

How Many Capitalisms?

A cluster analysis approach to the Varieties of Capitalism debate

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March 7, 2010

1 Introduction

The Varieties of Capitalism (VOC) literature hypothesizes that the advanced capitalist economies naturally group into two unique clusters, whose institutional configurations represent competing, optimal solutions to a range of coordination problems in modern capitalism. This hypothesis has strong implications for policy choices and outcomes in the advanced capitalism economies. However, the hypothesis itself has faced few strong tests of two major propositions: first, that these clusters are the correct ones given the quantitative measures available for measuring capitalist institutions; and second, that the complementarity between institutions inside these clusters can be inferred from the data. Indeed, most of the canonical work in the Varieties of Capitalism literature has examined only one or two of the suite of institutions; or has looked at only the archetypal countries used in the VOC case studies.

This paper proposes an two improved tests of these hypotheses: first, can the VOC cluster configuration be recovered from the quantitative measures, under a reasonably weak set of assumptions; and second, if the VOC clusters can be recovered, are they the optimal ones even under their own assumptions about specification and data sourcing?

Results of both tests suggest that while the VOC cluster configuration is superficially correct, it masks persistent diversity in the capitalist economies that can be recovered from the empirical data. Use of different metrics to test the “quality” of clusters of the advanced industrial economies suggests that other paradigms may be better supported even when using the covariates specified by the VOC model. Tests of the hypotheses at different points through the 1990s also show that the similarities and differences between the advanced capitalist economies continue to evolve, producing variation in natural clustering over time.

2 The Varieties of Capitalism

The Varieties of Capitalism (VOC) project [Hall and Soskice \(2001\)](#) attempts to ground the analysis of political economy and institutions in an analysis of the behavior of the modern firm. In its view, firms face a core set of coordination problems when working with labor, finance, and government regulation. Those coordination problems include how the firm attracts capital and maintains the confidence of its financiers; how it attracts labor and convinces labor to adopt skills appropriate to the job; how it coordinates with other firms to manage production chains and negotiate with labor unions; and how it plans for changes to the structure and regulation of product markets.

In the VOC paradigm, two optimum equilibrium solutions to this network of coordination problems exist. One, the Liberal Market Economy, manages coordination primarily through the market, with price functioning as the primary information conduit. Firms in LMEs conduct finance predominately through market-based structures of corporate governance; employ labor with general skills; have few restrictions on their hiring and firing behaviors; engage in radical innovation to seek decisive advantage in product markets; and rely on explicit legal contracting for inter-firm relations.

The other, the Coordinated Market Economy (CME), manages coordination through non-market mechanisms of concertation. Firms in CMEs seek finance through close relationships to banks; employ labor with firm-specific skills, which cannot easily be fired; engage in incremental innovation aimed at continuous improvement of goods in established markets; and conduct inter-firm relations through information-dense networks reliant on reciprocity more than explicit contracting. For the set of canonical VOC countries, there are 12 CME countries and 6 LME countries, distributed as shown in [table 1](#).

The VOC argument makes no assumption about the relative superiority of these two models. Instead, it suggests that either represents an efficient solution to this coordination problem. Moreover, mixed countries—those that combine market and non-market forms of coordination—may struggle to achieve the same levels of economic performance as more homogeneous economies, due to inefficiencies resulting from heterogeneity.

While this very strong set of hypotheses has proven extremely attractive to analysts of political economy, it has come under significant criticism for four major problems. First, few if any analysts believe that the firm-centric core of the VOC framework has any basis in history and thus anything to say about why a country might have become one or the other kind of economy. Second, the framework may suffer from too much attention to the state of the world as it existed in the late 1990s, when its archetypal economies—the United States and Germany—seemed to anchor two different forms of economic behavior. Third, its dual-equilibrium arguments depend heavily on the assumption of a particular definition of complementarity between different institutional forms; but it's not at all clear that these should take precedence over other forms of complementarity that would allow for greater institutional heterogeneity. ([Crouch, 2005](#)) Finally, the attempt to include all the major industrial economies in a single framework has led to accusations that par-

Country	VOC Classification
United States	LME
United Kingdom	LME
Australia	LME
New Zealand	LME
Rep. of Ireland	LME
Canada	LME
France	CME
Germany	CME
Italy	CME
Japan	CME
Sweden	CME
Denmark	CME
Norway	CME
Belgium	CME
Netherlands	CME
Switzerland	CME

Table 1: VOC Country Assignment

ticularly unique economies like Japan or France have been shoehorned into a model, and that information is lost in the process.

These critiques have generated a variety of attempts to test the VOC hypothesis. Few if any of them have used explicitly quantitative means. This is consistent with the VOC literature itself, which despite its very strong claims to cross-institutional conformity has usually considered only one or two institutions at a time. Even the major exception to this trend, [Hall and Gingerich \(2009\)](#), emphasized the labor relations-corporate governance relationship. Finally, most of these quantitative studies have attempted to study the effects of the clustering, rather than the validity of the clustering itself.

This omission is jarring as the VOC is only the latest in a long series of attempts to discover internal groupings of capitalist economies. [Shonfield \(1965\)](#) found three different groupings (liberal, statist, and conservative). [Esping-Andersen and Esping-Andersen \(1990\)](#) argues that the welfare state is the determining institution, and came in three variants (liberal, conservative, and egalitarian). In his analysis of European economic stagnation, [Sapir \(2005\)](#) agreed, but found four models: Mediterranean, Continental, Anglo-Saxon, and Scandinavian. Each of these attempts to group the advanced capitalist economies emerged from a specific model about the interaction between the state and the economy, and a specific idea of what constituted the core set of economic problems that required resolution.

3 Methodology

This paper will test the VOC clustering hypothesis, and in doing so attempt to adjudicate between several of these alternative models. It will do so in two ways. First, cluster analysis will be applied to the covariates specified by the Varieties of Capitalism framework, to determine if the VOC clusters can be recovered from the quantitative institutional measures specified by the VOC model. This analysis will then be compared to similar analysis for the Shonfield and Sapir models (specifying three and four clusters, respectively) via measures of cluster “quality.”

Second, matching methods will be used to test the implicit VOC hypothesis that at an individual country level, CME countries will prefer to match to other CMEs, and LMEs to LMEs. The individual matches in this stage may provide greater insight into the underlying heterogeneity of the two-cluster hypothesis. If, for instance, the matches persistently favor geographical proximity (i.e., Germany is always matched to Austria but rarely to Japan, another CME country) it would suggest that the micro-structure of the political-economic landscape is lost in the dichotomous VOC model.

3.1 Cluster analysis

Cluster analysis attempts to discover from a set of observations the natural groupings of observations on the basis of similarity across a set of covariate measures. Cluster analysis requires selection of three things: the clustering algorithm, the distance metric, and the data normalization process. For this study, these three are, in order, medoid clustering with Euclidean distances based on de-meaned covariates normalized to their standard deviation.

Medoid clustering operates via an iterated algorithm that attempts to construct clusters with maximum dissimilarity. It begins with a set of metoids, or cluster centers. Other observations are assigned to clusters around those centers, based on some distance metric. From these clusters, the medoid is swapped with the other members of the cluster until a medoid that minimizes the average distance between the medoid and all cluster members is found. The clustering is then repeated with these new medoids. This algorithm iterates until it settles on an equilibrium with a stable set of medoids.

The covariates listed above were normalized by de-meaning the data for each covariate by year, and dividing by the standard deviation of the covariate. That produced data scaled as the number of standard deviations each observation was from the mean. From this data, the Euclidean distance between each pairwise set of observations was computed. Covariates were weighted in this calculation according to the economic domain they represented. For instance, if four covariates each measured corporate governance, then each was given a 0.25 weight in the distance calculation. This process generated 10 distance matrices, one for each year between 1991-2000, containing the pairwise distances between all country observations for that year.

Medoid clustering was done using the `pam` clustering algorithm in R. Three different models were run on each year of data. The VOC model specified the starting cluster medoids as the United States and Germany, and grouped the observations into two clusters. The Shonfield model specified the US, Germany, and France as the starting medoids and generated three clusters. Finally, the Sapir model used the US, Germany, Italy, and Sweden as starting medoids and generated four clusters.¹

The average silhouette width was used to measure cluster quality. Silhouette width is calculated for each cluster in a given `pam` output as shown in equation 1. Here, b_i = minimum distance between observation i in cluster k and all other clusters $C_{!k}$; and a_i = average within-cluster difference between observations. Thus “better” clusters will have higher s_i if $b_i \gg a_i$ (that is, between-cluster distances are much greater than within-cluster differences).

$$s_i = \frac{b_i - a_i}{\max(a_i, b_i)} \quad (1)$$

For each `pam` model-year, the average of all s_i was computed as a measure of the overall quality of the clusters in that model-year. Figure compares the resulting average silhouette widths. With the exception of 1991, the Sapir model of clustering, starting from four centers and generating four clusters, produced higher-quality clusters. Note that this would not have been the case had the Sapir model merely subdivided already homogeneous VOC clusters into smaller groups: in that case, the average silhouette width would not have changed. Instead, here the larger number of smaller clusters appears to add information to the clustering outcome.

Under the `pam` algorithm, the final medoids need not correspond to the starting medoids, given the swap process that is an inherent part of the algorithm. The VOC framework implies that the medoids in a two-cluster framework should be the United States and Germany. But as table 2 shows, this was not the case. Indeed, Australia and Canada were the dominant “LME” medoids, while the Netherlands was the dominant “CME” medoid. Furthermore, in none of the three models was the US ever a medoid or cluster center; and in both the 3- and 4-cluster variants was Germany separated from another stereotypically “conservative” economy, the Netherlands.

Thus the VOC clusters could be recovered in part from the specified VOC covariates; but those clusters did not optimize cluster quality and appear to have obscured information about heterogeneity in the country sample. Where did the VOC countries end up, then, if the two-cluster model was incorrect? Figure 2 shows the proportion of CME countries in each cluster-year across the three different models. The figure makes three things clear. First, there is persistent heterogeneity within clusters across all cluster-years and models; no specification results in perfect partitioning between CME and LME countries.

¹Note that Italy was the only country in the data set representing Mediterranean economies from Sapir’s framework. The other three Mediterranean economies—Spain, Portugal, and Greece—did not have the necessary data to include them in the data set.

Table 2: Count of medoids by country for each model across all model-years.

	Country	Ct-VOC	Ct-Shon	Ct-Sapir
1	Australia	5	6	6
2	Austria	1	2	3
3	Belgium	0	0	0
4	Canada	5	4	4
5	Denmark	0	0	0
6	Finland	0	0	0
7	France	0	0	0
8	Germany	1	8	7
9	Ireland	0	0	0
10	Italy	0	0	1
11	Japan	0	0	2
12	Netherlands	8	8	8
13	New Zealand	0	0	6
14	Norway	0	0	0
15	Sweden	0	2	2
16	Switzerland	0	0	0
17	United Kingdom	0	0	1
18	United States	0	0	0

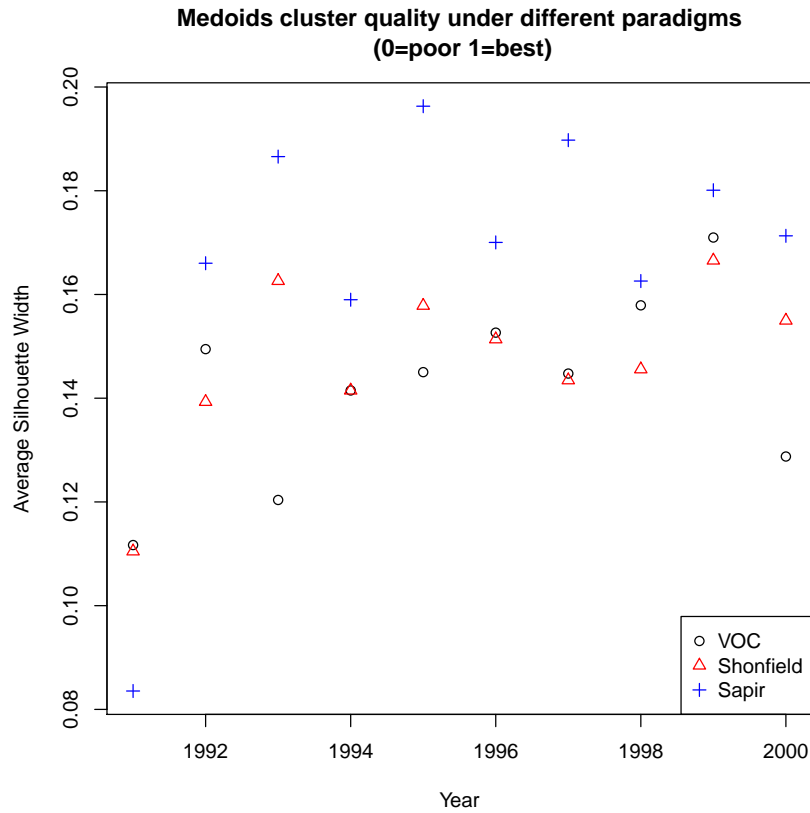


Figure 1: Average silhouette width by model-year

Second, homogeneous CME or LME clusters are much more common in more disaggregated specifications (the Shonfield or Sapir models) than in the VOC framework. Third, no homogeneous LME clusters appear in 2- or 3-cluster models. In the 4-cluster model. When they do appear, those clusters are comprised of New Zealand and the United Kingdom in five of six cases.

In conclusion, a medoid clustering approach to country-year data finds that the Varieties of Capitalism clusters cannot be perfectly recovered from the Varieties of Capitalism covariates; that the 2-cluster model around CME/LME medoids tends to optimize around medoids that are not the archetypal VOC LME and CME countries; and that the 2-cluster model obscures important variation in the clusters that appears in the 3- and 4-cluster models. This data is consistent with those critiques of the VOC that suggest that it throws out information about cross-national variation that can provide more analytic purchase on the variation of capitalist economies.

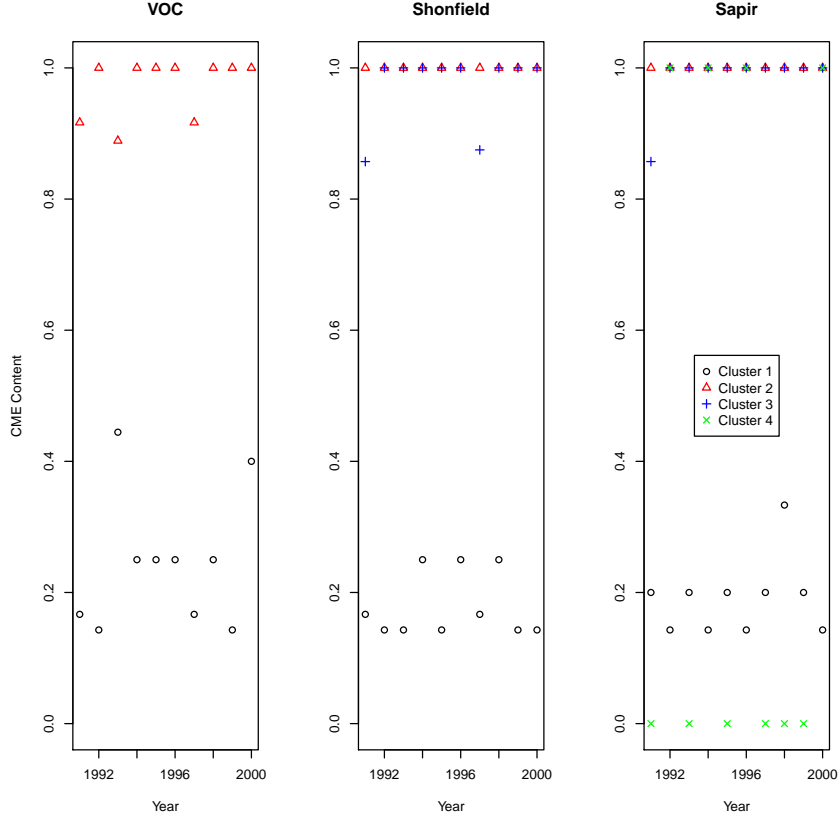


Figure 2: CME proportion by cluster-year across three paradigms

3.2 Matching

Matching methods attempt to balance the joint distribution of the observed covariates between two groups (treatment and control). Their rationale derives from the experimental principle of randomization as a means to make causal inferences about the effect of a treatment. Under successful random assignment of individuals to treatment, the treatment and control groups are exchangeable in expectation. That is, there is no systemic relationship between some unobserved characteristic and the receipt of treatment that would confound measurement of an externally valid treatment effect.

For the purposes of this paper, the matching algorithm is used to find pairs of countries as similar as possible as measured simultaneously across a set of covariates that represent their institutional characteristics. In this case, the treatment/control groups can be treated as two different samples from the same population, which have some unobserved CME/LME attribute. The set of matches between those samples represents an attempt

to recover that attribute. This can thus be interpreted as a test of whether countries assigned to a given category in the VOC framework naturally pair with countries in that same category.

Two hypotheses guided the matching analysis:

1. The quality of the matched data sets will improve as the “treatment” and “control” groups increase in heterogeneity. That will provide more chances to match CME:CME and LME:LME. Quality will be measured as the level of balance in the matched data set.
2. Selecting the best matched data sets from among all possible matches will result in data sets where CME:CME and LME:LME pairings dominate

Since the canonical VOC clustering divides countries into groups of 12 CME and 6 LME countries, the 12:6 split was chosen for the ratio of the size of the treatment and control groups. There are $\binom{18}{12}$ ways to pick 12 countries from a list of 18, equal to 18,564 possible ways to create two groups with the same number of members as the VOC classification. One of those groups will perfectly replicate the VOC sorting, with 12 CME countries in one group and 6 LME countries in the other. The remaining 18,563 possibilities have heterogeneous mixtures of LME and CME countries in each group.

To test Hypothesis 1, I use the `GenMatch()` algorithm in the `Matching` package for R. It takes as covariates the propensity score, calculated using logistic regression, and the set of covariates themselves. Both propensity score and Mahalanobis distance matching are used to determine which of the countries from the group of 12 best match each of the countries in the group of 6, and vice-versa. This is done for each of the 18,563 realizations of the assignment of countries to groups.² The quality of the matched groups is measured by the t-test for the difference in means, and the bootstrapped Kolmogorov-Smirnov test (Abadie, 2002) for difference in covariate distribution. The algorithm outputs a set of matched pairs and the balance measures that reflect the quality of the matches.

The matching algorithm outputs a set of paired data sets that have optimum balance across the joint distribution of covariates. It can thus be thought of as a set of best possible pairings of countries from the synthetic treatment and control groups, where “best” is defined as most similar as measured by differences in means and distributions of the descriptive covariates. Under the VOC hypothesis, that should occur most often in matched data sets with LME:LME pairs and CME:CME pairs.

The algorithm output 18,563 data sets. Quality of the matches was evaluated by checking the balance statistics against a threshold value representative of good balance. T-tests

²Computation of matching algorithm took approximately 4 minutes for each of the realizations, or a total of 620 hours. These runs were parallelized over 18 compute nodes using the `snow` package for R, leading to an approximate compute time of 34 hours. Special thanks go to the UC Berkeley Political Science department and Broadcom corporation for financial and material support for the compute cluster.

for the difference in means and Komolgorov-Smirnov tests for the difference in distributions were checked against a threshold p-value of 0.1. The set of matched data sets was subsetting to include only data sets with a count of p-values for the t and KS tests below the median for the entire data set.

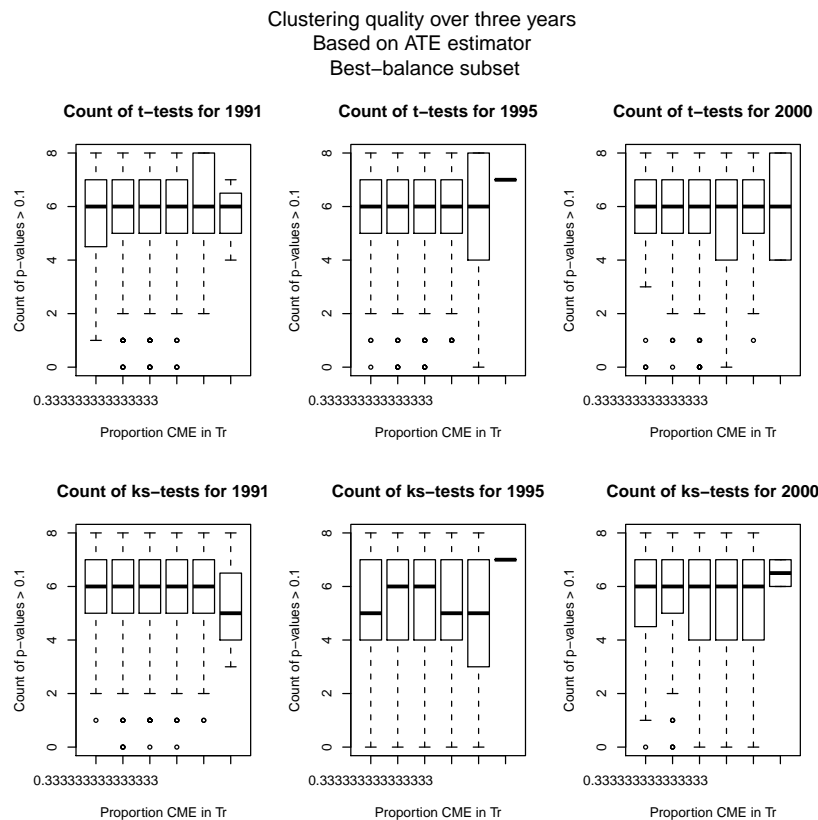
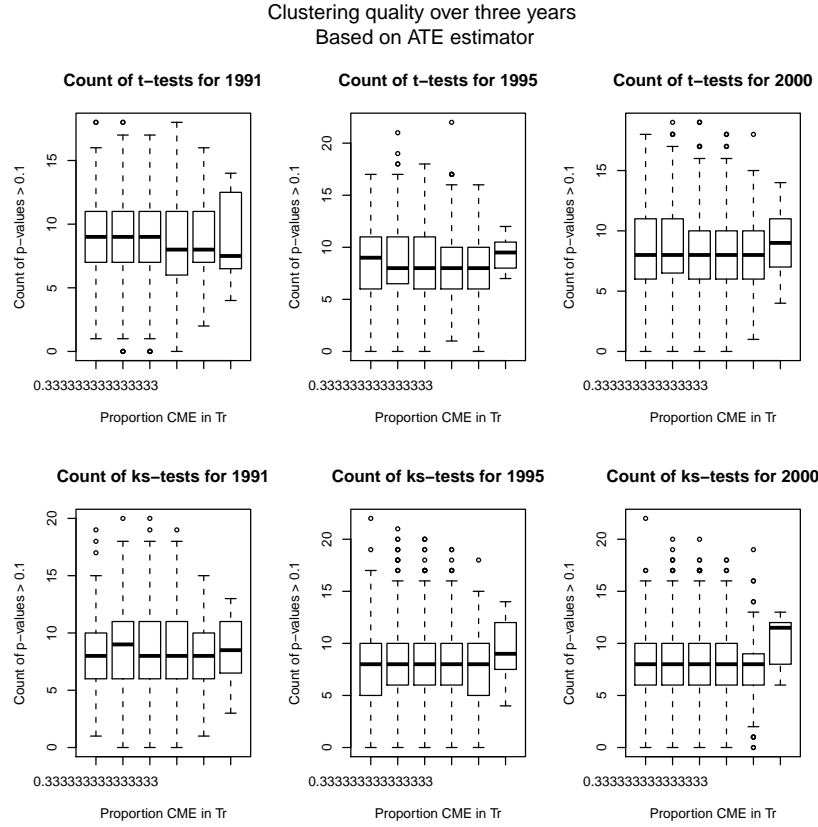


Figure 3: Balance statistics for the unrestricted data set

For this subset of data, two values were calculated to test the hypothesis that CME:CME and LME:LME matches should dominate. First, the “treatment” effect was calculated as the difference in the CME assignment vector for treated and control groups in the matched data set. Under the strong hypothesis that a perfectly-matched data set would have only CME:CME and LME:LME matches, the “treatment” effect should be zero. Deviations from zero indicate the proportion of heterogeneous matches in the data set. Figure 5 shows the distribution of this “treatment” effect for the full sample and the best-balanced



sample, respectively.

Second, the percentage of pairings for each country with each other country was calculated. Figures 3.2 - 3.2 display the results graphically. Here again, we should expect that CME countries were predominately paired with other CMEs, and LMEs with other LMEs. While this is in large part what happened, the heat maps suggest a finer substructure that the CME / LME dichotomy obscures. For instance, Ireland, which is understood to have an LME economy, pairs with France and some of the smaller economies of northern Europe as often as it pairs with LME archetypes. Additionally, there's a strong degree of geographic grouping. Germany and Austria pair frequently, as do Canada and the United States. The Scandinavian countries look more like each other than they do the other CMEs. This is not the first study to comment that this variation is washed out in the VOC framework, but it is among the few to confirm the persistence of this variation via statistical means.

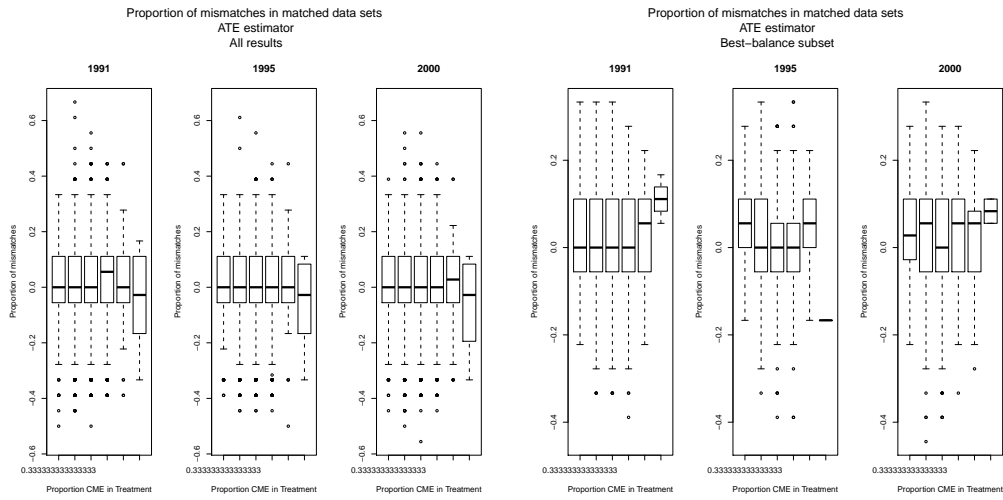
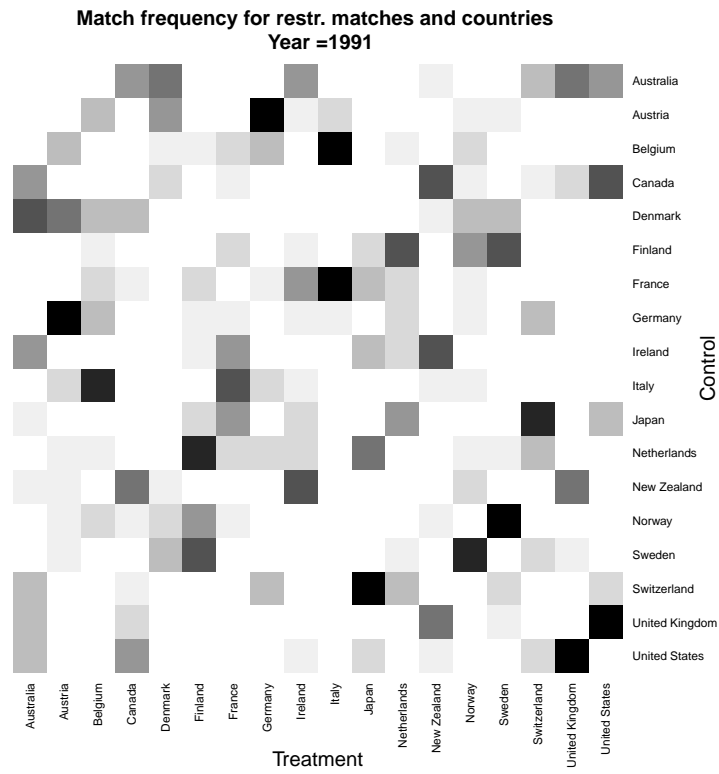
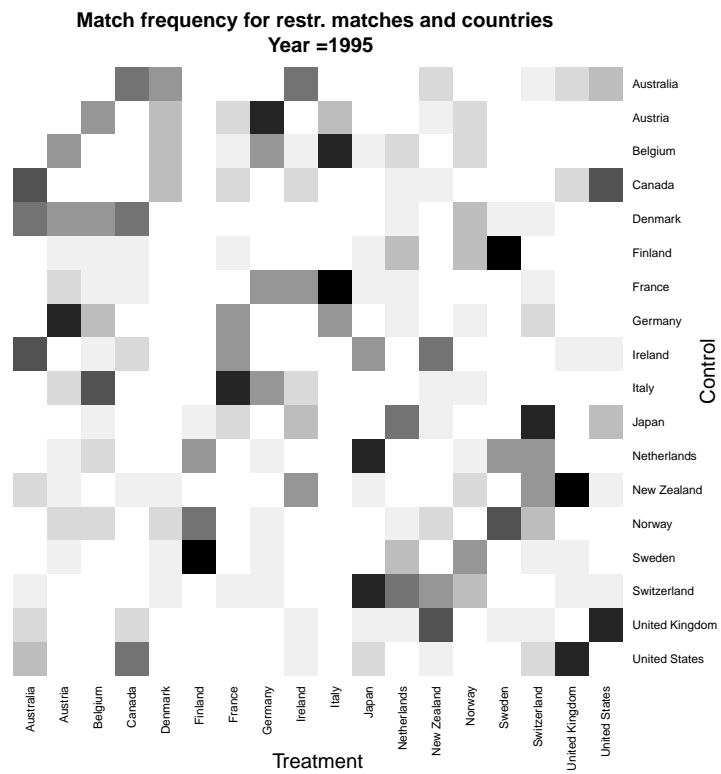
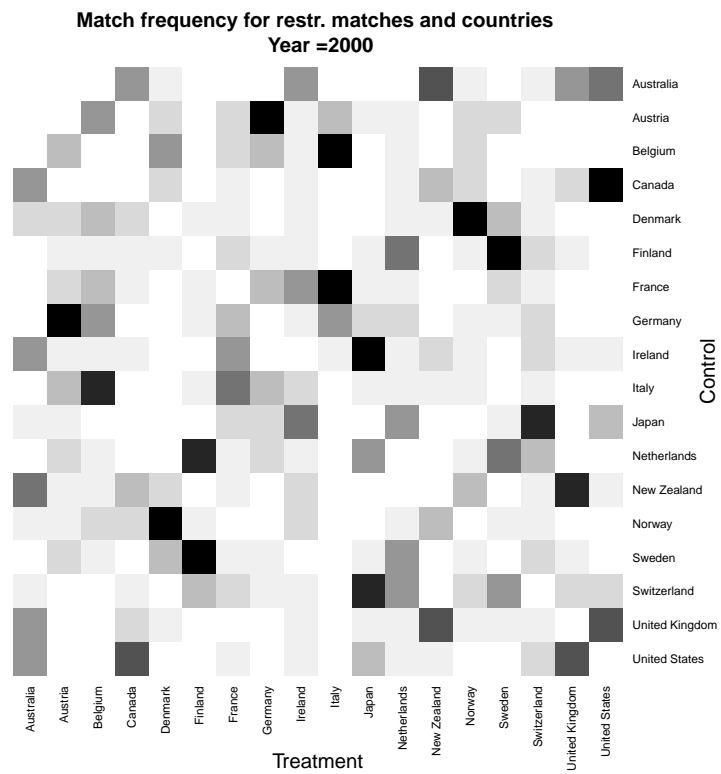


Figure 5: Treatment effects for the full data set and the best-balanced subsets







A Data Sources

The list of covariates used in both the medoid cluster analysis and the matching analysis is provided in table [3](#).

Covariate	Variable Name	Category	Source
Employment protection	emplprot	IR	OECD
Union density	unionDens	IR	OECD
Government spending (pct GDP)	pctGovGDP	SP	OECD
Gini coeff.	gini	SP	OECD
Fixed Capital Form. (pct GDP)	grFixCapFormpct	CG	OECD
Stock mkt capitalization as pct GDP	mkCapRatio	CG	OECD
Central bank indep.	CBI.cuk	CG	La Porta (1999)
Degree of share blockholding	blockHold	CG	La Porta (1999)
Judicial effectiveness	effjud	CG	La Porta (1999)
Index of shareholder protection	idx.shProt	CG	Hall & Gingerich (2009)
Index of creditor protection	idx.credProt	CG	Hall & Gingerich (2009)
Scientific publications per. Cap.	sciPubPC	PM	OECD
Pct of patents in inorganic chemistry	patA61Kpct	PM	OECD
Pct of patents biotech	patBiotpct	PM	OECD
Pct of patents in organic chemistry	patC12Npct	PM	OECD
Pct of patents electronics	patElecpt	PM	OECD
Pct of patents ICT	patCTpct	PM	OECD
Pct of patents Nanotec	patNanopct	PM	OECD
Median job tenure	medTenure	ER	VOC, Ch.4
Share of students in vocational training	vocTrainSh	SF	VOC, Ch.4
Share of workers with an upper secondary / univ education	pctUppSectr	SF	OECD
Pct of workforce with univ. educ.	pcUnivEduc	SF	VOC, Ch.4
GDP deflator	gdpDefl	CG	OECD
Kenworthy index of wage bargaining coord.	kenwcoor	ER	Kenworthy
Product market regulation	prodMktReg	PM	Nicoletti et al (1999)
Mergers and acquis. Per capita, avg, 1990-1997	ma_freq	FS	Hall & Gingerich (2009)

Table 3: Description and origins of country covariates. SP=social protection; CG=corporate governance; IR=industrial relations; PM=product market regulation; SF=skill formation; IR=interfirm relations; FS=firm strategy/interfirm relations; ER=employer-employee relations.

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