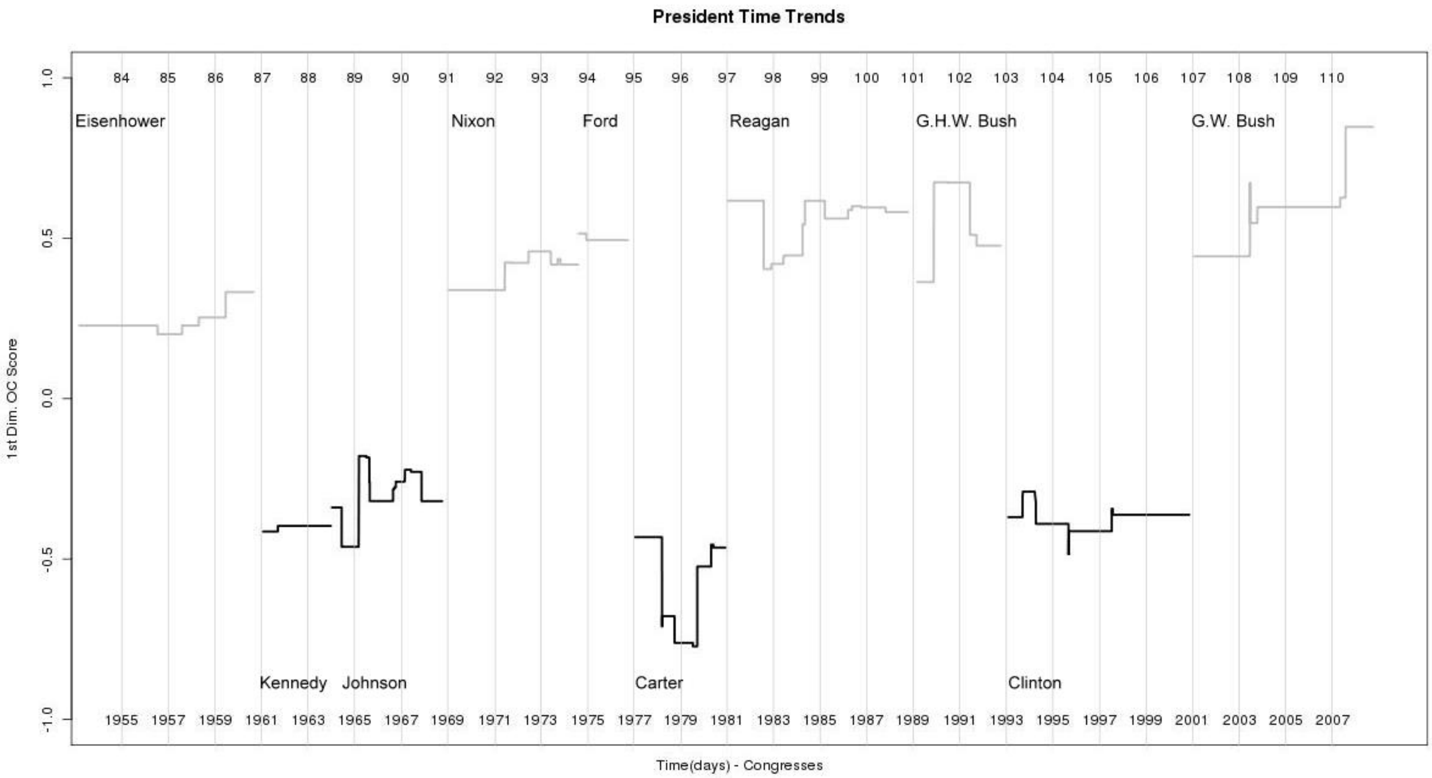


***Figure 7:*** Presidential Time trends from Eisenhower to G.W. Bush from a joint two-dimensional scaling of the $80^{th}$-$110^{th}$ US House and Senate.

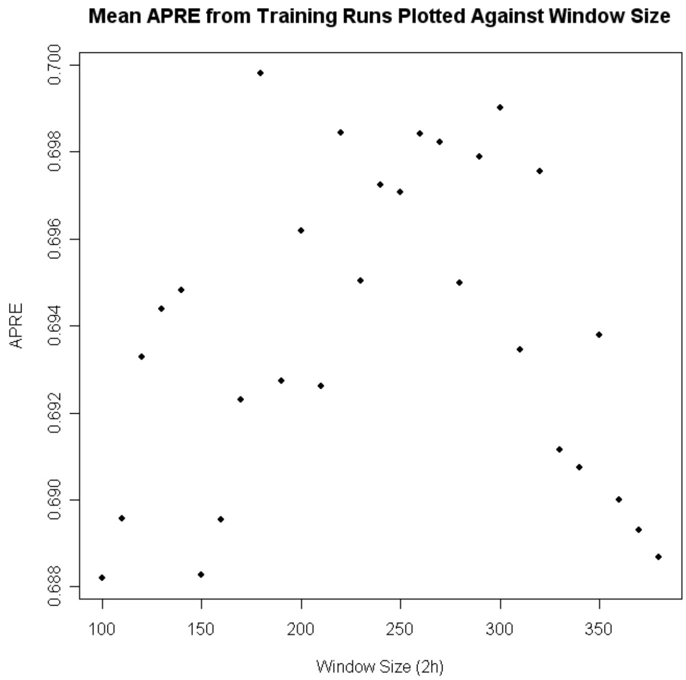


***Figure 8:*** APRE from held out votes from the training sets plotted against window size. Each point is a mean value over 10 training runs for the corresponding window width.