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The dimensionality of political space: Epistemological and methodological considerations

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Abstract
Spatial characterizations of agents' preferences lie at the heart of many theories of political competition. These give rise to explicitly dimensional interpretations. Parties define and differentiate themselves in terms of substantive policy issues, and the configuration of such issues that is required for a good description of political competition affects how we think substantively about the underlying political *space* in which parties compete. For this reason a great deal of activity in political science consists of estimating such configurations in particular real settings. We focus on three main issues in this article. First, we discuss the nature of political differences and from this construct an interpretation of the *dimensionality* of the political space needed to describe a given real setting, underscoring the essentially metaphorical and instrumental use of this concept. Second, we contrast ex ante and ex post interpretations of this dimensionality. Third, we illustrate potential hazards arising from the purely inductive estimation of political spaces using a spatial example from the physical world and political competition in the European Parliament as a political example.

Keywords
expert surveys, ideal point estimation, party competition, policy dimensions, policy positions

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Discussions of political competition inevitably use the language of space, direction and distance. It is more or less impossible to describe policy-based political competition without referring to agents' 'positions' and 'movement' on key issues. We describe such positions and movements, explicitly or implicitly, in terms of underlying conceptual spaces that may or may not 'really' exist. These spaces are spanned, explicitly or implicitly, by 'dimensions' that allow us to give substantively meaningful interpretations to position and movement. We are so accustomed to this language that it has become intrinsic to our thinking about political competition. This is not just a key part of the lexicon of professional political scientists, it is deeply ingrained in the everyday political discourse of ordinary decent civilians. Despite the ubiquitous use of spatial language to describe political competition however, the attribution of spatial characteristics to policy differences is essentially a metaphor: 'understanding and experiencing one kind of thing or experience in terms of another' (Lakoff and Johnson, 1980: 455). Notwithstanding the fact that this analogy to physical spaces has proved extraordinarily fruitful over the past half century as a way to think about party competition, policy 'spaces' remain purely conceptual and impossible to observe physically.

The most familiar political metaphor belongs to a class of pervasive metaphors that Lakoff and Johnson (1980: 461) term 'orientational'. Dating from the era of the French Revolution (Carlyle, 1871: 192), this is the well-known 'left–right' dimension, contrasting a more protectionist state with socially liberal values on the one hand with a more conservative social vision and more laissez faire economics on the other. Even this drastically oversimplified notion of a 'left–right dimension' refers to two potentially separable issues: one concerns economic policy, a second concerns state regulation of social behaviour. Indeed it is very common to need more than one dimension to describe key political differences, though we are typically much less certain about the number and substance of any additional dimensions that might be needed. Researchers who set out to 'map' policy spaces characterizing real-world political competition continually confront this uncertainty. A good example of the problems we confront when using the spatial metaphor can be seen in the relatively new phenomenon of transnational party competition in the European Union (EU).[1] The challenges are described starkly by Gabel and Hix (2002: 934):

> Scholars of EU policy-making have adopted conflicting assumptions about the dimensionality and character of the EU policy space. Since the shape of the political space – the number of dimensions, the policy content of these dimensions, and the location of actors in this space – is a central determinant of political competition and outcomes, these conflicting assumptions often lead to different conclusions about and interpretations of EU policy-making. This is a serious impediment to advancing our theoretical understanding of EU politics. A resolution of this theoretical conflict depends on assessing the relative value of the conflicting assumptions about the character of the policy space.

This motivates our main task here, which is to elaborate and review core epistemological and methodological issues that arise with any attempt to measure the dimensional structure of any given political space. We contrast two basic approaches to this problem. The first is an a priori approach whereby key dimensions are specified ex ante, in advance of measurement. The second is an ex post inductive approach in which key dimensions are estimated a posteriori as latent constructs that can be derived from some set of measurements that have already been made. With the a priori approach, the key methodological challenge is to identify and justify the number and substance of a set of dimensions specified in advance of any empirical research in which observations are to be collected. With the a posteriori approach, the challenge is just the opposite: to interpret the number and substance of latent dimensions inferred from inductive analyses of a set of observations that have already been made.[2] Whichever approach is used, the key epistemological challenge is the same. The 'spaces' of interest are ultimately metaphors and both the dimensions spanning these spaces and agents' positions on these dimensions are fundamentally unobservable. No matter how sophisticated our methodological tools, we ultimately lack the means to verify that we have 'correctly' characterized a political space and 'accurately' located the actors within it, because these are not only unobservable but also remain metaphorical, not physical, spatial objects.

In what follows, we begin by bringing parts of the methodological arsenal of modern political science to bear upon a 'real' physical space that we feel confident really does exist: the London Underground railway system. We do this to help us understand pitfalls that await us when we set out to use the same methodological arsenal to estimate metaphorical and/or conceptual political spaces. We move on to explore these same pitfalls as they arise when we try to estimate 'positions' of agents in the 'policy spaces' that are part of the bread and butter of modern political science, using the specific example of estimating the positions of party groups in the European Parliament. Before we do any of this, we dig a little deeper into what we have in mind when we talk about political 'spaces' and policy 'dimensions'.

From differences in preferences to policy dimensions

Different agents may have different preferences. Consequent perceptions of similarity and difference are naturally expressed in terms of distances. Think of three hypothetical agents, Angela, David and Nicolas. Are Angela's preferences more like David's, or Nicolas's? We can also ask, meaning the same thing, are Angela's preferences *closer* to those of Nicolas than to David's? In doing this, we describe Angela's perceptions of similarities and differences in terms of distances. We can aggregate perceived similarities and differences in the preferences of agents who interest us and organize these into a matrix of inter-agent distances. It is this matrix that underlies any 'spatial' representation of agents' preferences.

The notion of being able to perceive political dissimilarity and then describe this in terms of closeness and distance is more primitive than any discussion of spaces and dimensions. The standard utility function underlying most policy-based choice models in political science, for instance, involves aggregating Euclidean distances between alternatives but does not actually require *dimensional* representations of these (Adams et al., 2005; Austen-Smith and Banks, 2000, 2005; Schofield, 2008). Given such a matrix of distances and a desire to make substantive sense of these, it is a straightforward matter to go one step further and *scale* the distances, going on to describe agents' positions in terms of some underlying conceptual space (Gärdenfors, 2000). As a methodological matter, furthermore, the estimation of the underlying distance matrix may be based on some aggregation of agents' scores on particular substantively meaningful scales, for example survey responses to batteries of attitude questions. Meaningful substantive interpretation of the matrix of inter-agent distances, or of the conceptual space that can be derived from this, requires us to talk in terms of substantive 'dimensions' that span the space.

Similarities and differences in the preferences of agents on a domain of matters such as legalizing abortion, marijuana or same-sex marriage, for example, can be described and analysed in terms of a 'liberal–conservative' dimension that concerns the appropriate degree of public regulation of private social behaviour. This dimension, furthermore, may have little or nothing to do with other matters that interest people, such as whether to regulate carbon emissions or join a single European currency. Just as the north–south and east–west dimensions allow us to interpret relative positions of points in a geographical space, we use substantive policy dimensions to interpret systematic patterns in the policy preferences of political agents who interest us.

When considering which particular substantive dimensions we might use to do this, we have natural recourse to a set of concepts that are part of the established terms of political discourse – which we use when we talk to each other about similarities and differences in people's political preferences. Engaged citizens who know nothing at all about political science, and care even less, talk to each other in a meaningful way about candidate X being more liberal, or conservative, than candidate Y. They expect to understand each other when they communicate using these terms and, as part of this mutual understanding, they feel able to draw inferences about the relative positions of candidates X and Y on matters such as legalizing abortion, marijuana or same-sex marriage. One simple interpretation of the 'dimensionality' of a political space, therefore, concerns *how many* substantively relevant dimensions we need in order to say what we want to say about similarities and differences between agents who interest us. This is easy to say but hard to do, for two main reasons. First, we have no objective *empirical* criterion for what is 'substantively relevant' given the problem at hand. Second, there are many different, and potentially contradictory, ways to determine 'how many' dimensions are enough for any given purpose, and this notion of sufficiency may not only change over time but also be part of the continuing task of political redefinition (De Vries and Hobolt, 2012).

Thinking about what is and is not substantively relevant to the problem at hand, much of our work has already been done by generations of people who have talked about politics before us, using their own informal models of politics to specify what is substantively important and what is not. Ultimately, this is an inductive process since political discourse is rather like a giant feral factor analysis. The concepts that emerge – liberal versus conservative, left versus right – emerge because people over the years have found them simple and effective ways to communicate their perceptions of similarity and difference. Although in a strict sense these conceptual dimensions are not defined a priori for a state of nature, we may for all practical purposes take them as primitives that can be meaningfully used in our descriptions and analyses of politics in the place and time in which we live. The important point is that this exercise is conducted ex ante, before we engage in a particular piece of research. In this sense, these a priori dimensions of political similarity and difference form the building blocks of our research.

The second significant complication concerns the level of generality at which we specify dimensions of political difference. This in turn affects our answer to the question of 'how many' dimensions of difference are relevant. The issues that confront us arise because: (a) other things equal we prefer parsimonious descriptions of the world to complicated ones; (b) there are, *in theory*, very many potential dimensions of difference between agents that might be politically relevant; (c) *in practice*, bundles of these dimensions are 'correlated', in the sense that agents' positions on one dimension in some bundle can be reliably predicted from their positions on some other dimension in the same bundle. Thus, when talking above about a liberal–conservative dimension, we described this substantively in terms of a 'domain of matters such as legalizing abortion, marijuana or same-sex marriage'. Linguistically, this was a quick and effective way for us to use examples to show you what we have in mind when we talk about a liberal–conservative dimension. Conceptually, this trick works because of a general consensus that preferences on these three distinct matters are, *empirically*, closely correlated in the real word. Knowing someone's views on legalizing abortion and marijuana makes it easier to predict their views on same-sex marriage. In principle it need not, although in practice it usually does.

More generally, knowing an agent's views on issues A, B and C often allows us to make a good prediction of her unknown views on issue D. This allows us to treat observed preferences on some bundle of issues A, B and C *as if* these were correlates of some unobserved latent dimension, L (Converse, 1964). This is exactly what we did when we described agents' observed views on abortion, marijuana and same-sex marriage as if they all were related to an – unobserved – latent liberal–conservative dimension. We leave moot the question of whether the latent dimension 'really' exists, whatever *that* means. We use it *as if* it exists, as a device that helps us describe and analyse political competition. We are simplifying our description of the world in this case by using one general dimension of difference (liberal–conservative) to represent three more specific ones (abortion, marijuana and same-sex marriage). There is no 'right' answer to the question of which of these alternative representations is better but, because we always prefer parsimony, we prefer the lower dimensional representation if this does not destroy too much information about the preferences of the set of agents who interest us.

To summarize our argument so far, there are many potential dimensions of political difference between any set of agents in which we might be interested. If we want to talk about these dimensions, we rely upon a tried and tested conceptual language that has evolved over generations, a set of conceptual dimensions that, as a matter of empirical practice, enables meaningful political discourse. Looking forward to the design of any given future research project, we can take these dimensions as de facto primitives. Although there may be very many dimensions of difference between agents, in practice we observe that agents' preferences on bundles of these tend to be highly correlated. This allows us to summarize preferences in each bundle as if these were related to some underlying latent dimension, in turn allowing us to generate more parsimonious descriptions and analyses of political competition. All of this casts the question of dimensionality in relatively simple terms. How many latent dimensions of political difference do we need to describe and analyse the political problem at hand without destroying 'too much' information?

Not surprisingly, this question is much easier to ask than to answer. This is because the appropriate 'dimensionality' of some political space depends on the political problem at hand. There is no general 'dimensionality' that is applicable to any conceivable question regardless of context, but rather a range of possibilities that depend on which question we seek to answer. We illustrate this point with an example from the physical world, in which we may at least feel we are on solid ground.

Descriptive representations of (physical) spaces

If we 'know' the metric of distance and have firm beliefs about the dimensionality of the spaces we are dealing with, then representing locations within this space is much more simple. Because metrics and distances are really only knowable in the physical world, we use an example of physical mapping as a source of insight into our ability to estimate and interpret spatial dimensions. As we will see, however, how we approach this apparently simple problem of mapping well-understood geographical locations, even in relation to something as apparently fundamental as how many dimensions we should use, is determined entirely by the purpose of the map.

Physical descriptions using one dimension

The way in which a given map reduces a wealth of potentially extraneous and confusing detail into a usable simple representation depends critically on the purpose for which the map is needed. Nowhere is this more apparent than for maps of transport systems. Many will be familiar with the iconic map of the London

Underground (the 'Tube') the current design of which was first published in 1933 and can be traced to the engineering draughtsman Harry Beck. Simplifying the complex London Underground in the manner of an electrical wiring diagram, Beck's new map sacrificed geographical accuracy in exchange for dramatically enhanced passenger usability. It showed relations between Tube stations and interchanges between Tube lines very clearly. It was immediately seized on by the public as a much more useful tool for planning journeys on the London Underground railway system than the previous geographically accurate map. This was despite the fact that it was little better than useless, and sometimes positively misleading, when navigating between Tube stations at street level. Many other underground railway systems around the world subsequently copied this innovation. Thinking of the unprecedented success of the London Tube map as feral research project, we conclude that, despite its striking *geographic* inaccuracies, it is an excellent *conceptual* map of the London Underground railway system.

The top panel of Figure 1 shows a *two*-dimensional geographically accurate plot of the locations of Central Line stations on the London Underground (ignoring elevation and two small branch lines). This shows the configuration of stations to be a somewhat rotated U-shape. Harry Beck's key psychological insight was that two dimensions are *unnecessary* to map the Central Line in a way that is useful for Tube travellers, who need only the representation shown in the bottom panel of Figure 1. If the stations are ranked from west to east and plotted as a straight line, no information *relevant to Tube travellers* is lost. In this particular case, the north–south axis, although conveying perfectly accurate information about station locations, is a distraction that conveys no information for Tube travellers not already

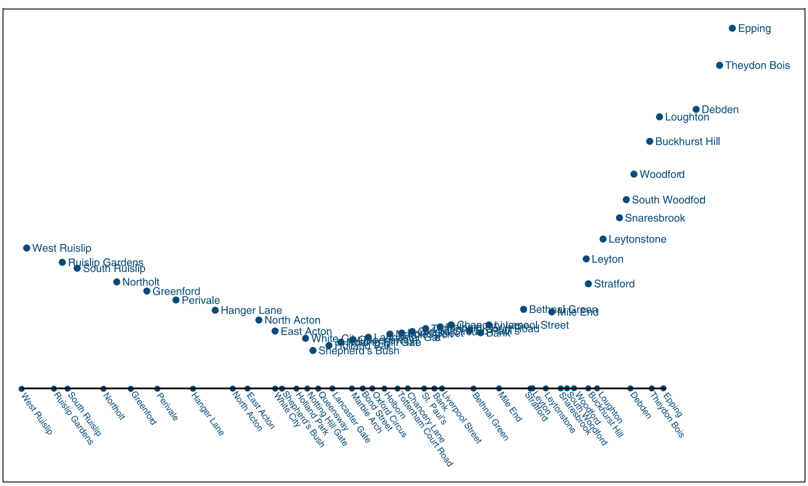

Figure 1. Location of Central Line stations on the London Underground.
Note: The top panel shows a two-dimensional geographically accurate plot; the bottom panel shows a one-dimensional plot consistent with Beck's stylized Tube map.

represented in the east–west axis. The physical locations are 'two-dimensional' in terms of their coordinates in physical space but, for transit from one point to the other using the underground railway system, the most useful representation has only one dimension. Just as it is for the one-dimensional denizens of 'Lineland' in Edwin Abbott's novel *Flatland* (1992), the addition of a second dimension is irrelevant because travel can occur only between adjacent stations along the line, even if this is curved in a two-dimensional graphical space. A crow seeking the shortest route between the surfaces of the Epping and West Ruislip stations, however, would be seriously misled by the one-dimensional map. Likewise, a voracious earthworm trying to tunnel from Epping to Holborn, the latter a particularly deep station, also needs to know elevations from sea level – a third dimension we typically ignore when we simply ride the Tube.

Physical descriptions in two dimensions

Although a one-dimensional representation serves Central Line passengers very well, we need look no further than the Circle Line to find an otherwise equivalent example where a one-dimensional representation would serve passengers very poorly. The top panel of Figure 2 is a geographically accurate representation of Circle Line stations in two dimensions (excluding the recently opened Hammersmith branch). This shows that the Circle Line is very far from being a circle, but that is it is, topographically, a loop – a very important piece of information for London Tube travellers to know. In stark contrast to the Central Line, if we plot Circle Line stations on a single dimension the results are extraordinarily misleading. The bottom panel of Figure 2 shows one such plot, plotting locations of Circle Line stations on the east–west dimension. This shows St James's Park and Euston Square stations as being both adjacent to each other and very close

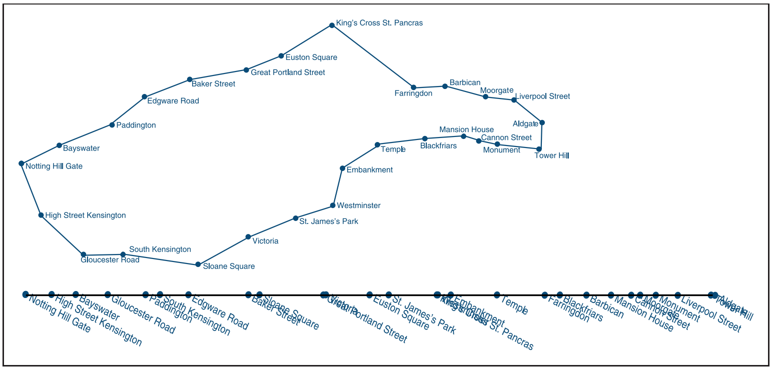

Figure 2. Location of Circle Line stations on the London Underground.
Note: Two-dimensional (top panel) and one-dimensional (bottom panel) geographically accurate plots.

together, for example, but any Tube passenger who acted on this basis would be in for a very nasty shock. These two stations are about as far apart *on the Circle Line* as it is possible to be. Without labouring the point, the 'best' map of any underlying reality, and the best dimensionality for this map, depends sharply on what the map is for.

Inductive representations of dimensionality

The issues raised in the previous section concern a setting for which we have perfectly accurate observations of positions on the basis vectors (east–west and north–south in this case) in which we are interested. Typically in the social sciences, however, the basis vectors that concern us are latent dimensions that are fundamentally unobservable even if, as we have seen, we may well approach these with reasonably solid priors about their possible number and content. The best we can do is to try to estimate agents' positions on these latent dimensions using their positions on observable components of these. Although we cannot directly estimate agents' positions on a latent liberal–conservative dimension, for example, we can indirectly do this by collecting information on more explicit dimensions such as legalization of abortion, marijuana and same-sex marriage and using this information to estimate positions on the latent dimension that interests us. This is essentially an exercise in scaling, and it is at this point that the distinction between a priori and inductive approaches becomes critical.

Estimating positions on a priori scales

Returning to the London Tube map, imagine we are interested in the geographical locations of the stations and have firm priors that a two-dimensional map, with east–west and north–south dimensions as basis vectors, is the best way to describe these.[3] The 'dimensionality' of the station space, and the substantive meaning of the dimensions, would not be left as a matter for empirical investigation but would be assumed a priori. Imagine furthermore that for some reason we cannot observe the positions of Tube stations on these dimensions directly, but have access only to noisy indicators of these. Finally, imagine that we have good a priori reasons to believe that some of these noisy indicators are associated with the east–west dimension and some with the north–south dimension. We are now in essence confronted with the problem of developing good unidimensional scales of east–west and north–south. A standard approach is to construct additive scales of these latent variables using our noisy indicators.

We simulate this problem by taking the true coordinates of the Circle Line stations, plotted in the top panel of Figure 2, and creating 10 unbiased noisy indicators for each of the east–west ('easting') and the north–south ('northing') dimensions. We do this for each indicator by adding a random disturbance term to the true value, drawn from a normal distribution with a mean of 0 and a standard deviation equal to the range of observations for the 'true' variable in question.

Table 1. Diagnostics of additive east–east and north–south scales built from noisy indicator variables

Noisy indicator of easting	Cronbach's alpha for easting indicators	Noisy indicator of northing	Cronbach's alpha for northing indicators
East0	0.904	North0	0.912
East1	0.897	North1	0.908
East2	0.904	North2	0.902
East3	0.899	North3	0.895
East4	0.905	North4	0.898
East5	0.896	North5	0.912
East6	0.899	North6	0.895
East7	0.910	North7	0.895
East8	0.900	North8	0.901
East9	0.898	North9	0.910
East scale Cronbach's alpha	0.910	North scale Cronbach's alpha	0.912
East scale correlation with 'real' easting	0.966	North scale correlation with 'real' northing	0.959

We then construct additive scales of east–west and north–south by averaging values from their 10 noisy indicator variables. Scale diagnostics arising from doing this, summarized in Table 1, would leave most social science researchers ecstatic, with Cronbach's alphas of 0.91 for each scale. The alpha values for individual noisy components, furthermore, are always less than or equal to the overall scale alpha, showing that scale reliability would not be improved by dropping any individual component. This is because the noise for each indicator, although substantial, is well behaved, so that additive scaling functions exactly as it should. The bottom row of the table shows that the correlations of the additive scales with the 'real' latent variable, which would be unknowable in any real application, are 0.97 and 0.96, showing that this would have been a superbly effective exercise in a priori unidimensional scaling. This success has been achieved by leveraging our prior knowledge that there are two dimensions, that the latent variables are east–west and north–south and that the respective sets of noisy indicator variables do indeed relate to these in some way. This is extremely similar to the type of prior knowledge we usually bring to analogous scaling problems in the social sciences.

The fruits of this scaling exercise are plotted in Figure 3. The top panel plots a single noisy indicator of east–west against a single noisy indicator of north–south. The results are horrible and very far from the 'true' picture. The Circle Line is

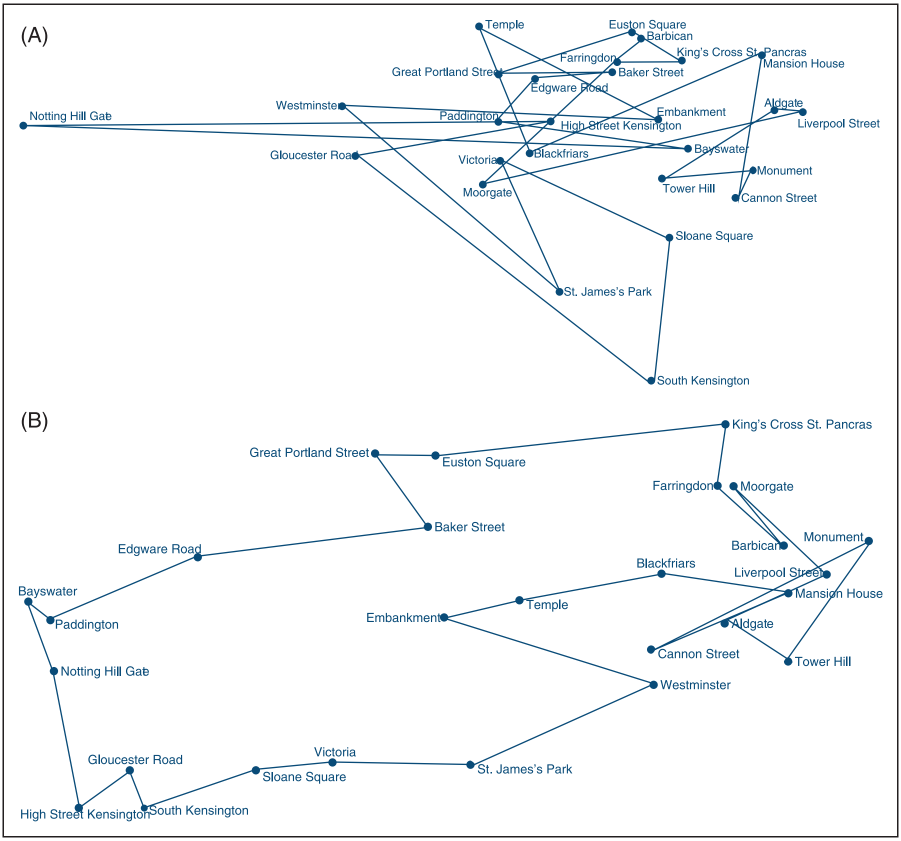

Figure 3. Plots of east3 vs. north3 (top panel) and east scale vs. north scale (bottom panel).

completely scrambled, though we would have had no way of knowing this if we had access to just a single noisy indicator for each latent variable.[4] The bottom panel of Figure 5 plots the two additive scales against each other and, comparing this with Figure 2, we see something that looks much more like the 'true' Tube map. It has detailed inaccuracies arising from the noisy data, especially at the east end of the line where Figure 2 shows that stations are in fact very close together, but at least stations that should be on the west are on the west, those that should be on the east are on the east, and so on. In this sense, the a priori scaling exercise has been a success.

Inductively estimating dimensionality and scale positions

Now consider the situation that would arise if we made no a priori assumption about the number and substantive nature of the latent dimensions spanning the space we wish to plot. The research task is now to use purely inductive methods to estimate both the dimensionality of the space and the substance of the latent dimensions spanning this. This is exactly what most of the 'mapping the policy space' research designs in political science in fact try to do. They take a series of noisy indicators and either use these to scale the locations of agents inductively or, alternatively, use data reduction methods to determine the number and content of the 'latent dimensions' producing the indicators, as do Bakker et al. (2012) for instance.[5] Continuing with our London Tube example, we can simulate inductive estimation by attempting to scale the two-dimensional representation from our noisy geographical variables (those in the first five rows of Table 1). Since in political applications we do not usually know exactly what the indicators should be – and are conditioned to think generally that more information is superior to less – we also supplement the noisy geographical variables with data on five other characteristics of the Circle Line stations, all related in some way to geography. The new variables concern: the date the station opened (*dateopen*); the number of passengers who used the station in 2008 (*npass2008*); the number of platforms in the station (*nplatforms*); the fare charging zone (*farezone*); and, for the London borough in which the station is located, the percentage of the population classified by the census as having Irish origins (*pctirish*). Since we now have no a priori idea about the number or substantive content of the latent dimensions of the space we want to estimate, we have no a priori idea whether these five new indicator variables, or indeed any indicator variable in our set, might be helpful in producing this map. A commonly used way forward would be to identify latent dimensions using a technique such as factor analysis. Referring back to our description of latent dimensions in terms of bundles of particular salient policy issues on which agents' preferences are inter-correlated, we can specify the research task as seeking to identify these bundles in a given empirical setting, leaving the number and content of the bundles as open questions.

The first task is to estimate the *number* of inter-correlated bundles in a given set of indicator variables that we take to describe the setting we wish to model. We can do this by estimating the number of orthogonal principal components satisfying some criterion, and this number can be interpreted as the 'dimensionality' of this setting. A common method is to use a technique such as factor analysis to generate a 'scree' plot of the eigenvalues of the common factors extracted from a set of indicator variables, plotting factor eigenvalues in descending order of variance explained. This downward-sloping plot may exhibit an 'elbow' as the eigenvalues suddenly level off, implying that adding another latent dimension does not substantially increase the amount of explained variance in the set of indicator variables. This elbow can be used to infer inductively that the 'best' low-dimensional representation of the set of indicator variables is d-dimensional, in the sense that using $d + 1$ dimensions does not capture significantly more of the variance in the original high-dimensional space. An alternative inductive approach is to retain latent dimensions for which eigenvalues are greater than unity. Crudely speaking, these are dimensions that contain more information than a typical dimension in the original high-dimensional space. These two techniques can generate very different

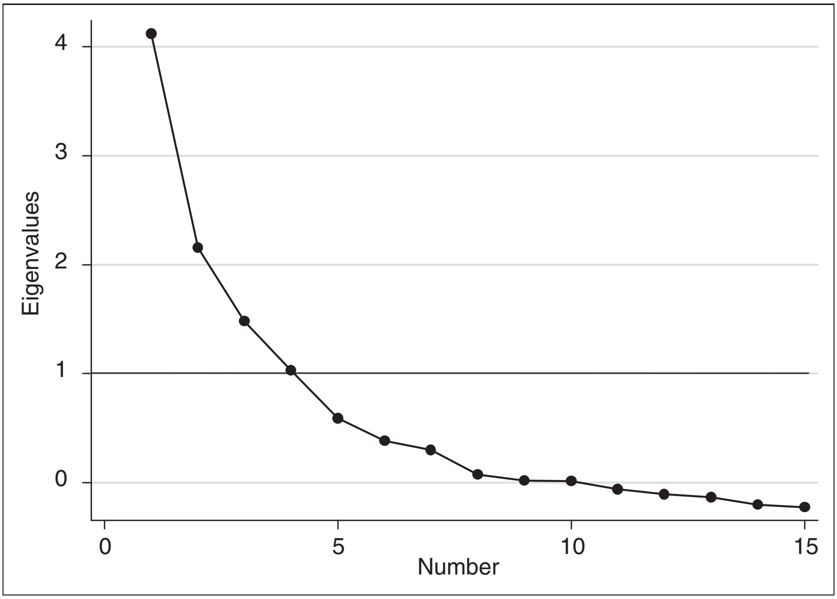

Figure 4. Scree plot of eigenvalues arising from factor analysis of noise data on London Tube station locations.

'empirical' estimates of dimensionality, especially when the original data space is high-dimensional, in which case there may be many more latent dimensions with eigenvalues greater than unity than the number of dimensions indicated by the scree plot.

Figure 4 shows a scree plot of a factor analysis of the 15 variables dealing with Central Line Tube stations and shows that this is inconclusive. There is possibly an elbow after the first dimension, which would suggest a one-dimensional representation, but the plot has a smooth slope after this, at least until five dimensions are reached. On this account, the space of Central Line Tube stations is either one- or five-dimensional. In contrast, the horizontal line in Figure 4 shows that the alternative test, keeping factors with eigenvalues greater than unity, implies four dimensions. No inductive method suggests the two dimensions of the 'real' Tube map we are trying to retrieve. A purely inductive approach does not help us determine the *dimensionality* of the space we want to plot in this case, at least not the sense that dimensionality can be inferred inductively from our data reduction analysis.

This is, of course, an extreme type of situation, implying that we have no prior expectation whatsoever about the number and substance of any latent dimensions that might be relevant. As we can see, this leaves us in an almost impossible situation, and there is no inductive magic bullet that gets us out of this. If, however, we do have prior information over and above the data set we have collected, then we are on firmer ground. Imagine in this case that our prior belief, based on observing real humans successfully navigating the Tube using two-dimensional maps, was

Table 2. Rotated principal components factor loadings for observations of Central Line Tube stations

Input	Factor1	Factor2
east0	**0.86**	0.20
east1	**0.62**	−0.02
east2	**0.56**	−0.09
east3	**0.67**	0.18
east4	**0.78**	0.19
north0	0.40	**0.62**
north1	0.16	**0.59**
north2	0.38	**0.53**
north3	−0.09	**0.68**
north4	0.22	**0.65**
dateopen	0.50	−0.38
npass2008	0.41	−0.29
pctirish	0.22	**0.53**
nplatforms	0.25	−0.27
farezone	−0.50	−0.15

that the space we want to plot is two-dimensional. Table 2 reports rotated factor loadings for a two-factor analysis of the 15 variables measuring aspects of Central Line Tube stations. Using a priori information that the solution we seek is two-dimensional, and following the convention in principal components analysis of using variables with factor loadings over 0.5 to interpret the inductively derived latent variables a posteriori, we see that the first factor identifies a bundle comprising all the east–west variables, and a second factor identifies a bundle comprising all the north–south variables. The only non-geographical variable loading over 0.5 is the percentage of Irish in the borough, as it happens reflecting a demographic pattern that London Irish tend to live in north London. Notwithstanding this empirical reality, attempting to interpret Table 2 by spinning some yarn about how ‘percent Irish’ is a substantively meaningful component of geographical north–south leads us down tortured paths that will be painfully familiar to all who have been involved in the vigorous hand-waving often associated with post hoc interpretations of inductively derived ‘policy’ dimensions.

Just as different combinations of policy locations will yield different results for measurements of the ‘dimensionality’ of policy spaces, our representation of physical spaces as the two principal components from a set of indicator variables is heavily influenced by the choice of indicator variables. Unlike most forms of data analysis where more information always gets us closer to the ‘truth’, in dimensional analysis, where our objective is to ‘map’ unknown policy ‘spaces’, our answers will

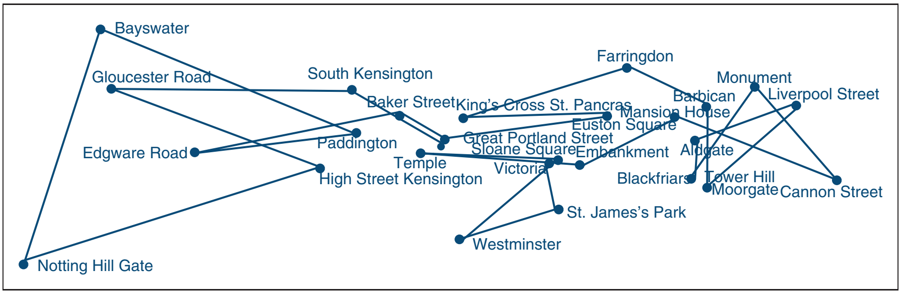

Figure 5. Two-dimensional MDS plot of Circle Line stations.

depend *entirely* on the questions we ask. This point was first explored by Weisberg (1974) but appears to have been largely ignored by most subsequent researchers.

Armed with results from factor analyses such as those reported in Table 2 and an a priori assumption about the dimensionality of the space described by a set of indicator variables, we can identify the substance of the latent dimensions inductively. We could then construct additive scales to measure agents' positions on these dimensions that combine the indicator variables identified in the factor analysis. Though in this case we would unwittingly do something a bit odd by including the London Irish, we would not go too far wrong and this scaling exercise is essentially the same as the one we report in Table 1. Leveraging our prior knowledge has got us a long way.

An alternative approach is to use classical multi-dimensional scaling (MDS) to scale an inter-station distance matrix generated by the 15 indicator variables listed in Table 2. Once more in this case, however, this does not help us with an inductive estimate of dimensionality. Percentages of variance explained by different dimensions are as follows: 56, 12, 9, 7, 5, 3, 2... Forced to make a purely inductive estimate of dimensionality, we would infer that the space is one-dimensional. If we had good a priori information that the space was indeed two-dimensional, we could use MDS to construct a two-dimensional plot based on all 15 indicator variables. This is shown in Figure 5 and does give a small amount of information about which stations are east and which are west, but we would have no way inductively to know that this was the good information and that the rest of the plot, frankly, bears little relation to the underlying 'reality' it purports to represent.[6] In effect, we would be terribly misled about the Circle Line by this plot if we thought that its two dimensions represented something meaningful in relation to physical geography.

The bottom line is that we have no good way to plot the Circle Line Tube stations from a set of noisy and potentially irrelevant data unless we have some a priori estimate of dimensionality. If we do, however, have an independent estimate of the 'right' number of dimensions, then we can use techniques of dimensional analysis such as factor analysis to identify bundles of inter-correlated variables that both help us interpret the substance of these dimensions and form the component parts of scales we can use to measure position on these.

Mapping the European policy space

In contrast to well-understood maps of the London Underground railway system, we do not have established priors about the dimensional structure of maps of the typical policy spaces in which political competition is assumed to take place. To illustrate the effects of this, we turn to a familiar political example: the much-debated nature of party competition in the EU. Our focus is specifically on dimensions of competition at the transnational level, represented by divisions between the party groupings in the European Parliament (EP). Our data come from expert surveys of the positions of these groupings, conducted by McElroy and Benoit (2007, 2012) in relation to eight unique dimensions of policy.[7] These groupings, along with their abbreviations and seat shares, are listed in Table 3.

The debate on the nature of party competition in the EU – referenced by Gabel and Hix (2004) at the beginning of this paper – has occupied a great deal of attention in EU studies. The EP policy space has previously been described as one-dimensional, with the substance of the principal axis of competition being either the traditional left–right or 'regulation' dimension (Kreppel and Tsebelis, 1999; Tsebelis and Garrett, 2000) or geo-political pressures (Hoffman, 1966; Moravcsik, 1998). Other scholars, however, have described the European policy space as being spanned by two dimensions: a left–right dimension that bundles economic and sociopolitical issues from the domestic arena; and an orthogonal dimension contrasting the desires for EU integration and national sovereignty

Table 3. Political party groups in the European Parliament in 2010

EP party group	Abbreviation	Percent of seats	No. of seats
European People's Party	EPP	36.0	265
Party of the European Socialists/Socialists and Democrats	PES/S&D	24.9	183
Alliance of Liberals and Democrats for Europe	ALDE	11.6	85
European United Left/Nordic Green Left	GUE/NGL	4.8	35
Greens/European Free Alliance	Verts/EFA	7.5	55
Europe of Freedom and Democracy	EFD	4.1	30
European Conservative and Reformist Group	ECR	7.3	54
Non-affiliated	NI	3.8	28
Total		100.0	735

Source: European Parliament official website.

(Hix and Lord, 1997; Veen, 2011). As far as the transnational EU party policy space is concerned, therefore, there are several open questions: How many dimensions characterize party competition in the EU? What is the content of these dimensions and how are these related? Where should we locate European party policy positions within the resulting 'spaces'?

Expert surveys typify the a priori approach because the scales on which experts are asked to locate political parties must first be clearly specified, in a way that experts find meaningful and relevant for locating political parties. This a priori specification traditionally follows an initial consultation of experts in the setting under investigation concerning which dimensions best describe the essence of political competition. In the case of the EP, for example, the first expert survey by McElroy and Benoit (2007) did not include the dimension of decentralization/subsidiarity, but this was included in later surveys because it was judged ex ante to be relevant. Although this a priori approach is most explicit in the case of expert surveys, it features to some extent in every research design that uses substantive indicators to measure distances between political agents – whether these indicators are coding categories for content analysis or survey items used to measure respondents' attitudes.

We start with the ubiquitous left–right dimension. Figure 6 plots expert survey estimates of the positions of the main EP party groups on the two main dimensions of difference identified by Benoit and Laver (2006) as a meaningful way to compare most political contexts: an 'economic' dimension concerning preferences on taxes and public spending; and a second dimension contrasting liberal with conservative social and moral attitudes. The configuration of party positions in this plot is almost 'one-dimensional' in the sense that, of all the party groups, only the liberal ALDE lies in an off-diagonal position. The OLS regression line of best fit shown in the plot clearly indicates that (with one important exception) we can more or less predict the position on one dimension from the position on the other.

If we consider these two dimensions to be manifestations of the same underlying dimension – call it 'left–right' – then we can compare these directly with other possible ways to measure left–right as a single dimension. What we find from this exercise is that the ordering and placement of party groups on this dimension varies according to the method used. Figure 7 contrasts three one-dimensional 'left–right' scales derived in different ways. The top set of party group locations is derived from a unidimensional scaling of the economic and social positions shown in Figure 6. The middle scale plots the mean of the direct placements by the experts of party groups on the left–right scale.[8] The bottom scale is derived from the scores of each party group on the first factor of a factor analysis of all expert placements on all policy dimensions except overall left–right policy (reported in Table 3).

Figure 7 shows that these placements are inconsistent. We would have a very different picture of the far-right and anti-EU party group Europe of Freedom and Democracy (EFD) depending on whether we used the unidimensional scale derived from economic and social placements, the direct left–right placements or the factor

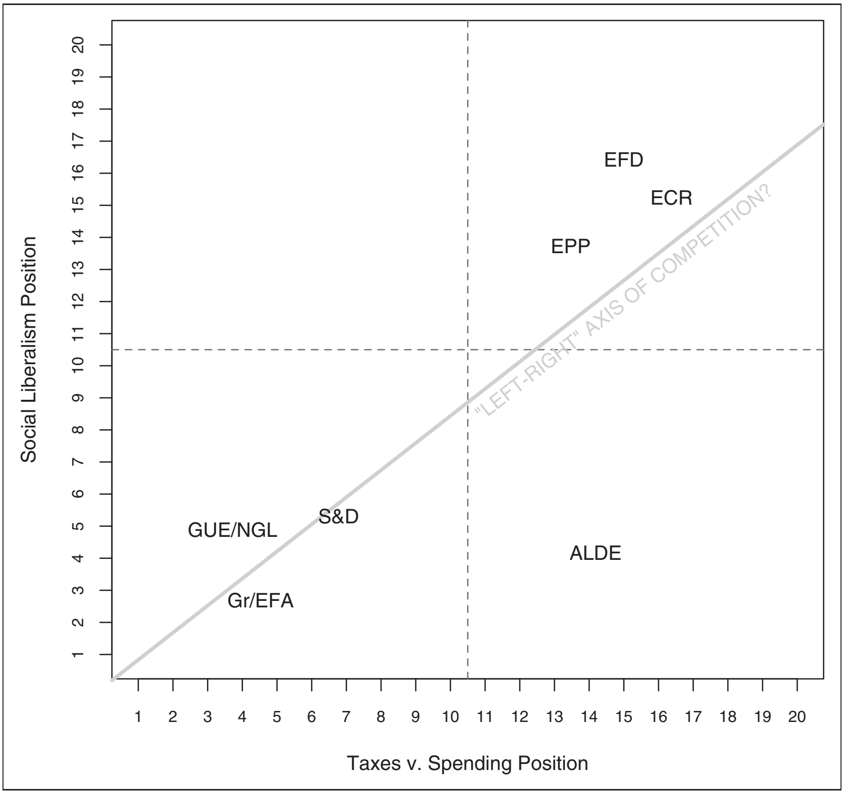

Figure 6. Descriptive mapping of the economic vs. social positions of the European party groups, 2010.

analytic scoring. The first scale fails to distinguish the more extreme anti-EU views of the EFD from those of the European Conservative and Reformist Group (ECR), while the third scale 'wrongly' places the EFD in the middle of the 'left–right' spectrum. Of course, we are only supposing – following Gabel and Huber and host of others who have tried to interpret plots from roll-call vote analysis (for example Hix et al., 2006) – that the first principal component can be interpreted as a conventional 'left–right' dimension.[9] These same roll-call analyses, however, suggest that distances between parties in the EP require more than one dimension for an adequate spatial representation.

One substantive interpretation of a potential second dimension arises from 'bipolar Euro-skepticism' (Marks et al., 2006: 162), which manifests in a non-linear relationship between left–right positioning and support for further EU integration. Simply put, the EU is a project of mainstream and relatively centrist parties, whereas parties opposing European integration tend to be on the extremes of the classical left–right scale (see also Hix and Lord, 1997; Marks et al., 2002). This gives rise to an inverted U-shaped configuration of party positions, plotting

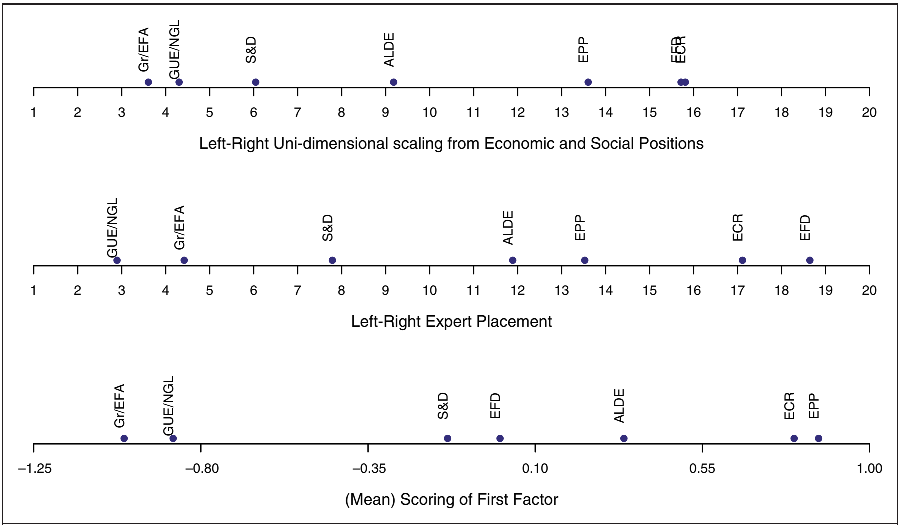

Figure 7. Three unidimensional scale positions of 'left–right'.

general left–right positions against support for EU integration. This pattern is shown in Figure 8, which plots expert survey estimates of party positions on a general left–right scale against their positions on expanding or reducing the scope of EU authority.

Figure 8 plots two dimensions that we assume a priori to be important in EU politics, and the results gives us a strong sense that we need more than a one-dimensional map of EU party positions. In an attempt to estimate this dimensionality inductively we could take estimated party positions on a wide range of issues and use a data reduction tool such as principal components factor analysis to estimate how many, and which, latent dimensions are needed for an effective low-dimensional representation of the data. Table 4, which is analogous to Table 2, reports a PCA factor analysis with varimax rotated loadings from our analysis of all specific dimensional placements, except those from the overall left–right dimension. Based on conventional interpretations, this is a 'two-factor' solution explaining two-thirds of the variation in placements – a result that would please most analysts. We also see that the first factor seems to consist of domestic policy issues while the second dimension consists mainly of transnational issues: the scope of EU authority, collective security, issues of national sovereignty surrounding the creation of more federal EU institutions, and the related issue of subsidiarity and the decentralization of decision-making. It would be quite reasonable, given these results, to interpret the first factor as a 'left–right' dimension and the second dimension in terms of attitudes to 'EU integration'. Such an interpretation would be completely consistent with most empirical work on the topic (for

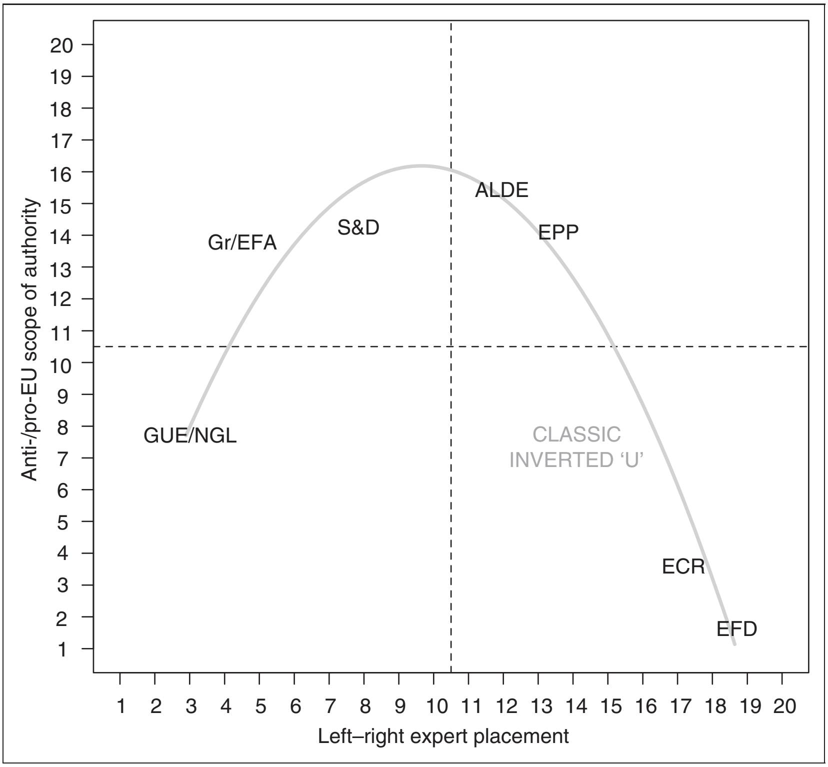

Figure 8. Descriptive mapping of the expert left–right placements against anti- vs. pro-EU authority. *Note*: The curved line is a quadratic fit weighted by seat share.

example, McElroy and Benoit, 2007) and thoroughly in line with our theoretical expectations.

For a distance matrix of unknown dimensionality, MDS is the most common inductive method for ‘mapping’ the positions of the parties – used in roll-call vote analysis, text scaling or just plain vanilla MDS from survey responses or other indicators. Indeed, if the distance matrix corresponded to physical locations as in our London Tube example – and assuming we know the correct orientation and number of dimensions – then we could easily turn this set of distances into a ‘map’. This is exactly what we have done and plotted in Figure 9. Echoing the results of the factor analysis, the two-dimensional solution also emerges very robustly from MDS.[10] The relative *locations* of the parties, however, compared with those from our descriptive mapping in Figure 8 based on direct locations by experts, show a number of key differences. The inductive map’s ‘wrong’ placements include:

- the extremist EFD is located in a more moderate position on the left–right scale than the somewhat less extremist ECR;

Table 4. Inductively derived 'dimensionality' of the EP policy space

Factor	Eigenvalue	Cumulative proportion
1	4.02	0.45
2	1.93	0.66
3	0.88	0.76
4	0.69	0.84
5	0.58	0.90
6	0.40	0.94
7	0.23	0.97
8	0.14	0.99
9	0.12	1.00
	Rotated factor loadings	
	1	2
Taxes vs. spending	0.84	0.02
Deregulation	0.80	0.15
Environment	0.82	0.05
Social liberalism	0.74	0.37
Immigration	0.67	0.48
Decentralization	0.34	−0.61
EU security	0.08	0.69
EU federalism	0.28	0.85
EU authority	0.17	0.86
N		106

- Gr/EFA is placed as more extreme than the in fact quite extreme GUE/NGL on the left–right scale;
- the two 'Green' party groups (Gr/EFA and GUE/NGL) are identified as more Eurosceptic than the ECR and EFD, both groups for which Euroscepticism is a core element of their identity;
- Gr/EFA is located as extremely Eurosceptic when it should be more moderately pro-EU;
- the extremist GUE/NGL is given the same left–right position as the centre-right ALDE, a location with which no expert would ever agree; and
- the EPP becomes the most pro-EU party, another highly implausible interpretation of the party groups' policies.

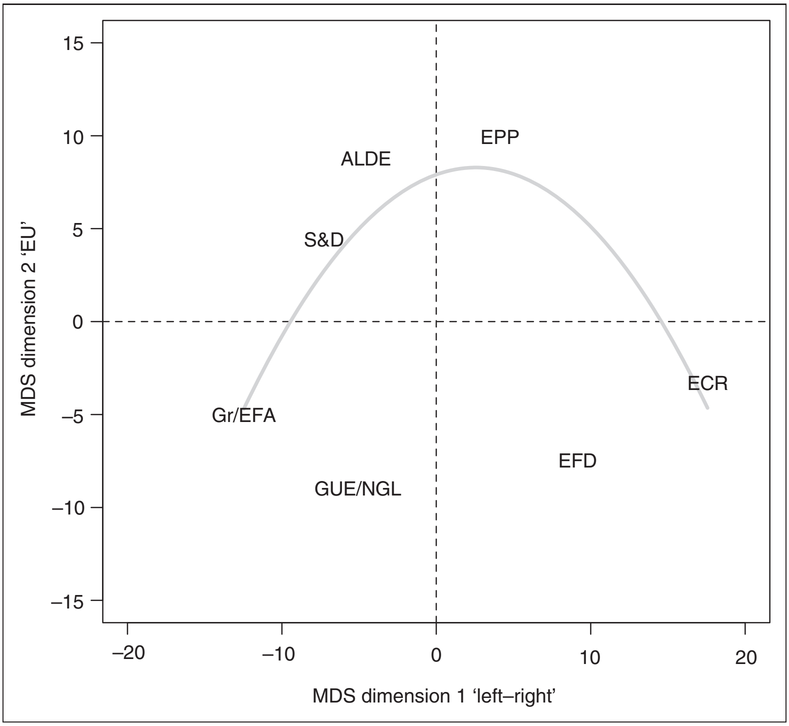

Figure 9. Inductive mapping of the left–right positioning against anti- vs. pro-EU authority.
Note: The curved line is a quadratic fit weighted by seat share. Results are from a classical MDS fit of expert placements of all party groups on all dimensions (except overall left–right).

In addition to these misplacements by the inductive scaling, there is also the *orientation* of the inductive map: in producing Figure 9 we had to invert the positions of the left–right dimension because these were 'clearly' flipped in the locations based on what we 'knew' about the extreme parties. This knowledge was, strictly speaking, external to the scaling process. Distance cannot tell the whole story and may produce a 'mapping' of the policy space that – like our attempts to generate the Circle Line map inductively – may be very different from other possibly more accurate and useful representations.

Concluding remarks and recommendations

Scholars use low-dimensional conceptual maps of political spaces as parsimonious and useful ways to represent a huge amount of information about political preferences and, it is hoped, to screen out confusing and/or irrelevant detail. There is no such thing as the 'one true' conceptual map of any given political setting, waiting to be discovered if only we could find it. Just as physical maps are spanned by physical dimensions, conceptual maps are spanned by conceptual dimensions, which we use to provide substantive orientation. Just as there is not one true map, neither is there ‘one true dimensionality’ for any given political setting. Sometimes, as with London’s Central Line, a one-dimensional map will tell us everything we want to know. Sometimes, as with London’s Circle Line, it will not. Nearly always, we ignore potentially salient dimensions in the name of a parsimonious description of the world, just as we typically do not seek three-dimensional maps of London Tube stations – despite the fact that these stations do in fact have substantively meaningful geographical coordinates in three dimensions.

Most maps of the physical world are based on strong a priori assumptions about the number and nature of the dimensions we use to interpret them. As we have seen, we also often have strong a priori assumptions about the number and nature of dimensions spanning useful conceptual maps of the political world. If we can indeed make such assumptions, the job of mapping is made much easier. It becomes a matter of locating the unknown positions of key political agents on known policy dimensions. This is a relatively well understood exercise in one-dimensional scaling. If, however, we insist on leaving the number and nature of the basis vectors of our conceptual space as completely open questions, then we face a task that is much more difficult, and arguably impossible. In essence, our estimation problem is left with too many degrees of freedom. Furthermore, a posteriori orientation and interpretation of spaces estimated using no a priori assumption about dimensionality will, in our view inevitably, make reference to a priori policy dimensions such as left–right or liberal–conservative that have emerged as part of the commonly understood language of political discourse. Our strong recommendation is to leverage our de facto knowledge of these dimensions as part of the estimation process rather than assuming, at the start of the investigation, that the space we are estimating may have *any conceivable* dimensionality and the dimensions we derive might have *any conceivable* substantive meaning.

Notes

1. Although especially common in EU studies (e.g. McElroy and Benoit, 2007; Marks and Steenbergen, 2002; Pennings, 2002; Selck, 2004), the ‘mapping spaces’ approach has been widely used in other contexts (e.g. Benoit and Laver, 2006: ch 6; Warwick, 2002).
2. In addition to contrasting the a posteriori and the a priori approaches, one could also distinguish the sociological from strategic approaches, contrasting dimensionality as rooted in fundamental social conflicts versus being found primarily in party competition. See De Vries and Marks (2012).
3. Where do these priors come from? We grew up from childhood observing adults successfully navigating the world using two-dimensional maps such as these.
4. To get a sense of the scale of the noise, the easting indicator correlated 0.53 with the ‘true’ easting, and the northing indicator correlated 0.68 with the true northing – correlations that we are accustomed to accepting in the social science as ‘not bad’.
5. Perhaps the ultimate example is Gabel and Huber (2000), who treat the entire Comparative Manifesto Project data set (Budge et al., 2001) as providing variables on

56 specific policy issues, and use factor analysis to reduce this to a one-dimensional solution they call 'left–right'.

6. An equivalent plot generated by excluding the five variables identified in the last five columns of Table 2 is not much better.
7. These are: taxes vs. spending; deregulation; social (liberalism); environmental policy; EU authority; immigration; EU federalism; EU collective security; decentralization/subsidiarity; and a general dimension of left–right whose interpretation was left to the experts. For full details see McElroy and Benoit (2007). The wording of the new decentralization/subsidiarity dimension was: 'Insists on the subsidiarity principle in all administration and decision-making (1). Accepts more centralized EU-level administration and decision-making (20).'
8. The wording is: 'Please locate each political group on a general left–right dimension, taking all aspects of group policy into account. Left (1). Right (20).'
9. Hix et al. (2006: 495): 'We find one main dimension of politics in the European Parliament. This dimension is the classic left-right dimension of democratic politics. A second dimension is also present, although to a lesser extent . . . interpreted as the pro-/anti-Europe dimension.' This contrasts with the findings of Veen (2011), however, whose inductive scaling of the dimensions of political conflict in the European Council found European integration to be the principal dimension of conflict and a left–right type of policy divide to be secondary.
10. Here we used positioning by each expert of each party group as inputs to a classical MDS, with variables consisting of every policy dimension except overall left–right. From 106 observations, we retained two dimensions explaining 43.7 percent and 21.6 percent of the variance respectively. To produce the locations in Figure 9, we took the party group mean dimensional scores as the positions reported in Figure 9, and inverted the first dimension. Our experiments with dropping various dimensional inputs showed that the scaling was extremely robust, yielding essentially the same placements when single dimensions or pairs of dimensions were left out as variables.

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