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Country Clustering in Comparative Political Economy

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Abstract

In the comparative political economy of rich democracies there is a long tradition of classifying countries into one of a small number of categories based on their economic institutions and policies. The most recent of these is the Varieties of Capitalism project, which posits two major clusters of nations: coordinated and liberal market economies. This classification has generated controversy. We leverage recent advances in mixture model-based clustering to see what the data say on the matter. We find that there is considerable uncertainty around the number of clusters and, barring a few cases, which country should be placed in which cluster. Moreover, when viewed over time, both the number of clusters and country membership change considerably. As a result, arguments about who has the "right" typology are misplaced. We urge caution in using these country classifications in structuring qualitative inquiry and discourage their usage as indicator variables in quantitative analysis, especially in the context of time-series cross-section data. We argue that the real value of both Esping-Andersen's work and the Varieties of Capitalism project consists of their theoretical contributions and heuristic classification of ideal types.

Zusammenfassung

In der vergleichenden Politischen Ökonomie reicher Demokratien gibt es eine lange Tradition, Länder aufgrund ihrer unterschiedlichen wirtschaftlichen Institutionen und Policies zu typologisieren. Die jüngste dieser Typologien – das „Varieties-of-Capitalism"-Konzept – erfasst zwei Gruppen von Ländern: koordinierte und liberale Marktwirtschaften. Da diese Klassifizierung einige Kontroversen hervorgerufen hat, nutzen die Autoren neueste Fortschritte im „mixture model-based clustering", um zu prüfen, welche Erkenntnisse die Daten zu diesem Problem liefern. Die Ergebnisse weisen eine beträchtliche Unsicherheit hinsichtlich der Anzahl der Cluster und, mit wenigen Ausnahmen, der Zuordnung der Länder zu Clustern auf. Betrachtet man größere Zeiträume, variieren darüber hinaus die Anzahl der Cluster und Ländermitgliedschaften erheblich. Als Folge dieser Befunde halten die Autoren Argumentationen über die „richtige" Typologisierung für unangebracht und raten davon ab, diese Länderklassifizierungen zur Strukturierung qualitativer Studien heranzuziehen oder als Indikatorvariablen in quantitativen Analysen zu nutzen. Dies gilt insbesondere im Kontext von gepoolten Zeitreihen- und Querschnittsdaten. Sie argumentieren, dass der substanzielle Wert sowohl der Forschung von Esping-Andersen als auch des „Varieties-of-Capitalism"-Ansatzes in den Beiträgen zur Theorie und den heuristischen Klassifizierungen von Idealtypen besteht.

Contents

Introduction

The remarkable variation in both political-economic institutions and outcomes across industrial democracies has provided fodder for political economists for at least a half century. To make sense of this variation, a long and distinguished tradition emerged of classifying countries into one of a small number of categories. Among the most influential works is Esping-Andersen's (1990), which sorts rich democracies into "three worlds" labeled Liberal, Conservative, and Social Democratic. The "varieties of capitalism" project (Hall/Soskice 2001), henceforth VoC, builds on the "three worlds" approach by incorporating insights from the new institutional economics, but shifts emphasis to the role of the firm. The VoC literature argues that these same twenty-odd countries can be assigned the labels of either "liberal market economy" (LME) or "coordinated market economy" (CME). This dichotomy is so intuitively compelling that it has begun to structure empirical research, both quantitative and qualitative. On the quantitative side, indicator variables representing whether a particular country is an LME have appeared as regressors (Ringe 2006; Rueda/Pontusson 2000; Taylor 2006), sometimes in an effort to explain a variable that others have cited as determining the initial classification (Hamann/Kelly 2009). On the qualitative side, the VoC logic has been used to justify case selection as well as the dimensions for comparative case study (Campbell/Pedersen 2007; Culpepper 2007; Thatcher 2004).

To date, this exercise in classification has been the result of rankings on additive indices and expert judgments along a large number of dimensions. Unsurprisingly, the clustering of countries has generated a fair degree of controversy. Are there only two varieties of capitalism? Where should we put Portugal? Are these categories immutable, at least over the period from 1980 to the present? Indeed, Thelen (2004: 2) states that "all these various categorization schemes also have trouble sorting the same set of 'intermediate' or hard to classify countries." The purpose of this article is to tackle questions about classification of countries theoretically and empirically.

In this paper, we leverage recent advances in mixture model-based clustering (Fraley/Raftery 1998, 2002; Raftery/Dean 2006) to see what the data say on the matter. By positing the data as a mixture of some to-be-estimated number of multivariate Gaussian densities, the mixture model approach gives cluster analysis a strong basis in probability theory. In so doing, model-based clustering has three notable advantages over traditional clustering methods. First and most importantly, the choice of clustering method now becomes a problem of model choice. We have strong guidance from well-understood principles of likelihood theory in this regard. Second, the model-based approach identifies the number of clusters in the data. Other methods either require a priori assumptions (e.g., k-means) or only describe how "far" various observations are from one another (agglomerative clustering). Third, model-based clustering can accommodate several cluster shapes; traditional methods are special cases of the more flexible cluster geometries available in the model-based approach.

In the analysis, we identify the dimensions along which countries are purported to vary and collect time-series measures on each for 21 OECD countries, 1980–2005. We then examine these data for clusters both in the cross-section and over time. We find that the data parallel the experts' arguments: There is considerable uncertainty around the number of clusters and, barring a few cases, over which country should be placed in which cluster. Moreover, when viewed over time, both the number of clusters and country membership change considerably. Therefore, we urge caution in using country classifications in empirical analysis.

We have two objectives in this paper. First, we hope to expand the use of mixture models in the social sciences by applying them to a substantive controversy. Second, our findings have several implications for the literature in comparative political economy. Specifically, arguments about who has the "right" typology are misplaced; these data do not exhibit sufficient structure for any time-invariant all-encompassing clustering to be empirically useful. Therefore discussions of LMEs or CMEs should be used as heuristics or Weberian ideal types only. These categories do not measure anything meaningful in the data analytic sense, especially in the context of time-series cross-section data, and should therefore not be employed as indicator variables. Finally, we argue that the real value of both Esping-Andersen's work and the varieties of capitalism project persists in their theoretical contributions, which have been largely obscured by easy-to-remember typologies.

The paper proceeds in four parts. Section 1 briefly reviews the long tradition of classification in comparative political economy (CPE), with an emphasis on the controversies and uses of the VoC and "three worlds" perspectives. Section 2 discusses mixture models and model-based clustering in more detail, with special attention to their relationships to other clustering and data reduction techniques commonly used in the social sciences. Section 3 explores the variables purported to define the VoC clusters and discusses the limits of our analysis. We conclude in Section 4 with observations on how best to employ the theoretical insights from the VoC project in empirical research, given our findings from the cluster analysis.

1 Welfare regimes and institutional complementarities: Clustering in comparative political economy

Attempts to generate typologies of advanced democracies started in the late 1950s with the distinction between residual and institutional welfare states (Wilensky/Lebeaux 1958). Literature on corporatism continued this proclivity for developing country typologies and made it a mainstay in political science (see Siaroff 1999 for a recent example).[1] The most recent classifications, presented in Table 1, are the motivation for

1 We thank Martin Höpner for pointing out this trajectory.

Table 1 Twenty-one OECD economies and their categorizations

Country	Country code	Three worlds	Types of capitalism	Varieties of capitalism
Australia	AUS	Liberal	LME	LME
Canada	CAN	Liberal	LME	LME
Great Britain	GBR	Liberal	LME	LME
Japan	JPN	Liberal	NC/C	CME
Switzerland	CHE	Liberal	SCME	CME
United States	USA	Liberal	LME	LME
Austria	AUT	Conservative	SCME	CME
Belgium	BEL	Conservative	SCME	CME
Germany	DEU	Conservative	SCME	CME
France	FRA	Conservative	SCME	NC/C
Italy	ITA	Conservative	SCME	NC/C
Denmark	DNK	Soc. Dem.	NCME	CME
Finland	FIN	Soc. Dem.	NCME	CME
Netherlands	NLD	Soc. Dem.	SCME	CME
Norway	NOR	Soc. Dem.	NCME	CME
Sweden	SWE	Soc. Dem.	NCME	CME
Greece	GRC	NC/C	NC/C	NC/C
Ireland	IRL	NC/C	LME	LME
New Zealand	NZL	NC/C	LME	LME
Portugal	PRT	NC/C	NC/C	NC/C
Spain	ESP	NC/C	NC/C	NC/C

Note: The country codes are based on ISO 3166. The country classifications are: LME = Liberal Market Economy, CME = Coordinated Market Economy, NCME = National Coordinated Market Economy, SCME = Sectoral Coordinated Market Economy, NC/C = not categorized or controversial.

our paper. The table lists the classification of 21 advanced democracies according to Esping-Andersen's (1990) three worlds of welfare states, Kitschelt et al.'s (1999) institutional diversity of contemporary capitalism, and Hall and Soskice's (2001) firm-centered classification of varieties of capitalism.

We do not intend to review the theoretical arguments surrounding the three worlds and VoC classifications, but there is a significant empirical implication worth describing. Broadly speaking, each of these attempts at clustering is driven by theoretical arguments positing self-reinforcing linkages across economic policies and institutions. Esping-Andersen refers to these linkages as "regimes" of welfare state effort and traces their emergence to the form of cross-class coalitions emerging in the postwar period. Specifically, he focuses on the choice of the new middle class as determining the type of welfare state regime that later emerged. The VoC literature is based on the notion of "institutional complementarities" in which "the presence (or efficiency) of one [institution] increases the returns from (or efficiency of) the other" (Hall/Soskice 2001: 16). These institutional externalities reinforce (or undo) one another and generate distinct equilibrium clusters of institutional arrangements, corporate strategies, and social policies and outcomes. Both the historical arguments of Esping-Andersen and the strong notions of equilibrium in the VoC literature directly imply that clusters of countries should be time-invariant or, at the very least, should change very slowly. Much of the recent work in the VoC literature aims to discover how resilient these clusters are in the face of exogenous changes in the international economy (Campbell/Pedersen 2007; Culpepper 2005; Thatcher 2004).

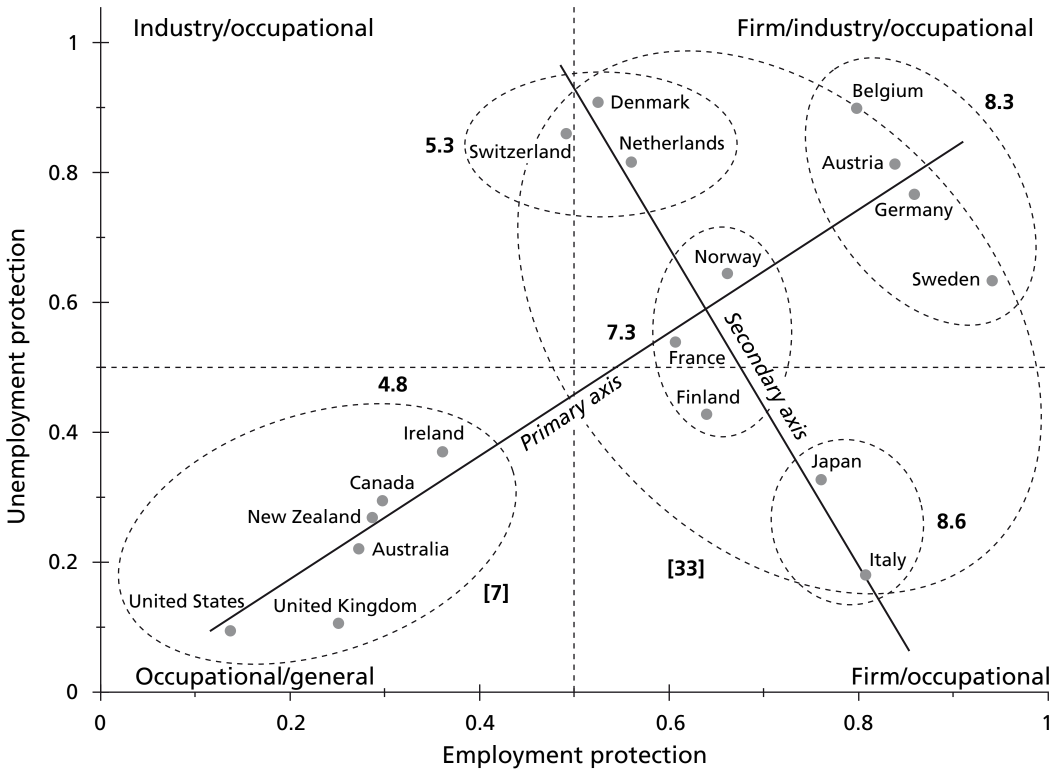
Where do these clusters come from?

The inspiration for clustering in the comparative political economy literature springs from the stark differences in labor market organization, social spending, and firm structure across the relatively successful countries of Western Europe, North America and the Pacific basin. While Germany and the United States are frequently contrasted as archetypal cases for VoC, the major theoretical works emphasize that the typologies are meant to generate Weberian ideal types through which to evaluate actual cases, *not* specific empirical groupings. Hall and Soskice (2001: 8) state that "the core distinction we draw is between two types of political economies … which constitute ideal types at the poles of a spectrum along which many nations can be arrayed." Nevertheless, these same works also attempt to empirically identify clusters and map them onto their ideal types. Many subsequent authors seem to have taken up the empirical clustering more than the theoretical arguments.

Before turning to some of the empirical applications of the VoC classification, let us briefly consider how the initial clusterings were generated. The typologies have emerged from two major sources: direct comparison of a set of countries along a limited number of dimensions and expert classifications. We focus on the former. Esping-Andersen constructed several additive indices of decommodification, corporatism, pensions, etc. for circa 1980 and then ranked countries using these indices. He finds that certain groups of countries tend to jointly rank highly on some indices and near the bottom on others. On this basis he argues for his three worlds. The earlier VoC works tend to rely on visual heuristic methods that are also frequently based on additive indices and specific time points. Figure 1, from Estévez-Abe, Iversen and Soskice (2001), is an example of a visual classification of countries according to the level of social protection and skill formation. We will return to these data and this plot below.

Subsequent authors have attempted to revise these classifications. Some have disputed the placement of certain countries, most notably the southern European economies of France, Spain, and Portugal, and argued for the inclusion of a "Latin" or "Mediterranean" regime (e.g. Saint-Arnaud/Bernard 2003: 504). Others have proposed similar revisions (Amable 2003; Obinger/Wagschal 2001). Alternatively, a second dimension of classification has been proposed (Höpner 2007). Most directly related to our project, several papers attempt to put the VoC classifications on more rigorous footing using data reduction techniques such as principal components analysis (Hicks/Kenworthy 2003), latent factor analysis (Hall/Gingerich 2004), traditional clustering methods (Obinger/Wagschal 2001; Saint-Arnaud/Bernard 2003), or all three (Amable 2003). Schröder (2008) has even proposed integrating VoC and welfare regimes using cluster analysis. We discuss how our analysis extends these exercises in detail below.

Figure 1 Heuristic visual clustering



Note: This is figure 4.2 from Estévez-Abe/Iversen/Soskice (2001: 172).

Empirical application of the VoC classification

The empirical applications of the VoC arguments have focused on either exploiting the VoC classification scheme, testing it, or, in at least one instance (Taylor 2006), exploiting the VoC classifications to argue against the VoC theoretical apparatus. VoC classifications have been employed empirically in both quantitative and qualitative analysis.

On the quantitative side, dummy variables representing cluster membership have been either directly included as regressors (Ringe 2006; Taylor 2006) or used to split the dataset into parts and then test for the equality of coefficient estimates across models fit to data from CMEs and LMEs (Rueda/Pontusson 2000). All these analyses use time-series cross-section (TSCS) data and treat cluster membership as time-invariant. In this paper we do not attempt to show the extent to which these authors' findings are sensitive to cluster allocation, but it is worth mentioning that Taylor (2006) shows that findings relating patent counts to VoC clusters are sensitive to the inclusion of the United States as an LME.

The VoC classification has, if anything, found its broadest application in qualitative work. Indeed, while the initial clustering of countries was shown heuristically in bivariate scatterplots, the most extensive discussion of empirical differences in Hall and Soskice's introduction was a comparison of the United States and Germany. Case studies have most frequently used the VoC classification to justify case selection. To take a few recent examples already mentioned above, Thatcher (2004) argues that his choice of cases for comparing telecommunications regulations (Germany, France, Italy, Great Britain) is driven by their positions in the VoC pantheon. Campbell and Pedersen (2007) use the VoC classifications to justify both the choice of case (Denmark) and dimensions of analysis (labor markets, vocational training, and industrial policy). The journal *Governance* recently dedicated an entire issue to comparisons of economic crisis management in Japan and Sweden. The introduction (Immergut/Kume 2006) specifically invokes the VoC in justifying this emphasis.

2 Cluster analysis and the social sciences

Cluster analysis (and its close relative, discriminant analysis) is a well-developed branch of applied statistics that attempts to identify groups in data such that objects within groups are as similar as possible while the differences between groups are maximized. Cluster and discriminant analysis have found wide application across disciplines as diverse as botany, chemistry, computer science, genetics, geography, medicine, and zoology. Within the social sciences, cluster analysis has appeared most frequently in sociology but has been less common in political science and economics. In this section we briefly introduce traditional cluster analysis and then go into a detailed discussion of the mixture model-based clustering (MMBC) approach we employ below. We then contrast MMBC analysis to both traditional methods and other data-reduction techniques, as well as to latent-variable models such as principal components and factor analysis.

Hierarchical and relocation clustering methods

Throughout we will use the term "group" to refer to the true, existing groupings of objects and "cluster" to denote the collections of observations identified via some algorithm or statistical model, i.e., a cluster is an estimated grouping. Cluster analysis has at least one of two objectives: identifying some sort of cluster structure in a set of observations and/or assigning observations to clusters in some optimal manner. Kaufman and Rousseeuw (1990) offer an accessible introduction to traditional cluster analysis. Relocation methods,[2] k-means being the most well-known, require that the researcher

2 Sometimes, they are confusingly referred to as partitioning methods.

posit the number of clusters in the data a priori and then proceed to iteratively move observations between clusters until an optimal allocation can be identified. In hierarchical cluster analysis, the number of groups is unknown. Hierarchical cluster analysis uses intuitively plausible procedures based on various distance metrics to either merge or partition observations into clusters.

Hierarchical cluster analysis can take one of two forms. The "agglomerative" approach starts by regarding each object on its own and proceeds to combine them into clusters that maximize within-cluster similarity and between-cluster difference, as determined by a distance metric. Several different metrics can be employed here, and the literature provides little guidance about their appropriateness. The "divisive" approach proceeds in the opposite direction, beginning with all objects in one cluster and subdividing them until each object is on its own. Frequently these methods yield different solutions.[3] Presentation of hierarchical clustering results is most commonly done through dendrograms, where the length of line segments is directly interpretable as the dissimilarity between clusters. The longer the segment before two clusters combine into one, the more dissimilar the observations.

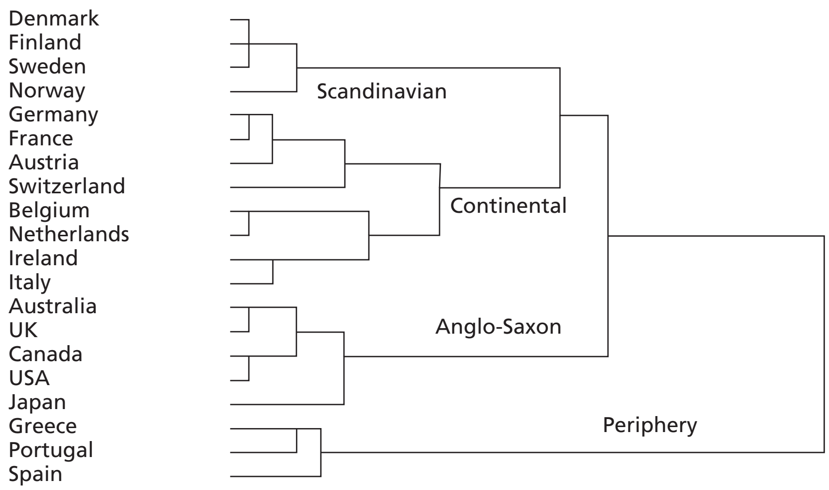
Hierarchical cluster analysis is primarily an exploratory rather than confirmatory or inferential activity. There are many attributes on which to measure similarity and difference across objects, and numerous algorithms for identifying clusters given some set of attributes. There is no statistical basis on which to prefer a particular clustering solution over another and no possibility of evaluating the uncertainty around a particular observation's assignment to a given cluster. The choice of both the number of clusters to focus on and the substantive interpretations assigned to them is solely the responsibility of the researcher. Referring to the traditional clustering methods, Venables and Ripley (2002: 316) argue that "there are many different clustering methods, often giving different answers, and so the danger of over-interpretation is high."

The hierarchical approach has been applied at least twice to problems similar to the one we address below (Obinger/Wagschal 2001; Saint-Arnaud/Bernard 2003). Though these authors analyze somewhat different sets of data and use slightly different time frames, both conclude that there are four relevant clusters among advanced industrial nations, though the exact membership varies across studies and time. Figure 2 displays some results from both papers.

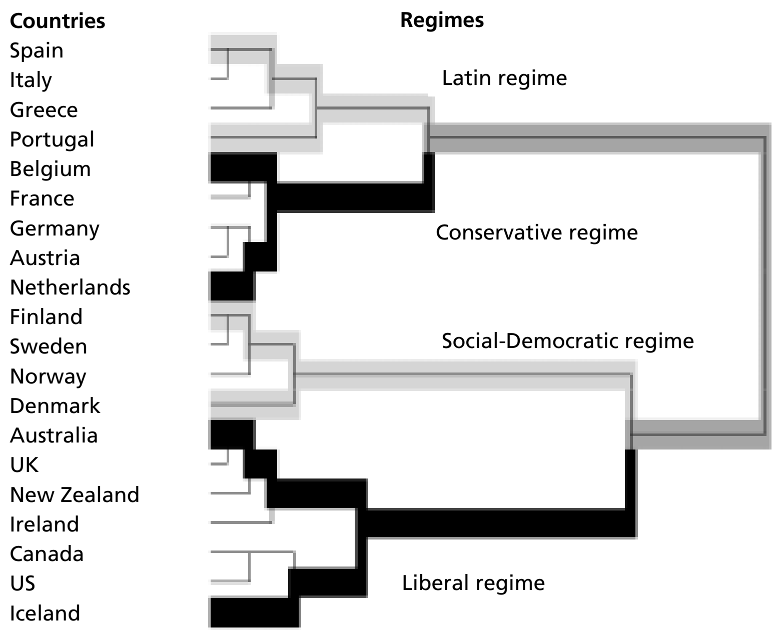
As can be seen from Figure 2, it is up to the researcher to identify, justify, and interpret a four-cluster solution. A two-, five-, or six-cluster solution seems just as plausible for both dendrograms in Figure 2. Traditional methods provide no principled way out of this problem.

3 The divisive approach is much less common, as its computational demands increase exponentially in the number of observations (Venables/Ripley 2002).

Figure 2 Illustrative results from two studies relying on traditional hierarchical clustering



(a) Obinger/Wagschal (2001: Fig. 3, p. 106).



(b) Saint-Arnaud/Bernard (2003: Fig. 4, p. 513).

Mixture model-based clustering

Mixture models have a long tradition in statistics and have more recently been applied to the clustering problem by Fraley and Raftery (1998, 2002) and Raftery and Dean (2006). This second generation of clustering methods assumes that the observed data are generated by some finite mixture of probability distributions.

Let $\mathbf{x}=\mathbf{x}_1 \ldots \mathbf{x}_n$ be the $n \times k$ matrix of n objects measured along k dimensions. The density of $\mathbf{x}$ can then be expressed as a finite mixture model of the form

$$f(\mathbf{x}) = \sum_{g=1}^{G} \pi_g f_g(\mathbf{x})$$

where G is the number of groups, π_g is the proportion of objects in group g, and $f_g(\cdot)$ is the density function for observations in group g. We assume that all groups are defined by multivariate normal densities, yielding

$$f(\mathbf{x}) = \sum_{g=1}^{G} \pi_g \phi(\mathbf{x} \mid \theta_g)$$

where $\phi(\cdot|\theta)$ is the multivariate normal density function with parameters $\theta_g=(\mu_g, \Sigma_g)$. The model classifies an observation as being in group g if $\tau_g(\mathbf{x}) > \tau_h(\mathbf{x})\ \forall h \neq g;\ h \in 1,\ldots,G$ where

$$\tau_g(\mathbf{x}) = \frac{\pi_g \phi(\mathbf{x} \mid \theta_g)}{\sum_{h=1}^{G} \pi_h \phi(\mathbf{x} \mid \theta_h)}$$

τ_g can be interpreted as the (posterior) probability that an observation belongs to group g. We can now express the full mixture likelihood:

$$\mathcal{L}(\theta_1,\ldots,\theta_G;\tau_1,\ldots,\tau_G \mid \mathbf{x}) = \prod_{i=1}^{n} \sum_{g=1}^{G} \tau_g \phi(\mathbf{x}_i \mid \theta_g) \qquad (1)$$

It is clear from equation 1 that the number of parameters estimated grows rapidly with the number of clusters G and the number of dimensions k. Baneld and Raftery (1993) partially mitigate this problem by placing restrictions on the covariance matrices Σ_g. Covariance matrices are parameterized using eigenvalue decompositions of the form

$$\Sigma_g = \lambda_g \mathbf{D}_g \mathbf{A}_g \mathbf{D}_g^T \qquad (2)$$

where λ_g is the largest eigenvalue of Σ_g, $\mathbf{D}_g$ is the orthogonal matrix of eigenvectors, and $\mathbf{A}_g$ is a diagonal matrix of scaled eigenvalues. The parameters θ_g determine the geometry of the clusters. Specifically, clusters are ellipsoids centered at the mean vector. The decomposition of Σ_g determines other geometric features of the clusters: λ_g determines the cluster's volume; $\mathbf{D}_g$ controls the orientation of the cluster; and $\mathbf{A}_g$ governs the shape of the ellipsoid. MMBC admits a wide variety of cluster geometries.

We can modify the complexity of the models estimated by restricting the various components of the matrix product on the RHS of equation 2 to be constant across clusters. The most restricted version, $\Sigma_g=\lambda I$, constrains clusters to be spherical and of equal

Table 2 Cluster geometries generated by differing parameterizations of the covariance matrices Σ_g

Model	Distribution	Volume	Shape	Orientation
λI	Spherical	Equal	Equal	NA
$\lambda_g I$	Spherical	Variable	Equal	NA
λA	Diagonal	Equal	Equal	Along the axes
$\lambda_g A$	Diagonal	Variable	Equal	Along the axes
λA_g	Diagonal	Equal	Variable	Along the axes
$\lambda_g A_g$	Diagonal	Variable	Variable	Along the axes
λDAD^T	Ellipsoidal	Equal	Equal	Equal
$\lambda D_g A D_g^T$	Ellipsoidal	Equal	Equal	Variable
$\lambda_g D_g A D_g^T$	Ellipsoidal	Variable	Equal	Variable
$\lambda_g D_g A_g D_g^T$	Ellipsoidal	Variable	Variable	Variable

volume.[4] Table 2, reproduced from Fraley and Raftery (2007: 7), describes the various cluster geometries generated as restrictions on the covariance matrices are relaxed.

In fitting the model, the actual cluster to which observation i belongs is treated as missing data. The "complete data" $\mathbf{x}_i$ can be expressed as $\mathbf{x}_i=(\mathbf{y}_i, \mathbf{z}_i)$ where $\mathbf{y}_i$ are the observed data on which we seek to fit the clustering model and $\mathbf{z}_i$ is a G-vector, the gth element of which takes on 1 if i belongs to cluster g and 0 otherwise. Assuming that $\mathbf{z}_i \sim multinom(\tau_1 \ldots \tau_G)$, the resulting complete data likelihood is given by

$$\mathcal{L}_c = \prod_{i=1}^{n} \prod_{g=1}^{G} [\tau_g \phi_g [(\mathbf{y}_i \mid \theta_g)]]^{z_{ig}} \tag{3}$$

(3) is maximized via EM (Dempster/Laird/Rubin 1977). For the M-step, (3) is maximized wrt $(\tau_1,\ldots\tau_G; \theta_1 \ldots \theta_G)$, holding $\mathbf{z}$ at $\tilde{\mathbf{z}}$. Given estimates $(\tilde{\tau}_g, \tilde{\theta}_g)$, $\tilde{\mathbf{z}}_g$ is given from the E-step:

$$\frac{\tilde{\tau}_g \phi_g (\mathbf{y}_i \mid \tilde{\theta}_g)}{\sum_{h=1}^{G} \tilde{\tau}_h \phi_h (\mathbf{y}_i \mid \tilde{\theta}_h)} \tag{4}$$

For the multivariate normal mixtures used here, Fraley and Raftery (2002) give closed form solutions for $\tilde{\tau}_g$ and $\tilde{\mu}_g$: $\tilde{\tau}_g = n_g/n$, where $n_g = \Sigma_{i=1}^{n} \tilde{\mathbf{z}}_{ig}$, and $\tilde{\mu}_g = (\Sigma_{i=1}^{n} \tilde{\mathbf{z}}_{ig} \mathbf{y}_i)/n_g$.

Model choice and MMBC

The challenge of MMBC is to select both the number of clusters and the parameterizations of the covariance matrix. Since each combination of these choices represents a (non-nested) statistical model, MMBC recasts the clustering problem as one of model selection. We have strong guidance from statistical theory in this regard: Non-nested

4 Note that this is equivalent to the sum-of-squares distance measure most frequently employed in hierarchical clustering (Ward 1963).

models can be compared using approximate Bayes factors (Kass/Raftery 1995).[5] Bayes factors are frequently difficult to integrate so we use the Bayesian information criterion (BIC) approximation

$$BIC = -2\log \mathcal{L}(\mathbf{x}, \hat{\theta}) + m \log n$$

where $\hat{\theta}$ is the maximum likelihood estimate of θ and m is the number of free parameters in the model. In comparing models, we choose the parameterization(s) that maximize the BIC. Conventionally, two models with a BIC difference less than two are difficult to distinguish, whereas a difference of ten or greater constitutes strong evidence for favoring one model over another (Kass/Raftery 1995).

Variable selection and MMBC

Any collection of objects can be measured and classified according to a large number of attributes (or dimensions). This is especially true when looking at complex entities, such as nations, over time. Intuitively, one can imagine that as the number of dimensions approaches the number of objects to be classified there must be increasingly tight clustering to discern any pattern in the data.[6] Technically, as the number of dimensions increases so does the number of parameters to estimate for θ, imposing constraints on the effective number of dimensions we can consider.[7] In our application, we have a maximum of 21 cases for any point in time. Even restricting attention to "just" the standard variables of comparative political economy (industrial and labor market structure, social policy, and political-economic institutions) we still have to consider literally dozens of potential attributes and several different measures for each attribute. It is simply not feasible to simultaneously consider all the plausible or proposed variables when determining the varieties of capitalism.

It is worth noting that this problem is implicit in the major works classifying countries. Esping-Andersen relies on a small number of constructed indices to identify his "three worlds." The VoC literature rarely considers more than two particular attributes at a time. Some authors have resorted to data reduction techniques: Hicks and Kenworthy (2003) rely on principal components to reduce the dimensionality of the data in order

5 The Bayes factor is the posterior odds for one model compared to another under the assumption that there is no prior reason to favor one over another. Formally, let M_1 and M_2 be two competing models and y be the data. The Bayes factor is given by

$$\frac{p(y \mid \mathcal{M}_1)}{p(y \mid \mathcal{M}_2)} = \frac{\int p(\theta_1 \mid \mathcal{M}_1) p(y \mid \theta_1, \mathcal{M}_1) d\theta_1}{\int p(\theta_2 \mid \mathcal{M}_2) p(y \mid \theta_2, \mathcal{M}_2) d\theta_2}$$

6 As a simple example, consider two points on a page. On what basis can we say there is one cluster or two?

7 How quickly this constraint prevents EM convergence clearly depends on the restrictions imposed on Σ_g. Agglomerative methods suffer from the same problem; it is merely less transparent here, since there is no underlying statistical parameterization to consider.

to classify different modes of welfare capitalism. Hall and Ginderich (2004) perform factor analysis on a cross-section of data and interpret the first factor extracted as representing the CME-LME division. Amable (2003) goes even further, conducting agglomerative analysis on the first three principal components.

Traditional data reduction techniques and cluster analysis do not easily go together. Chang (1983) proves that clustering information is not monotonically related to the eigenvalues of the principal components. There is no reason to believe that principal components with the largest eigenvalues are those retaining the greatest amount of clustering information. Reducing the dimensionality of the data by selecting principal components with the largest eigenvalues and then performing a cluster analysis, whether mixture model, hierarchical or relocation clustering, is usually not justified.

The MMBC-model selection approach provides one way around this problem. Raftery and Dean (2006) extend the notion of BIC-based model selection to include variable selection. They develop an algorithm in which the data, Y, are partitioned into three sets: variables already selected for clustering (Y_1), variables being considered for inclusion or exclusion from Y_1, denoted Y_2, and all remaining variables (Y_3). The algorithm is initialized by choosing the variable on which there is the most evidence of clustering. With each subsequent step, two models are considered.[8] In the first step, Y_2 gives no additional information on clustering *conditional* on Y_1. In the second, Y_2 does improve clustering. At each step the models are compared and a variable is included or excluded based on its effect on the BIC, maximized over the number of clusters and model parameterizations.[9] Moreover, the variable selection procedure provides a way in which to use dimension reduction techniques, such as principal components. The MMBC algorithm, applied to principal components, chooses the extracted component with the greatest amount of clustering information rather than the one that maximizes "explained" variance, as the eigenvalue criterion does.

To summarize the discussion on clustering and MMBC: To date, social scientists attempting to classify rich democracies have employed methods best characterized as exploratory. We see unstable results and findings that hinge on the researchers' interpretations. These works implicitly avoid dimensionality problems by relying on additive indicators or data reduction techniques such as principal components analysis. In contrast, the MMBC and model selection approach improves previous efforts by (1) allowing for more flexible clustering geometries based on well-understood parametric distributions; (2) providing a principled way for selecting the optimal clustering solutions by comparing non-nested models via the BIC; (3) generalizing the variable selec-

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8 Formally, we are interested in models characterizing $p(Y|\mathbf{z})$, where $\mathbf{z}$ defines cluster membership. Model 1 factors this into $p(Y_3|Y_2,Y_1)p(Y_2|Y_1)p(Y_1|\mathbf{z})$ whereas model 2 posits $p(Y_3|Y_2,Y_1)$ $p(Y_2,Y_1|\mathbf{z})$.

9 The maximum number of clusters must be set prior to analysis. For our application below we set this maximum to seven unless otherwise noted. See Raftery/Dean (2006: 176–177) for a detailed elaboration of the algorithm.

tion problem to one of model selection, thereby providing guidance on which variables to use, be they single variables or principal components.

3 Three worlds, two varieties, and the data

In this section we use the MMBC approach to explore the data for clustering structure and compare our findings with assertions from both Esping-Andersen's "three worlds" approach and the varieties of capitalism approach. Before turning to the data analysis, we outline our rationale for data selection. First, in order to keep the gap between theoretical concepts and operationalization as small as possible, we replicate data used in key studies. Second, we assemble a large batch of variables that previous works have identified as relevant for distinguishing countries. Specifically, we follow the theoretical development in the VoC literature. We start with the core dimensions of the VoC approach – the production regime measures as identified in Hall and Gingerich (2004). From there, we follow the literature on advanced capitalist democracies, including three areas. First, we include measures of welfare, because of the proposed link between production regime and welfare states (Iversen 2005; Mares 2001; Swenson 2002). A second strain of literature adds the importance of political institutions (Gourevitch/Shinn 2005; Iversen/Soskice 2006; Iversen/Stephens 2008). Finally, recent efforts (Soskice 2007) link the production regime with macroeconomic policy.

We approach the analysis in steps.[10] We begin by using MMBC to explore the clustering reported in Figure 1 (Estévez-Abe/Iversen/Soskice 2001: 172) and Hall and Gingerich (2004). Both these analyses are static and we use them to illustrate the value-added of the MMBC approach even when our findings are similar in flavor to the VoC clustering. We next describe the data we have gathered and then take a more dynamic perspective, employing MMBC and the variable selection algorithm to look at cross-sectional slices at different time periods. We then show that our non-finding of stable clustering solutions over time corresponding with either the VoC or "three worlds" approaches is robust for clustering on different subsets of variables. Rather than using the variable selection directly, we break the variables into institutional/policy domains and consider clustering within each of those. Finally, to put the temporal stability argument to an even stronger test, we randomly select a time slice for each country and examine these temporally mixed datasets using MMBC. Across all these analyses, we find little evidence of clustering of the form described by literature on either "three worlds" or VoC.

A few words on the presentation and interpretation of results are in order. Our goal here is not to attempt to identify specific clusters and impose any interpretation on them; rather, we are concerned with determining the empirical robustness of typology devel-

10 All analysis was performed in *R* 2.6.1 (R Core Development Team, 2007) using the `mclust`, `mclust02`, and `clustvarsel` libraries (Fraley/Raftery 2002, 2007; Raftery/Dean 2006).

Table 3 Clusters of welfare production regimes

Country	Cluster	Uncertainty
CAN	1	0.00
FIN	1	0.00
FRA	1	0.00
NOR	1	0.00
SWE	1	0.00
AUT	2	0.00
BEL	2	0.00
CHE	2	0.00
DEU	2	0.00
DNK	2	0.00
NLD	2	0.00
IRL	3	0.01
JPN	3	0.00
NZL	3	0.00
AUS	4	0.00
GBR	4	0.00
ITA	4	0.00
USA	4	0.00
No. of clusters	4	
Variance decomposition	EEE	
BIC	–429	

Note: Entries of the same color are classified in the same VoC category. Blue entries are LMEs, black are CMEs, and red entries are not classified or otherwise controversial.

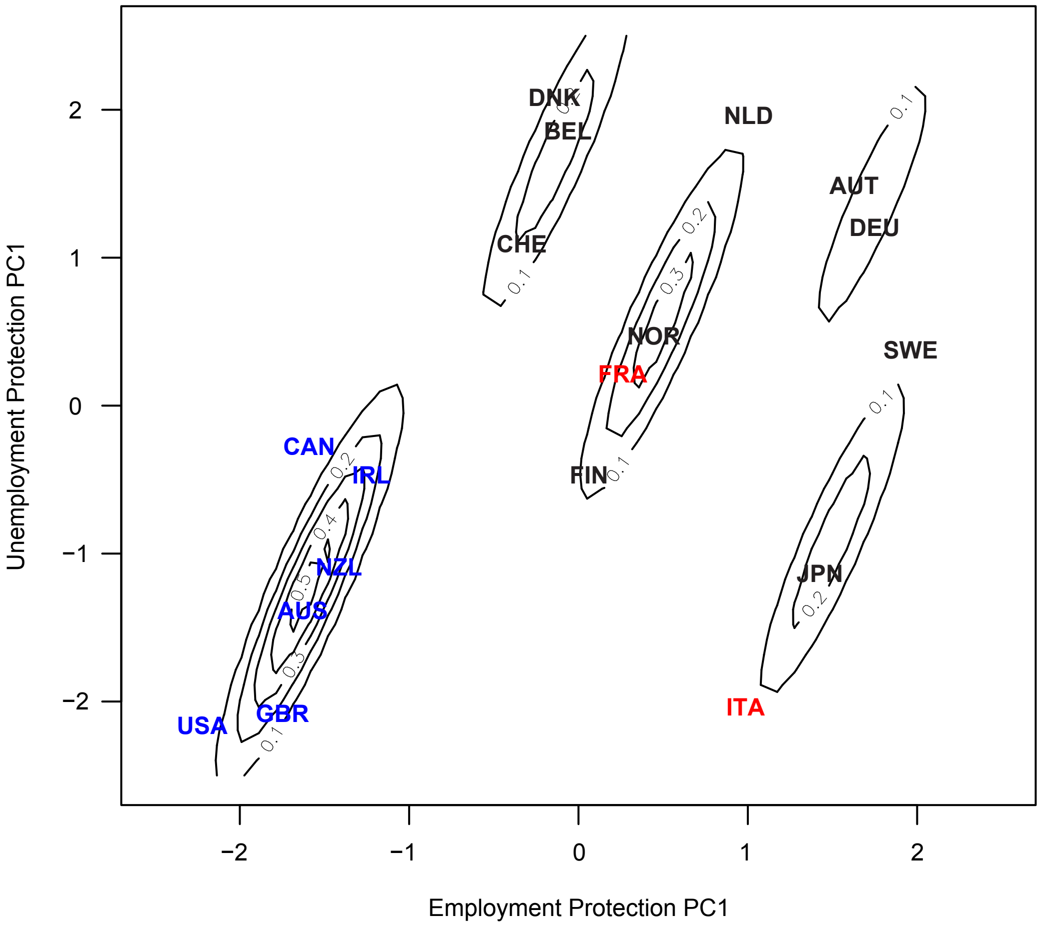
oped elsewhere. Wherever possible, we attempt to present results graphically in which clusters are identified by the density contours of the estimated cluster distribution. This has the advantage of visually displaying the uncertainty surrounding each point, but becomes impossible when clustering in more than two or three dimensions. In these cases we report tables of results. When evaluating clustering solutions, we frequently come upon situations in which the MMBC/model selection procedure identifies solutions with either only one cluster or more than six as the best-fitting model. We interpret either of these solutions as demonstrating the absence of any interpretable clustering structure in the data.

MMBC applied to pre-selected variables and indices

Clustering of welfare production regimes

Before turning to the dynamic analysis, we illustrate the MMBC approach on two static datasets. In this section, we apply MMBC to variables already identified as defining welfare production regimes. The data are those reported in Estévez-Abe, Iversen and Soskice (2001), Iversen (2005: ch. 2), and summarized in Figure 1. As a first step, we apply the variable selection algorithm to their original six variables: three variables on employment protection and three on unemployment protection, using collective dis-

Figure 3 Clusters of employment and unemployment protection



Note: Entries of the same color are classified in the same VoC category. Blue entries are LMEs, black are CMEs. and red entries are not classified or otherwise controversial.

missal protection as the sole employment protection measure selected. All three unemployment measures – net unemployment replacement rates, generosity of benefits, and definition of suitable jobs – have been used in the cluster analysis.[11] Table 3 displays the resulting country clusters. The BIC-maximizing MMBC algorithm chooses an ellipsoidal model with equal volume, shape, and orientation. It also identifies four clusters (and not two as with the VoC approach, or five as Figure 1 illustrates). Moreover, the country classifications do not mirror those of Iversen.

As an alternative to the heuristic classification from Figure1, we run the MMBC algorithm on the first principal component for unemployment protection and for employment protection.[12] The resulting clusters and their probability densities are displayed in

11 Interestingly, if all six of the original six measures are used in the cluster analysis, no clustering can be distinguished. We attribute this to the fact that we are estimating a model where $k = 6$ using only 21 cases.

12 Each of these principal components represents 60 and 69 percent of the variance for employment and unemployment protection, respectively.

Table 4 Clusters of corporate governance and labor relations

Country	Cluster	Uncertainty
AUS	1	0.00
CAN	1	0.00
ESP	1	0.00
AUT	2	0.00
BEL	3	0.00
ITA	3	0.00
GBR	4	0.00
USA	4	0.00
DNK	5	0.00
FIN	6	0.00
FRA	6	0.00
SWE	6	0.00
DEU	7	0.00
PRT	7	0.00
No. of clusters	7	
Variance decomposition	EEE	
BIC	–40	

Figure 3. While this analysis recovers the same major clusters as the visual method used in Iversen (2005) and Estévez-Abe, Iversen and Soskice (2001), some additional features are apparent. First, MMBC identifies five, not two, as the optimal number of clusters. Second, the probability densities provide us with an assessment about how certain one is about the country clusters. While Australia and New Zealand are close to the peak of the densities and thus represent the core of the "occupational/general skill" profile, we are less certain about the placement of the Netherlands, Sweden, or even Austria and Germany in one particular cluster. Belgium, the Netherlands, and Sweden are assigned to different mini-clusters than what others researchers have identified. Third, the ellipsoidal clusters that MMBC identifies are not possible under traditional clustering methods that are restricted to spherical cluster geometries.

Institutional complementarities in the macro-economy

In order to capture the theoretical core of the VoC argument, we now rely on the six indicators suggested by Hall and Gingerich (2004) to measure the institutional variation in corporate governance and in labor relations. We attempt to employ the same data as their study. This reduces the time period to one observation per country for 1990–1995 and, due to missingness on various indicators, fourteen countries (see Hall/Gingerich [2004: 11] for their data and sources). We concentrate on the MMBC analysis of the principal components (PCs) for the corporate governance and labor relations dimensions.[13] The variable selection procedure chooses the first and third PC of corporate governance and the first PC of labor relations for the analysis. They explain about 65 and 66 percent of the total variance, respectively. Note that the third PC provides more

13 MMBC on the original six variables generates clusters highly dependent on *G*, the upper bound for the number of clusters considered in model selection.

clustering information than the second one in this case. As Table 4 shows, the MMBC produces a classification of seven clusters. This result should be interpreted as a lack of structure in the data and indicates that countries cannot be grouped into LMEs and CMEs based on the operationalization of corporate governance and labor relations as employed by Hall and Gingerich (2004). In short, even for the core dimensions of production regimes, it is not possible to distinguish countries based on the quantitative indicators employed in the literature.

Data

For our dynamic analysis, we look to the extant literature on comparative capitalism to identify the variables purported to define the "three worlds" or VoC approaches. As mentioned above, there is an enormous number of dimensions along which countries vary, and several plausible measures for each dimension. Additionally, as the comparative capitalism literature has grown, numerous idiosyncratic indices and coding schemes have emerged. As we are concerned with what the underlying data can tell us about clusters, we avoid constructed indices and, whenever possible, variables derived from expert coding. Since we are interested in both the classification of controversial cases and the assessment of the stability of clusters over time, we privilege the measures that provide some sort of time series and that maximize cross-sectional coverage.

It is clearly debatable what the proper indicators of welfare regimes and VoC are and whether some indicators represent constitutive features of a system or outcome variables. We sidestep this theoretical discussion here and simply assume that previous research efforts have correctly identified some valid measurements of the two concepts. In our initial variable selection, we therefore rely only on measures that have been identified by the initial theoretical literature, as well as the subsequent attempts to empirically identify country grouping as discussed above. In short, we rely on the previous judgment of scholarly work when identifying variables characterizing welfare production regimes and VoC. The model selection step in our MMBC algorithm then identifies those variables providing the most clustering information.

We are concerned with the actions of governments and economic actors, so we focus on political-economic institutional, policy, and structure variables. In addition, the focus on time-series cross-sectional data and our reluctance to assume time-invariance of quantitative indicators obviously results in the omission of some variables that are claimed to be theoretically important. Among them are cross-shareholding measures, skill specificity, firm-bank relations, and inter-firm relations (e.g. measures of the density of supply chains).

Missing data and our initial variable selection

Table 9 in the appendix presents the variables we have identified from the VoC and "three worlds" literature. Our data are characterized by a high degree of missingness, confounding the already thorny problem of classifying a relatively small number of countries existing in a high-dimensional space. To get the most out of our analysis, we use multiple imputation techniques to generate ten complete datasets.[14] We then break the data into three disjoint time slices: 1980–84, 1990–94, and 2000–03. We break the data up in this way for three reasons: first, focusing on fairly restricted time slices is consonant with the strong notions of equilibrium institutions and complementarity that underlie both the "three worlds" and VoC approaches. Second, these windows are short enough to provide a snapshot but long enough to allow for some smoothing within the window. Finally, we allow for some time between slices, since institutions are purported to change slowly, if at all. Within each slice we take country averages for each variable. We therefore have 30 smaller datasets with 21 observations in each. We denote by $d_{m,t}$ the imputed data subset from imputation $m = 1,\ldots,10$ at time slice $t = \{\text{early, middle, late}\}$.

There is currently no method to propagate the measurement uncertainty represented by the cross-imputation variation into a mixture model and model selection algorithm. We attempt to make preliminary statements on clusters while also incorporating as much of the imputation-based uncertainty as possible. We recognize that our solution is suboptimal and discuss in the conclusion some ways in which future research might proceed in addressing this problem.

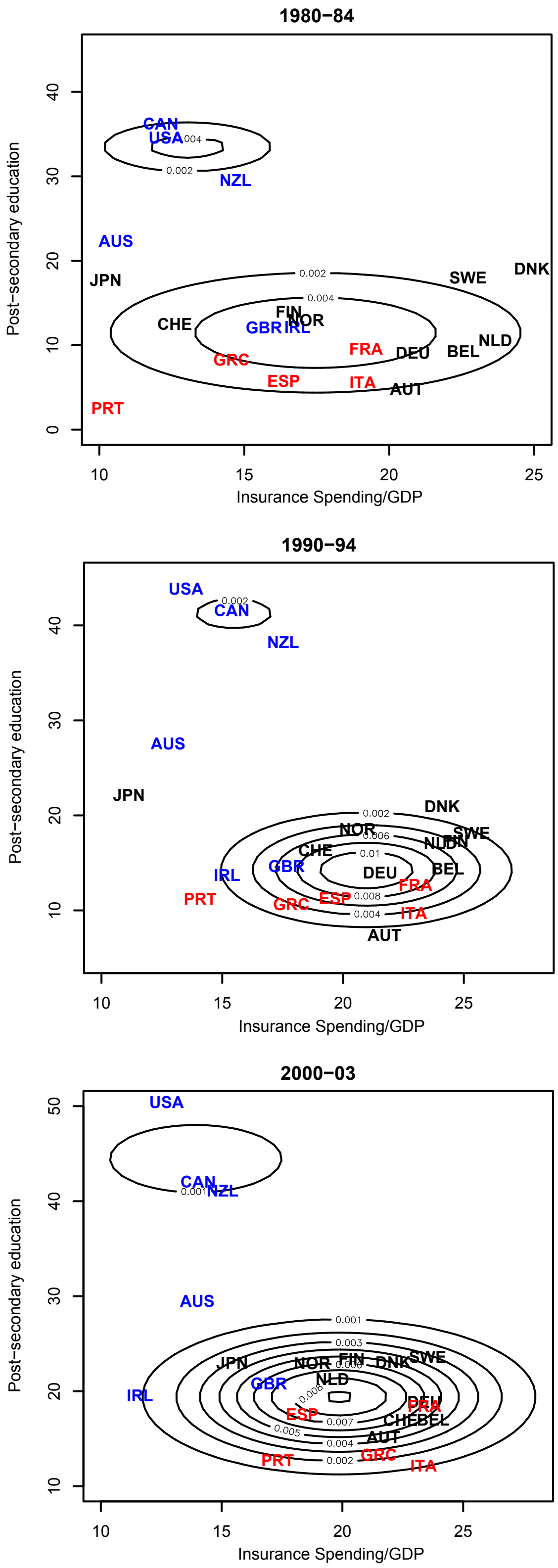
Specifically, we proceeded as follows: First, we conducted several exploratory variable-selection experiments across different $d_{m,t}$ to gather some idea as to what the most commonly selected clustering variables are. We then attempted to select from among these variables a subset that had the lowest cross-imputation variation (relative to their means) and at the same time represented the major concepts from the VoC literature. The variables selected here were percent of labor force with tertiary education, social security spending as %GDP, social insurance spending as %GDP, unemployment benefit generosity, pension generosity, unemployment replacement rate, restrictiveness of employment protection legislation, level of collective dismissal protection, proportion of those age 25 and over with post-secondary education, benefit replacement rate, benefit duration, the tax wedge, total R&D personnel per 1,000 people, and patents awarded per 1,000 people. We then took these variables and performed the variable selection exercise across all the $d_{m,t}$.

From the variable selection procedure, the following variables were selected most frequently (listed here in descending order of the frequency selected): social insurance spending as %GDP, post-secondary educational attainment, number of patents awarded

14 We used the *R* implementation of the Amelia software (Honaker/Blackwell/King 2006) for imputation.

Figure 4 Clustering in two dimensions using the two most frequently selected variables across time and imputations. The cluster assignments vary over time and do not coincide with the VoC classications.

Note: Countries with the same color text are classified into the same VoC groups.



per 1000 people, total R&D personnel per 1000 people, and pension generosity. The analysis presented below is the result of clustering performed on three datasets (one for each time slice), each of which is composed of the mean values across all imputed datasets for that time slice. While we recognize that this throws away important information about the variability of these estimates, there is no readily available better method by which to proceed: Limiting our analysis to only the variables or countries for which complete data are available is not a preferable solution, especially when there are so few cases available.

Clustering with variable selection

Here we present four cluster analyses in which we gradually alter the variables under consideration. We begin with two baseline analyses. In the first, we use only the two most commonly identified variables in the cross-imputation investigation described in the previous section: social insurance spending as %GDP and post-secondary educational attainment. In the second, we include the two variables mentioned and add to these patents, workers employed in basic R&D as proportion of the workforce, and pension generosity. Again, these variables are selected because they provide "more information" on country clusters and not because they are especially pertinent theoretically.

When clustering in only two dimensions, results are most easily viewed graphically. Figure 4 depicts contour plots describing the results across the three time periods. Text in the same color corresponds to the same VoC category.

Several things are immediately apparent. First, the number of clusters and the clustering solutions do not correspond to either the VoC or "three worlds" perspectives. While the United States, Canada, and New Zealand (LMEs all) are consistently grouped together, Great Britain and Ireland, also purported to be unambiguous LMEs, are at the core of the larger cluster that includes continental European economies for the early period. Australia and Japan are ambiguously classified and move between groups over the time periods. As the contour lines indicate, the spread around the clusters is generally fairly small, but it is greater for the Canada-New Zealand-United States cluster and largest for the Australia-Japan mini-cluster.

We extend the analysis by including more variables. Visualization becomes more difficult in six dimensions, so we report the results in Table 5. These results are largely consistent with what we see in the two-variable case: Both the number of clusters and cluster membership change over time. The United States, Canada, and New Zealand continue to be grouped together, but Australia, Ireland, and Great Britain are lumped with other groups and change group affiliations.

Table 5 Clustering results over time on the mean values of five variables from ten imputed data sets

Country	1980–1984	1990–1994	2000–2003
AUS	1	1	1
CAN	1	4	2
NZL	1	4	2
USA	1	4	2
ESP	2	2	1
GRC	2	2	1
ITA	2	2	1
PRT	2	2	1
AUT	3	2	1
BEL	3	3	1
CHE	3	3	1
DEU	3	3	1
DNK	3	3	1
NLD	3	3	1
SWE	3	3	1
FIN	4	3	1
FRA	4	3	1
GBR	4	2	1
IRL	4	2	1
JPN	4	1	1
NOR	4	3	1
No. of clusters	4	4	2
Variance decomposition	EEE	EEE	EEE
BIC	–285	–270	–249

Note: The number of clusters maximizing the BIC varies over time as does membership within clusters. The cluster results do not coincide with expert classifications.

Clustering within major substantive areas

The objection could be raised that we have not considered enough variables or that several variables have been used to measure the same underlying concept. From the literature we can identify two broad types of variables that purport to define the varieties of capitalism: labor market regulations and education/training. In the former we include average unemployment insurance replacement rate, level of collective dismissal protection, employment protection legislation, social benefit replacement rate, benefit duration, pension generosity, and the tax wedge. In the latter we include the percent of the labor force with tertiary education, proportion of the population over 25 with post-secondary education, number of patents awarded per 1,000 people, total R&D personnel per 1,000 people, and average years of schooling.

Employing the data from both groups, we utilize the variable selection algorithm with G ranging from 2 to 10. Recall that G is the maximum number of groups that the model selection algorithm considers when comparing competing models. As Table 6 indicates, training variables appear to provide more clustering information than labor market indicators. The number of patents per 1,000 people in the labor force, as well as the proportion of people with post-secondary education, are especially useful in clustering

Table 6 Selection of variables across labor market and skills/training variables

Variable	No. of times selected bythe algorithm (maximum times possible = 30)
Patents	16
Post-secondary eduction	13
Average years of school	12
Benefits duration	10
R&D personnel	10
Unemployment replacement	10
Tertiary education	8
Tax wedge	8
Unemployment generosity	8
Benefit replacement rate	7
Dismissal protection	2
Employment protection	2
Pension generosity	2

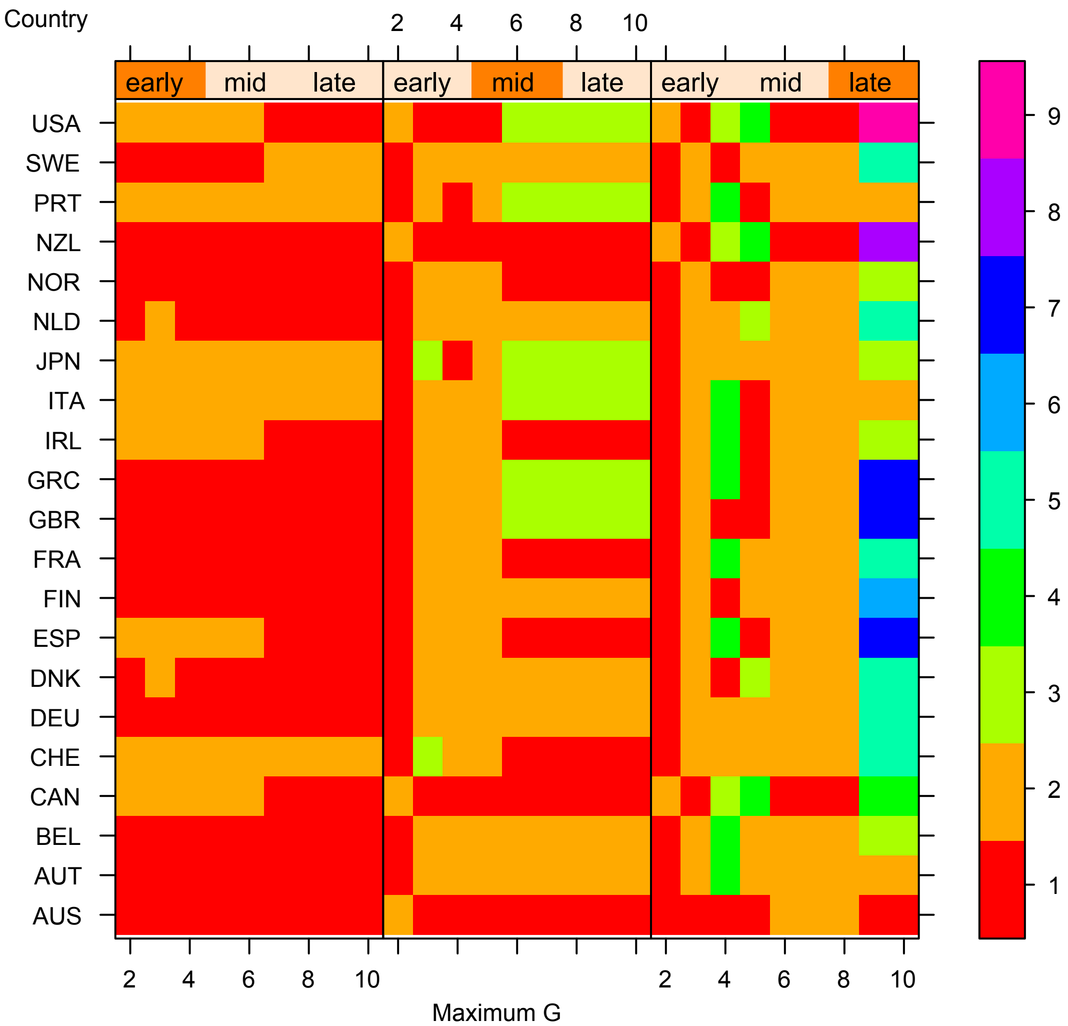
countries. Among the labor market institutions, the benefit duration and replacement rates are helpful for identifying clusters. Below we reveal how the cluster results turned out, based on these variables.

The following MMBC demonstrates how fragile the classification process within policy domains truly is. We employ the variables chosen by the selection algorithm for each time slice and conduct the MMBC using different values of *G* ranging from 2 (the theoretically proposed number of clusters) to 10. In Figure 5 we illustrate the results. For the early period, a two-cluster solution dominates. Yet as the number of maximum allowed clusters increases, the country classifications change. For the middle period, a three-cluster solution is dominant. Clustering in the most recent period is noisy. Here up to nine clusters are proposed, and sensible clustering therefore becomes impossible. There are two more features worth noting. First, when we force the MMBC to consider solutions with a maximum of two or three clusters, it yields that number. Second and more importantly, not a single pair of countries is clustered together throughout the three time periods and the various values for *G*. In short, Figure 5 shows that countries cannot be classified based on quantitative indicators of skills/training and labor relations over time.

What if we privilege the VoC classification by constraining the maximum number of clusters and pre-selecting some important variables? We set the maximum number of clusters to seven. Variable selection identifies three variables (unemployment replacement rate for a single worker, patents, and average years of schooling) for at least two periods.[15] We present results from MMBC using those three variables in Table 7. Country clusters once again vary over time, so that even in this very restricted case, classification is not consistent.

15 When all selected variables of each time period are employed, the MMBC cannot distinguish between countries.

Figure 5 Cluster results on training and labor institutions, based on the selection of G, for each time slice



Note: Each color represents a cluster number, so that similarly colored observations cluster together. If the countries were ordered in the same two clusters over time, the graphs would show a red-orange stripe.

As a last attempt, when each institutional domain is examined independently, average unemployment insurance replacement rate and the percent of the labor force with tertiary education appear to provide the most clustering information across all time slices. When using only these two variables, the observations indeed split into two clusters for each time period, as reported in Figure 6. In this two-cluster result, the United States, Canada, and New Zealand cluster together, while Australia moves into the CME category.

Table 7 Country clustering according to three key features of the labor market and skills/training regime

Country	1980–1984	1990–1994	2000–2003
AUS	1	1	1
CAN	1	1	1
DNK	1	1	1
IRL	1	1	2
NOR	1	1	1
NZL	1	1	2
SWE	1	1	1
USA	1	1	1
AUT	2	1	1
BEL	2	1	1
CHE	2	1	1
DEU	2	1	1
ESP	2	1	2
FIN	2	1	1
FRA	2	1	1
GBR	2	1	2
GRC	2	1	2
JPN	2	1	1
NLD	2	1	1
ITA	3	1	2
PRT	3	1	2
No. of clusters	3	1	2
Variance decomposition	EEE	XXI	VII
BIC	–0.32	13.76	15.27

Clustering with sampled country-years

As noted above, the VoC literature relies on a strong notion of equilibrium; the so-called institutional complementarities imply that the VoC classification should be time-invariant, or at least should change very slowly. Indeed, the major theoretical criticism of the VoC project has been its inability to provide insight into institutional dynamics (Crouch 2005; Deeg/Jackson 2007; Schmidt 2008).[16] As a final examination of VoC clustering, we propose a harder test of the strong equilibrium assertions found in the VoC approach. We interpret VoC's institutional stability assertion to imply empirically that country observations should be exchangeable across time periods for the purposes of clustering. Specifically, we construct 1,000 datasets in which each country observation is randomly sampled from one of the imputed datasets and one of the three time slices within that dataset. If VoC-style clustering is present in the variables we examine, this should have little appreciable influence on the clustering. This is not what we find. While two is the modal number of identified clusters, this only occurs 35 percent of the time. Across the 1,000 datasets and using the same variables employed in the analysis reported in Table 5, over one-third of the data sets yielded clustering solutions of either only one cluster or six or more. We interpret these values to mean that there is no way to discern a cluster pattern in the data. Figure 7 provides the distribution of clustering solutions in these sampled data.

16 However, Hall's recent work (Hall 2007 and Hall/Thelen 2009) responds to this criticism and outlines a more dynamic understanding.

Figure 6 Cluster results on the most important training and labor institutions, for each time slice

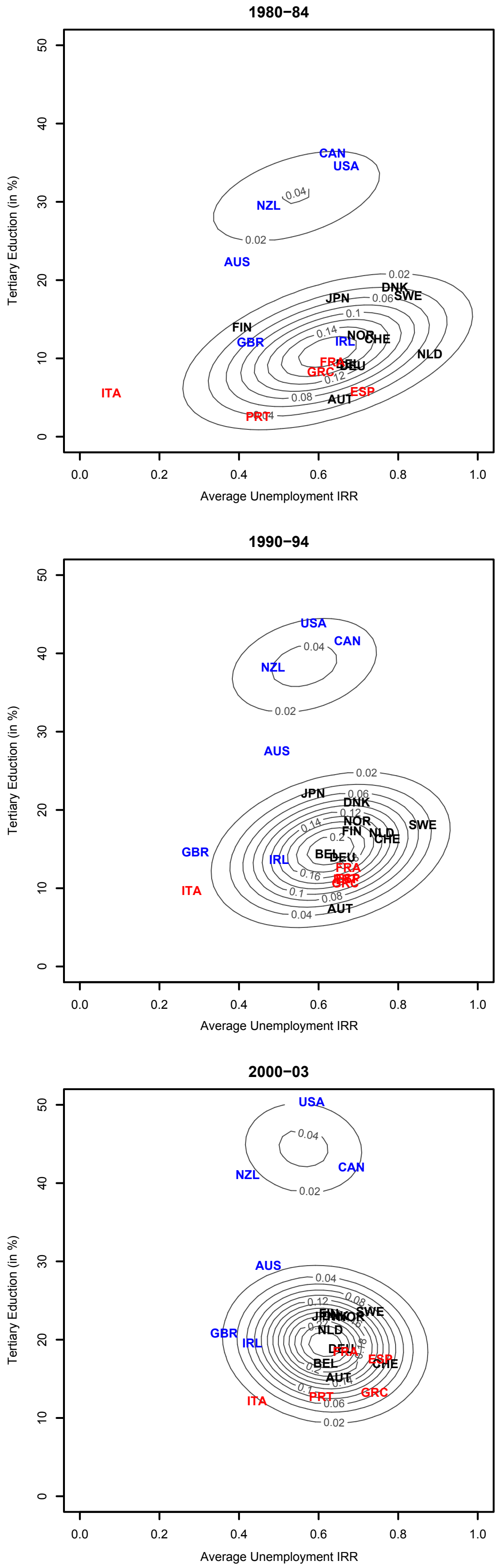
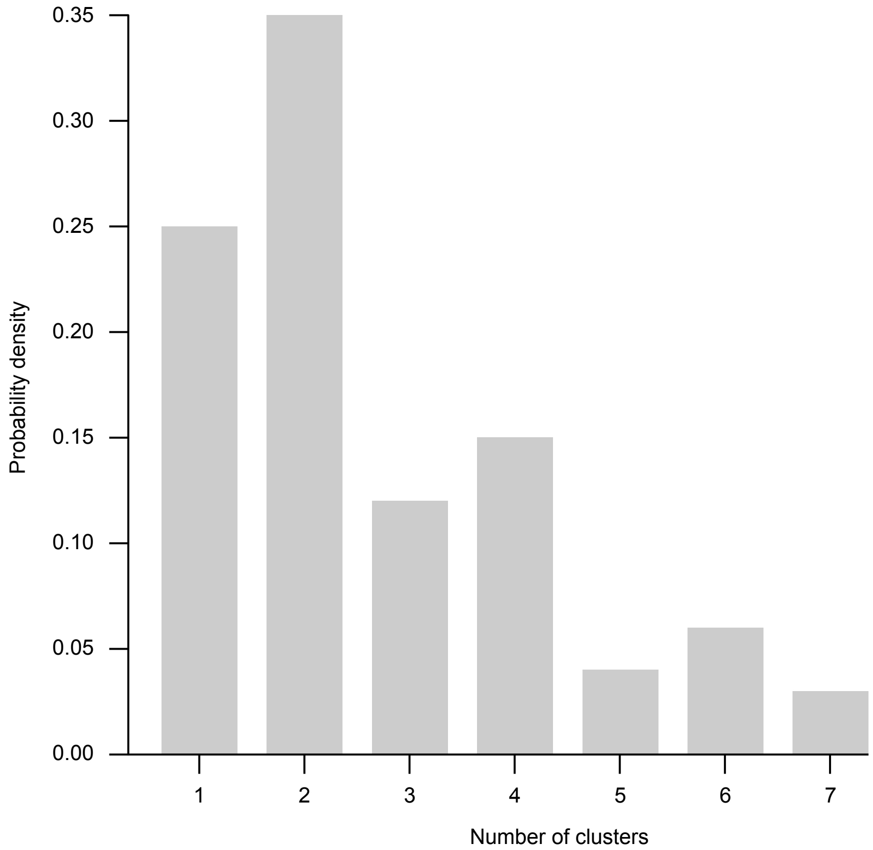


Figure 7 Number of identified clusters in datasets generated by randomly sampling country-observations across time periods



Two further methodological considerations

Multivariate normality

One important caveat is in order: We have not yet examined the multivariate normality assumption of the mixture models. Given the flexibility of the parameterizations considered, this is unlikely to cause major problems. Nevertheless, a possible robustness test would be to use a common transformation (log, root, standardization) and compare. Alternatively, one might use univariate or multivariate tests for normality (Aitchison 1986). If the data fail to conform to our distributional assumptions, transformation may be necessary. This awareness also leads to possible extensions for multivariate discrete data.

Multiple imputation and MMBC

One of the major limitations of this analysis is an inability to fully account for the uncertainty across imputed datasets. We believe that we have been able to partly address this uncertainty in variable selection, albeit in an ad hoc manner, by systematically comparing the selected variables across imputations. Our inability to address this uncertainty is more pronounced in the MMBC/model selection results from datasets of cross-imputation means, though we do not believe that incorporating imputation uncertainty would change our major conclusions about the overall lack of stable clustering coinciding with the VoC approach. We briefly speculate about two ways in which future research might proceed in order to develop methods to account for this uncertainty.

Suppose we have a dataset with N observational units over K dimensions with some observations missing at random. Let Q be the $q \times N \times K$ array of q imputed datasets. In each dimension $k \in \{1,\ldots,K\}$ we therefore have q observations for each unit $i \in \{1,\ldots,N\}$. Denote by $\mathbf{q}_i^k$ the vector of values for unit i along dimension k. The elements of $\mathbf{q}_i^k$, under mild conditions, follow a t distribution with parameters (ξ_k, σ_k^2) (Little/Rubin 2002). We can recover unbiased estimates $\hat{\xi}_k$ and $\hat{\sigma}_k^2$ from the mean and variance of $\mathbf{q}_i^k$. This suggests that one way to proceed is to view the imputation-clustering problem as a hierarchical model, in which each observation is multivariate-t with parameters estimated from the imputation results. From these distributions we can then sample data points and estimate the mixture model generated. Important assumptions will have to be made about the covariance structure for the ξ_k.

An alternative though possibly complementary way of proceeding might relax the notion that there exists a unique point measurement for unit i on dimension k. Rather we can consider each observational unit as defined by a *region* in k-dimensional space, specifically by the convex hull of the data Q_i where Q_i is a $q \times k$ matrix of values for unit i. We might then use the centroids of these N regions as observations on which to estimate mixture-model results and then characterize the proportion of the density from cluster g that falls within the region defined for unit i. In this way we could compare the relative probabilities of region i coming from cluster g or h. Neither of these solutions is likely to be computationally trivial and will certainly be difficult to implement in situations with only 21 observational units, as we have here.

4 Discussion and conclusion

In the analysis presented above, we have attempted to investigate the clustering pattern among 21 OECD democracies across three time periods using variables identified in the literature as important for defining VoC clusters. We find that both the clusters identified and their stability do not coincide with the expectations from the literature. Indeed, stable country clusters are not prevalent in the two replication datasets presented in Section 3 as well as in the large cumulative data set (Section 4).

The rationale for the two replication exercises was a desire to keep theoretical concepts and operationalization as close as possible. We employed a large number of variables generally identified in the literature in order to (1) incorporate additional functional attributes of both theories; (2) identify variables that provide “clustering information” via a model selection procedure; and (3) assess the equilibrium notion of the welfare regime and VoC theories. By relying on both strategies, we strived to achieve a close match between theory and operationalization and to identify the variables that provide the most information on clustering. A caveat regarding the cumulative dataset and the reliance on model-based clustering might be that the distance between some of the employed variables and the theoretical core of the welfare state regimes and VoC approaches would become too great. Neither strategy, however, turned out to be successful in producing stable country clusters conforming to VoC expectations.

While the results of our analysis are problematic for the strong notions of institutional complementarity and stickiness in the VoC literature, we do not claim to have “disproved” the varieties of capitalism project or to have uncovered the definitive clustering solution in the data; far from it. Instead, we have three goals: first, and most directly relevant to researchers, our results show that these data are not sufficiently structured to productively employ these heuristic typologies as indicator variables in the regression analysis that is the bread and butter of empirical political economy. Using these categories in TSCS analysis, where they most frequently appear, is even more problematic, as the cluster patterns identified vary significantly across time. We also hope to have clarified the relationship between the theoretical notions defining clusters and our ability to discern these clusters in noisy data. In so doing, we hope to prevent researchers from engaging in the circular reasoning implied by using typology-derived indicators to “explain” other variables previously used in defining the original typologies.

The second contribution of this article is in applying model-based clustering and variable selection to clarify a substantive debate in comparative political economy. By starting with the assumption that the data are the result of a mixture of multivariate Gaussian densities, we are able to ground cluster analysis within probability theory. With the help of approximate Bayes factors and a suitable search algorithm, we are able to provide better estimates in the number of clusters, their shape, and their composition than have been achieved using previous methods.

On the theoretical level, our findings reinforce the fact emphasized in the major VoC works: The CME-LME division is meant to characterize two ideal-typical cases that may help us understand real-world political economies. The extent to which these constructs can help will depend on the ability of researchers to identify specific institutional linkages and the important agents acting within them. From there we can more constructively evaluate the existence and importance of “institutional complementarities” in explaining apparently robust differences in political economic structure and outcomes among rich democracies. This exercise has been most fruitful to date in the fields of monetary policy and wage-price bargaining (Franzese 2001; Iversen 1999), and the insights drawn from there are now being extended into discussions of skills and skill acquisition in different labor markets (Mares 2003; Thelen 2004). We hope to reorient the VoC literature away from simple typologies and toward a focus on the theoretical arguments that underpin the discussion of the CME-LME division.

Similarly, Esping-Andersen is now most well-known for his assertion of the "three worlds," not for the historical arguments based on class interests and the emergence of differing party systems that he used to generate his typology. We hope that this paper will serve to rejuvenate research into the underlying theoretical argument he presented rather than to serve further borrowing of his typology. Important work in this area is already emerging (Cusak/Iversen/Soskice 2007; Iversen/Soskice 2001, 2005).

In conclusion, this paper broadens the appeal of mixture-model clustering tools in the social sciences by applying them to the substantive problem of clustering among rich democracies. Specifically, we have empirically examined the existence and stability of Esping-Andersen's "three worlds" approach and the varieties of capitalism clusters of coordinated and liberal market economies. We find that the clusters of countries asserted to exist in the literature are not robust in the face of mixture-model tools and are not stable over time. As a result, we recommend that researchers do not use cluster membership as indicator variables in regressions, particularly with time-series cross-section data. We also caution qualitative researchers in their use of the CME/LME categories for case selection and other research design decisions. Rather than emphasizing easy-to-remember typologies and empirical clusters, we hope comparative political economists of all methodological persuasions will sharpen their focus on the theoretical arguments about strong complementary relationships between certain institutions, policies, and organizational structures. Outside of the wage-price bargaining literature, these linkages are under-specified, under-formalized, and in need of much improved cross-national measurement.

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Data Appendix

Table 8 Data and sources – Replications

Variable	Description	Source
Iversen (2005) and Estevez-Abe et al. (2001)		
Employment protection legislation	Index of the "restrictiveness" of individual hiring and firing rules	Iversen (2005: 47)
Collective dismissal protection	Index of restrictions on collective dismissal	Iversen (2005: 47)
Company-based protection	Measure of company-level employment protection	Iversen (2005: 47)
Net unemployment replacement rates	Net unemployment replacement rates for 40-year-old representative worker	Iversen(2005: 50)
Generosity of benefits	% of GDP paid in unemployment benefits divided by % of unemployed in total population	Iversen (2005: 50)
Definition of suitable jobs	Index of restrictions on the definition of suitable jobs	Iversen (2005: 50)
Hall and Gingerich (2004: 11)		
Shareholder power	Composite measure of legal regulations between ordinary shareholders vis-à-vis managers and dominant shareholders	La Porta et al. (1998)
Dispersion of control	Number of firms that are widely held relative to the number with controlling shareholders	La Porta/Lopez-de Silanes/ Shleifer (1998: Table 2)
Size of stock market	Market valuation of equities on the stock exchange as percentage of GDP	Nestor/Thompson (2001)
Level of wage coordination	Level at which unions coordinate wage claims and employers coordinate wage offer	Layard/Jackman/ Nickeil (1991: 52)
Degree of wage coordination	Degree of (strategic) wage bargaining coordinated by unions and employers	OECD (1997: 71)
Labor turnover	Number of employees who had held their jobs for less than one year as a percentage of all employees	OECD (1997: 138)

Table 9 Variables collected für multiple imputation and their sources

Variable	Description	Source
Bargaining coordination	Kenworthy's five-point scale	Kenworthy (2003)
Union density	Adjusted union density	Visser (2006)
Trade restrictions	Amended country fixed effects of gravity model	Hiscox and Kastner (2006)
Adjusted coverage	Adjusted coverage for union contracts	Golden/Wallerstein/Lange (2002)
Part-time employment	Part-time employment as % of total employment	International Labour Organization (2005)
Part-time female employment	Female share of part-time employment	International Labour Organization (2005)
Service sector employment	% employment in service sector	International Labour Organization (2005)
Service sector female employment	% of service sector employment that are female	International Labour Organization (2005)
Hours worked	Total hours worked per person	International Labour Organization (2005)
GDP per hour worked	GDP per hour worked in 1997 $US, manufacturing	International Labour Organization (2005)
Labor force education	% of labor force with tertiary education	International Labour Organization (2005)
Capital controls	Capital account liberalization on a scale of 0 to 100	Quinn/Inclan
Social expenditure % GDP	Total public social expenditure as % of GDP	OECD (2004)
Health expenditure % GDP	Public health spending as % of GDP	OECD (2004)
ALMP expenditure % GDP	Active labor market policies as % of GDP	OECD (2004)
Pension expenditure % GDP	Old age/pension as % of GDP	OECD (2004)
Survivors' expenditure % GDP	Survivors benefits as % of GDP	OECD (2004)
Disability expenditure % GDP	Disability spending as % of GDP	OECD (2004)
Unemployment expenditure % GDP	Unemployment spending as % of GDP	OECD (2004)
Insurance	Sum of unemployment, labor market, survivor, old age, health expenditures	own calculation
Unemployed.lfs	Unemployed persons, in thousands from household surveys	International Labour Organization (2005)
Unemp.rate.lfs	Unemployment rate from Labor Force Survey	International Labour Organization (2005)
Unemployed.reg	Registered unemployed persons, in thousands	International Labour Organization (2005)
Unemp. rate, reg	Unemployment rate for registered unemployed	International Labour Organization (2005)

Table 9, continued

Population	Population, in thousands	International Labour Organization (2005)
Labor force	Labor force, in thousands	International Labour Organization (2005)
Elderly	% of population over 64 years	World Bank (2006)
Unemployment generosity	Unemployment expenditure per GDP divided by % of unemployed persons of the population)	calculation following Iversen (2005)
Pension generosity	Old-age pension expenditures per GDP divided by % of population over 64 years	calculation following Iversen (2005)
CBI	Central bank independence	Cukierman et al. (1992); Adolph (2004)
ENPP	Effective number of parliamentary parties	Golder (2005)
District magnitude	Electoral district magnitude	Golder (2005)
Employment protection	Legislative restrictiveness of employment protection	OECD (2004: 117–119)
Dismissal protection	Collective dismissal protection	OECD (2004: 117–119)
UE rate	Unemployment replacement rate for single persons	Scruggs (2004)
UEF rate	Unemployment replacement rate for families	Scruggs (2004)
No education	No schooling	Barro/Lee (2000)
Primary education	Primary schooling	Barro/Lee (2000)
Secondary education	Secondary schooling	Barro/Lee (2000)
Post-secondary education	Post-secondary schooling	Barro/Lee (2000)
School years	Average years of schooling	Barro/Lee (2000)
Secondary enrolment	Enrolment total secondary. Public and private. All programs. Total	UNESCO (various years)
Secondary general	Enrolment total secondary. Public and private. General programs. Total	UNESCO (various years)
Secondary vocational	Enrolment total secondary. Public and private. Technical/vocational programs. Total	UNESCO (various years)
Secondary public	Enrolment total secondary. Public. All programs. Total	UNESCO (various years)
Secondary public general	Enrolment total secondary. Public. General programs. Total	UNESCO (various years)
Secondary public vocactional	Enrolment total secondary. Public. Technical/vocational programs. Total	UNESCO (various years)
Tertiary enrolment	Enrolment total tertiary. Public and private. Total	UNESCO (various years)
Tertiary enrolment in 5a	Enrolment tertiary, university level, research-oriented (5A). Public and private. Total	UNESCO (various years)
Tertiary enrolment in 5b	Enrolment tertiary, professional training (5B). Public and private. Total	UNESCO (various years)
Benefit replacement rate	Benefit replacement rates	Nickeil et al. (1999)
Benefit duration	Benefit durations	Nickeil et al. (1999)
Tax wedge	Tax wedge	Nickeil et al. (1999)

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