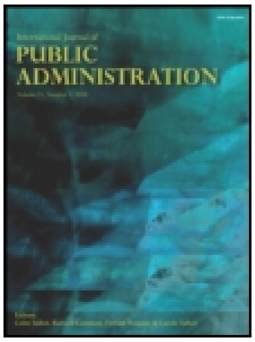

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Combining the Strengths of Qualitative Comparative Analysis with Cluster Analysis for Comparative Public Policy Research: With Reference to the Policy of Economic Convergence in the Euro Currency Area

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Qualitative Comparative Analysis (QCA) is a well-established method for comparing national public policy similarities and differences. It is argued that Cluster Analysis can add additional benefits to such research when used concurrently with QCA. Cluster Analysis provides a better method for the initial exploration of multivariate data and examining how countries compare because it can work with the full range of available interval data while patterns are created and viewed. This provides the best first method for exploring patterns and likely groupings of countries. QCA then provides a more robust method for theorizing about the construction of such groupings and their relationship around similar variable scores. QCA makes such theorizing transparent. The research example used to illustrate the benefits of combining Cluster Analysis and QCA is an analysis of the evolving of macroeconomic policy for the countries sharing the Euro, comparing 2005 (precrisis) with 2010 (postcrisis).

Keywords: case-based methods, Cluster Analysis, Qualitative Comparative Analysis

INTRODUCTION

Case-based methods in comparative public policy seek to maintain the integrity of each country as a unique case (Ragin, 1987). Some quantitative methods calculate multivariate scores that represent an aggregate of variables and therefore a summary of all cases. Examples of such methods are linear regression and logistic regression. As an alternative, case-based methods allow an understanding of both similarities and differences of cases rather than a single overall representation of the typical case. Byrne and Ragin (2010), in their seminal text on case-based methods, encourage the exploration of a range of case-based methods. Cluster Analysis is a case-based method that uses a quantitative approach, but the case-based approach also includes some established methods that overlap both qualitative and quantitative methods, for example, Qualitative Comparative Analysis (QCA) (Rihoux, 2006; Rihoux, Rezsöhazy, & Bol, 2011). Case-based methods allowed for consideration of what Ragin (1987) described as configurational complexity where the same policy outcomes can be linked to several different causal patterns, rather than researchers having to establish that one multivariate model of independent variables determines a common dependent variable outcome.

The comparison of countries is well documented for its methodology challenges (Rose, 1991). Countries are not historically permanent. They are defined by their geographical boundaries. The "fuzziness" of the country case over time is, however, in its social and economic history and the construction of political and economic institutions. Countries have the levels as follows: subnational, regional, local, and neighborhood identities. They belong to higher associations and linkages, defined by geography, politics, and economics (e.g., the European Union and Euro currency). There are difficulties with the integrity of the country "case", but nevertheless countries can be demonstrated to be "real" by various forms of social science evidence.

Mahoney and Larkin Terrie (2010) discuss comparative historical analysis. The main methodological problems are a

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dependence on small samples and unreliable measures. As a result, the comparative historical approach uses a variety of methods. Often there is a combination of quantitative and qualitative data. Considering the reliability of variables and their global validity is part of the task of country comparison (Kennett, 2001).

In the last decades, QCA has been argued to be a robust and systematic comparative case-based method that includes aspects of both qualitative and quantitative approaches (Rihoux et al., 2011). In this article, the argument is to demonstrate the possibilities and benefits of combining both Cluster Analysis (as an exploratory quantitative method) and QCA (as a qualitative method for explanation and the production of theory) while examining a real comparative public policy research question. The comparative research question used to explore the workings of the method is the extent to which the Euro Crisis of 2010–12 can be understood as evidence of the failure of the convergence of macroeconomic policy because of an increasing divergence of national macroeconomic policy trends and outcomes; these still being evident after the setting up of the single currency. Convergence theory has historically argued that with the right dynamic of global market conditions, poorer and developing countries will evolve to catch up with the wealth of richer countries (Aghion, Howitt, & Mayer-Foulkes, 2005). The setting up of the single European market and soon afterwards the single European currency for many European countries was designed not only to increase market efficiencies via reducing transaction costs such as currency exchange, but also to allow convergence in wealth and income levels between member countries with large differences in gross national income (Borsi & Metiu, 2013). In order to answer this comparative policy question about the nature of persisting divergence, the 17 Euro countries are examined for similarities and differences in 2005 and in 2010. All data used are taken from the International Monetary Fund's (IMF's) World Economic Outlook Database.

CLUSTER ANALYSIS

Cluster Analysis (Aldenderfer & Blashfield, 1984) assumes that similar and dissimilar cases exist rather than all being heterogeneous. Cluster analytical methods do not use inferential statistics but calculate algorithms to model similarity (Pastor, 2010). Therefore, when a small group of countries such as members of the European Union are used, the intention is not to generalize results from a small sample to a bigger population.

Patterns of cases are constructed simultaneously exploring the interrelationship of the key variables entered into the cluster model. The clusters of cases are defined by their relative relationships in a matrix of scores from the chosen variables. The analysis reduces the available data detail and places cases into groups where similar cases are together (Norušis, 2010; Uprichard, 2009). Hierarchical Cluster Analysis is an appropriate form of analysis with small data (small-*n*) sets.

Hierarchical Cluster Analysis can start with either all cases separated, or all cases together. When each case is separate at the first point of the analysis, the method is agglomerative (Bailey, 2012). The analysis works to gather the individual cases into logical groups. Conversely, divisive analysis puts all the cases in one cluster and then separates them. The advantage of the agglomerative approach when studying countries is that it can be argued to be "critically realistic" in the sense that countries as cases are very complex and different (Blackman, Wistow, & Byrne, 2013; Gerrits & Verweij, 2013). An attempt to argue countries are similar is best worked from looking for some similarity between individual cases rather than the opposite analytical approach of assuming all countries are very similar and then seeking to divide them up into groups (divisive methods). A limitation of the hierarchical method is the selective and overtly structured construction of cluster levels (Norušis, 2010). A hierarchy maybe imposed on the data where no real hierarchy exists.

Agglomerative hierarchical Cluster Analysis enters all variables at the same time, and searches first for a maximum number of groups. It starts with the task to find the maximum number of most likely clusters and then uses progressive simplifications and reductions to remove the number of clusters at each stage. Across the various stages of the hierarchical analysis, the clusters are multidimensional or what some refer to as "fuzzy" and not "crisp," even though the final computer analysis has to separate them into hierarchical levels. The first run of the analysis produces the largest number of clusters. These small clusters are then reduced further and combined into larger groups at each stage in the calculation. At any one point in the running of the hierarchical model, clusters are artificially crisp and separated. For example, 12 countries might be argued to represent four different clusters, but the computer analysis can also observe "higher" sets, such as two cluster groups from the 12 countries. Hierarchical clusters display multiple levels.

Hierarchical Cluster Analysis informs the researcher about the possible similarities of cases but cannot make the research decision and judgment about which level of cluster groups is most valid and realistic in its portrayal of political and economic realities. The researcher must use their own qualitative judgment about the optimal cluster solution, or number of clusters, from which to argue the existence of a theoretical model. This is one of the weaknesses of Cluster Analysis that there is an epistemological gap between data exploration and theory development. Nonhierarchical Cluster Analysis places less emphasis on the qualitative judgment of the researcher because a mathematical method calculates the final number of clusters.

However, the hierarchical routine of staging how countries evolve into patterns demonstrated by hierarchical Cluster Analysis can be argued to add to the robustness of the exploratory modeling because analyzing the agglomerative hierarchy of groups and cases gives depth and transparency to the analysis. For example, all Southern European countries might cluster together at one stage in a hierarchy, but also two separate Southern European subclusters might be evidenced together before the analysis reduces to individual countries. As Norušis (2010) argues, "There is no right or wrong answer as to how many clusters you need" (p. 364).

In this article, the clustering of cases in the research example is derived from comparative international data provided by the IMF. Variable scores are standardized using the method of *z* scores. This reduces the chances of a wide range in one variable having more influence on the cluster formulation than other variables. Nevertheless, Aldenderfer and Blashfield (1984) and Pastor (2010) caution that standardization can have undesirable effects. It might limit the power of a variable with a substantial range when the reality is that the range of that variable does explain substantive country differences. As the majority of variables used in this research example where related to the percentage of gross domestic product (GDP), a need to allow large variance effects was not judged necessary. Therefore, *z* scores were used.

The IBM SPSS computer statistics package used in this research is one of a number of statistical software programs that can be used to run Cluster Analysis (Norušis, 2010, ch 16). These types of software-based Cluster Analysis measure the distance between cases or their similarity. One frequently used mathematical calculation for similarity and difference is the Euclidean distance. It is "the sum of the squared differences over all of the variables" (Norušis, 2010, p. 365). Using the squared Euclidean distance, a proximity matrix is calculated from the variables to show the difference between each pair of cases. The proximity matrix produced by SPSS shows the two countries that are most similar and those two that are most different. The matrix output appears similar in construction to a correlation coefficient matrix. The difference of measurement in a proximity matrix when compared to a typical correlation coefficient matrix is that the scores between pairs are highly variable, and not fixed between -1 and +1.

Cluster Analysis goes beyond understanding the relationship between pairs of cases and provides mathematical evidence for the formation of groups as sets of cases. There are different mathematical methods to form clusters. One method is to average the difference between pairs of cases. Another method is to use the smallest or largest difference. The clustering method used in this article is the average linkage between groups. This method is known to assist maximizing the heterogeneity of cluster formation, does not have a bias toward creating clusters of equal size, and is relatively less likely to force homogeneity on the structure of clusters. A drawback with this method is the management of outliers and deciding when to exclude outliers. As with the alternative single linkage method, the removal of outliers can merely lead to further heterogeneity in the remaining model and a new outlier is subsequently dislocated from the weakest cluster each time the most obvious relative outlier is fully removed. The assumption of using average linkage is that countries—as types of cases—are fundamentally more heterogeneous than homogenous.

The Icicle plot is a tool for seeing how cluster groups are constructed. The bottom of the plot shows in the rows the maximum number of hierarchical clusters. Each row above is an agglomeration of clusters and therefore the number of groups that has been reduced at each stage in the computer calculation. The dendrogram is another graphics tool that reveals the hierarchical selection of clusters according to the mathematical method chosen. In this article, the dendrogram is the preferred form of graphical analysis.

In summary, hierarchical Cluster Analysis is a good method for analyzing small data sets where there is a need to be exploratory rather than explanatory and where cases may belong to overlapping and "fuzzy" clusters (Norušis, 2010, p. 363). Cluster modeling works by putting similar cases together in logical ways, but is a relatively unstable form of model creation that is dependent on the mathematical method used. It is important that the clusters observed be related to a theoretical model that explains why country cases might be co-located. This is where QCA can assist and help the researcher to move from exploration to explanation.

QUALITATIVE COMPARATIVE ANALYSIS

QCA is a contemporary method in the social sciences that promotes the analysis of cases and is suitable for the examination of smaller and intermediate data sets (Rihoux & Ragin, 2009). It promotes the systematic comparison of cases and can be used to theorize the configuration of patterns amongst cases—in terms of explaining similarities and differences. It can be used to model case-based outcomes with the designation of an outcome variable and is unique in promoting the theoretical examination of multiple routes to the causation of outcomes. In other words, two different clusters of cases might experience the same outcome, but with different explanations given, or with part of the explanation being different while there is also a shared common component of the explanation.

QCA, in its development as a method (csQCA), focused on dichotomous categorical variables (Rihoux & De Meur, 2009). This was the so-called Crisp set method. For example, either a country has a particular policy or political characteristic or it does not: an example would be classifying a nation as having either a state-funded health service or an insurance-funded health service. With this type of QCA, when quantitative variables like macroeconomic variables are used, they are either above or below a threshold set by the researcher. Binary thresholds have to be set by the judgment of the research and can be criticized as rather arbitrary, but when cross-triangulated with the statistical synthesis of Cluster Analysis, such analysis of individual variable effects on cluster membership provide complementary levels of understanding and detail not readily offered by Cluster Analysis alone.

Boolean algebra is used to analyze and theorize the patterns and overlapping clusters created from a series of ones and zeros generated by QCA (Gullberg, 1997, pp. 252–256). Much QCA literature prefers to call its groupings "sets" rather than "clusters", although for the purposes of this article the distinction is not important or problematic, but it should be noted that QCA "sets" require a high degree of specification with regard to group membership. Case-based patterns can be associated to an outcome variable and "different constellations of factors may lead to the same result" (Berg-Schlosser, De Meur, Rihoux, & Ragin, 2009, p. 8). Therefore, one of the advantages of QCA is that the theoretical models it produces demonstrate multi-routes to causation rather than a single aggregate linear score with numerous residual effects. This is also referred to as "Multiple Conjunctural Causation" (Berg-Schlosser et al., 2009, p. 8). QCA has been described a useful methodological development for comparing nation states (Berg-Schlosser et al., 2009, p. 4). But QCA is "not an end to itself; rather a tool to enhance our comparative knowledge about cases in small . . . research designs" (Rihoux & De Meur, 2009, p. 33). QCA provides a robust method for constructing theory, with the definition of theoretical clusters (sets) and their boundaries being demonstrated by Boolean algebra. This is the explicit theoretical labeling of cluster groups to describe and construct their meaning in public policy on the basis of statements about shared variable scores. Using Boolean algebra, threshold variable scores shared by two or more countries can be recorded as "Primary Implicants." These Primary Implicants are Boolean "expressions" indicating above or below threshold scores that are consistent for a group of countries. An example might be; for cluster group one, the Primary Implicant is $A + b$, where above threshold scores on variable A and below threshold scores for variable b are always present for members of that group. Uppercase notation and lowercase notation is one convention that has been used in QCA to illustrate above and below threshold variable scores.

The use of QCA in addition to Cluster Analysis gives the researcher a more robust and transparent method for theorizing about the construction of clusters and how clusters are defined by the influence of specific variables. There is an opportunity for the researcher to experiment with different threshold settings of certain variables and to observe in a more robust and systematic manner the effect on the fuzziness—or overlap—of clusters.

THE ADVANTAGES OF COMBINING CLUSTER ANALYSIS AND QUALITATIVE COMPARATIVE ANALYSIS

Table 1 shows the strengths and weaknesses of Cluster Analysis and QCA given they are both case-based methods designed to preserve the integrity of the case and allow cases to be systematically compared. Both methods accept that there is not likely to be one "ideal" solution but various possibilities and arguments for comparing case patterns.

Cluster Analysis allows full use of the available continuous data. A cluster method like hierarchical Agglomeration is designed to work with continuous and interval scores, even if standardization is often required to minimize the distortion of one variable with a larger range. This avoids some problems of data degrading and reduction. In contrast, QCA often requires the variables to be degraded, for example, QCA(cs) requires continuous variables to be transformed into dichotomous variables based on the judgment of the researcher and fuzzy set QCA (fsQCA) requires a limited number of ordinal ranks to be applied to interval data. These fundamental differences are related to the analytical strengths and weakness of the different methods. Cluster Analysis can use an interval data range to create logical patterns of cases, although this means multiple versions of the same sorts of patterns can result in repeat modeling, and the researcher still has to make an informed decision on which final model to use in theory and practice. QCA, however, because of its simplified data input allows a more systematic and theoretical view of the configuration of cases and how this is related to variables. Higher level abstraction of theory can be explained with a more consistent logic applied and this demonstrated in Boolean algebra.

TABLE 1
A Comparison of Cluster Analysis and QCA

	Similarities	*Differences*	*Strength*	*Weakness*
Cluster analysis	Allows focus on case	Continuous variables	Empirical use of continuous variables to explore possible logical patterns of cases	Instability of modeling associated with the specific mathematical method used
QCA		Degraded variables	Theorizing the configuration of cases to explore the complexity of case-based patterns	Empirical simplification

Methodological strengths can lead to paradoxical weaknesses of method, so the problem for Cluster Analysis is the instability of modeling that the data quality creates. The researcher must guide against "statistical artifacts"—sophisticated mathematical patterns that cannot be logically attached to theoretical concepts and constructs of real social and economic explanatory value. The weakness of QCA, however, might lead the researcher to argue impressive logical theorizing about the comparability of cases that is not empirically justified by the underpinning data variables and measurements.

When both methods are used to explore the same research questions and data sets, they can assist coverage of the methodological weakness that the other method displays. If a model is at first generated by Cluster Analysis, QCA can be used to understand the variable interactions with clusters and to explore "fuzziness," where some cases appear to be less clearly linked to clusters than others. While Cluster Analysis does have a "cluster by variable" option, this only shows a holistic connection of the variables used, and is of limited value when wanting to understand the dominate variable influences on specific cases and clusters. QCA gives added insight into the effect of variables on cluster construction.

QCA can also be used to add a dependent variable as an outcome element to a model and this is not an option in Cluster Analysis. For example, the researcher might wish to see if cluster groupings can be associated in some way with the determining the scores of one dependent variable. An example with country comparison might be to assign GDP as an outcome variable and to test this in the context of the cluster patterns that already developed. QCA provides novel ways for looking at outcomes given its ability to express multiple paths to causation.

Like a number of complex research issues, country comparisons will often benefit from longitudinal coverage (Byrne & Callaghan, 2013). This option is available in both Cluster Analysis and QCA by repeating a consistent cross-sectional model that is judged to have value and consistency of measurement over time. For example, organizations like the IMF and OECD (Organisation of Economic Cooperation and Development) repeat the same data measurements each period and have done so for many years. In longitudinal work, the policy researcher is particularly interested in the consistency of patterns over time and the elements of a pattern that start to change. By using a combination of Cluster Analysis and QCA, the researcher has an improved chance of understanding the reasons for any movement of country cases over time, and how this might be related to changes in specific variable scores.

RESEARCH EXAMPLE

The example used to demonstrate the combined use of these methods examines economic and social data before and after the financial crisis of 2007–08. The countries used as cases are the 17 Euro currency member nations. The data used is taken from the IMF. A precrisis model uses country scores from 2005. The postcrisis model uses 2010 data. The research question is: to what extent do countries sharing the Euro currency achieve a convergence of economic policy?

Similar models were first developed as part of an earlier and larger research project that included all OECD countries (Haynes, 2012) but the data in this article have been simplified to focus only on countries sharing the Euro currency and use IMF data. This makes the focus simpler for the purpose of an assessment of the triangulation of the two methods. Cluster Analysis involves the researcher undertaking an exploratory analysis of the interrelationship of country cases based on the variable scores available. The task is to explore how country cases can be grouped together into clusters and if they can be demonstrated to be similar within those groups. The researcher is interested to observer evidence about the relative exclusivity of groups or the extent to which they are overlapping and appear to share some general characteristics. The researcher can make a judgment from the initial exploratory analysis about the status of outliers and the most heterogeneous country characteristics. This happens before QCA is applied.

A Cluster Analysis was formed with each of the IMF data sets for 17 countries and using eight variables (2005; 2010). IMF variables used (2005, 2010) are as follows:

- Gross domestic product, constant prices, percentage change in GDP
- Gross national savings, percentage of GDP
- Inflation, average consumer prices, percentage change
- Unemployment rate, percentage of working age population
- General government revenue, percentage of GDP
- General government total expenditure, percentage of GDP
- General government net lending/borrowing, percentage of GDP
- Current account balance, percentage of GDP

Hierarchical Agglomerative Cluster Analysis is used. The calculation uses the statistical software program PASW (v18) with the method of the squared Euclidean distance examining average linkage between groups. All the continuous variables are standardized as z scores. The data are standardized using z scores to prevent variables with more distributed scales and variance from having a more profound effect on the final model. With z scores, all variables will have equal impact on the clusters formed. The dendrogram is used as the main visual method of analysis, and the number of clusters is then checked by programming the software to select the observed number of clusters in the dendrogram analysis. Membership of clusters can then be validated.

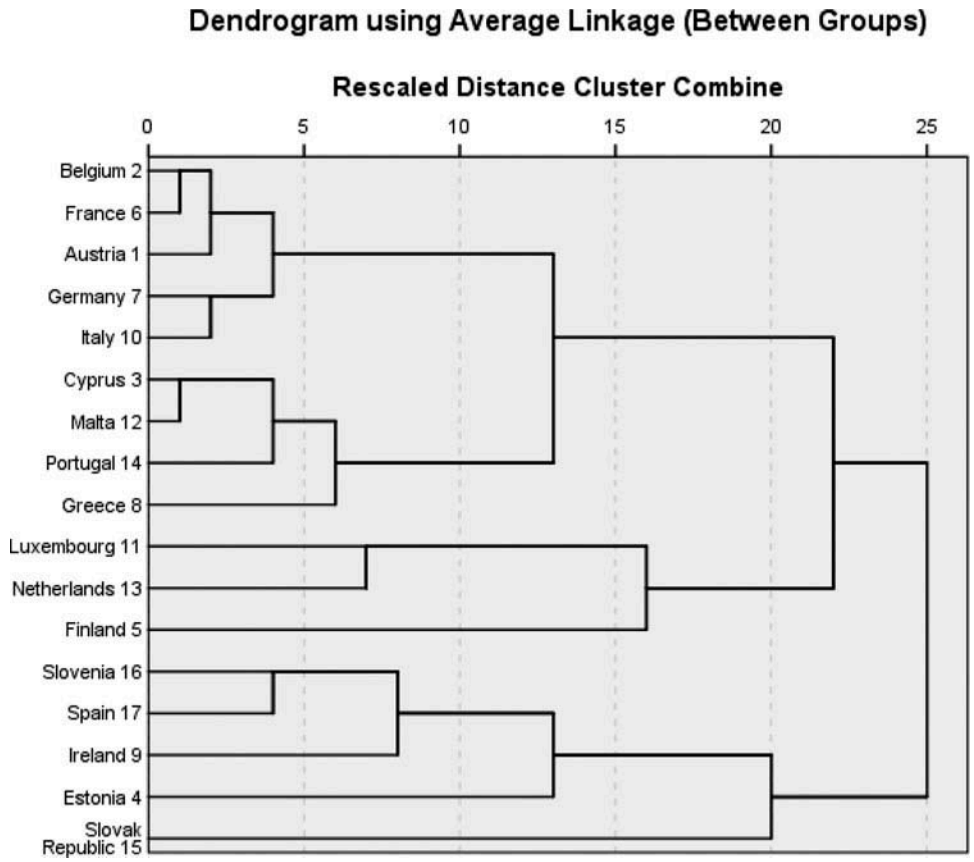

FIGURE 1 Cluster analysis dendrogram: Pre-financial crisis 2005 model of Euro zone countries.

In the first model, the IMF indicators for the precrisis period (2005) are computed into a Cluster Analysis with the 17 Euro countries each being the individual cases.

The resulting dendrogram is shown in Figure 1. Analysis of the agglomeration schedule suggests that four clusters are likely to be optimal with two additional outliers. This logical separation into groups can be observed clearly in the dendrogram and are defined as follows:

1. Belgium, France, Austria, Germany, Italy *Core Europe*
2. Cyprus, Malta, Portugal, Greece *New Southern*
3. Luxembourg, The Netherlands *Northern*
4. Finland
5. Slovenia, Spain, Ireland, Estonia *New Growth*
6. Slovak Republic

QCA is used to apply a theoretical label to each of the cluster groups of countries present (labels in italics above). QCA in Table 2 assists with the theoretical explanation of the relative homogeneity of the clusters in terms of variable effect and explaining the relationship of variable scores with cluster definition. The most homogeneous clusters in terms of variable effects are Clusters 2 and 5. Cluster 5 has four countries that share six primary implicants: strong growth (GDP), strong savings (GNS), low tax revenue (revenue) related to below threshold government expenditure (govexp), a healthy government current account (GOVCA), and negative trade and capital flows (bop). This cluster is therefore named "New Growth" as a collection of countries that seemed to demonstrate the early benefits in 2005 of being members of the Euro.

Cluster 2 is four countries that share five primary implicants: low savings (gns), low tax revenue (revenue), high government expenditure (GOVEXP), a below threshold government current account that reflects low tax update against high expenditure (govca), and a negative trade balance (bop). This illustrates Euro countries with weak economic profiles. Of course, Greece and Portugal did later experience severe difficulties after the 2007–08 crisis (Lynn, 2011). This cluster is named "New Southern."

Cluster 1 is five countries that include the largest Euro economies. The defining features of this group are their large tax take from the economy (REVENUE) and relatively high government expenditure (GOVEXP). This cluster includes the countries that politically drove the Euro project and showed openness toward southern and eastern integration with a commitment to strong fiscal intervention. This cluster is named "Core Europe."

Clusters 3 and 4 are strongly performing northern countries with strong savings (GNS), government current account

TABLE 2
QCA Truth Table for Validation of Pre-Crisis 2005 Clusters

GDP	*GNS*	*CPI*	*Unemp*	*Revenue*	*GovExp*	*GovCA*	*BoP*	*Cluster*	*Id*
0	1	1	1	**1**	**1**	0	1	1	Belgium
0	1	0	1	**1**	**1**	0	1	1	Germany
0	1	0	0	**1**	**1**	1	1	1	Austria
0	0	0	1	**1**	**1**	0	0	1	France
0	0	0	0	**1**	**1**	0	0	1	Italy
1	**0**	1	0	**0**	**1**	**0**	**0**	2	Malta
1	**0**	0	0	**0**	**1**	**0**	**0**	2	Cyprus
0	**0**	1	1	**0**	**1**	**0**	**0**	2	Greece
0	**0**	0	0	**0**	**1**	**0**	**0**	2	Portugal
1	**1**	1	**0**	0	0	**1**	**1**	3	Luxembourg
0	**1**	0	**0**	1	1	**1**	**1**	3	The Netherlands
0	**1**	0	1	1	1	**1**	**1**	4	Finland
1	**1**	1	1	**0**	**0**	**1**	**0**	5	Spain
1	**1**	1	0	**0**	**0**	**1**	**0**	5	Estonia
1	**1**	1	0	**0**	**0**	**1**	**0**	5	Slovenia
1	**1**	0	0	**0**	**0**	**1**	**0**	5	Ireland
1	0	1	1	**0**	**0**	0	**0**	6	Slovak Republic

Thresholds (1 = threshold or above: 0 = below threshold) **Primary Implicants**.
Cluster 1 gdp*REVENUE*GOVEXP.
Cluster 2 gns*revenue*GOVEXP*govca*bop.
Cluster 3 GNS*unemp*GOVCA*BOP.
Cluster 4 (linked to 3 by GNS*GOVCA*BOP).
Cluster 5 GDP*GNS*revenue*govexp*GOVCA*bop.
Cluster 6 (linked to 5 by GDP*revenue*govexp*bop).

balance (GOVCA), and positive trade balances (BOP). This cluster is called "Northern."

In the second model, data from 2010 are used. The same mathematical Cluster Analysis method is applied. The following post-financial crisis clusters result (Figure 2):

1. Austria, The Netherlands, Germany, Luxembourg *Northern Plus*
2. Italy, Slovenia, Belgium, France, Finland *Core Europe*
3. Estonia
4. Cyprus, Malta, Portugal *New Southern*
5. Slovak Republic, Spain *Other Southern*
6. Greece
7. Ireland

The QCA in Table 3 provides the theoretical explanation of the new cluster labels added in italics above, and movement in cluster groupings compared with 2005, and the analysis of overall cluster homogeneity for the 2010 model. There has been some change between the Northern and Core European clusters. Germany has moved into the economic stronger northern group (now cluster 1) reflected by the primary implicants of above threshold growth (GDP) and savings (GNS) and a positive balance of payments (BOP). There is overlap with part of Cluster 2, as Belgium and Finland also share these characteristics. The new larger Core Europe cluster (Cluster 2) is rather heterogeneous with no primary implicants and seems to be better explained using QCA as two distinct groups. Belgium and Finland can be identified by the variable thresholds as having overlap with Cluster 1, leaving Italy, France and Slovenia defined by the variable thresholds: low inflation and negative balance of payments (cpi*bop). In some respects, Clusters 1 and 3 from 2005 have evolved into overlapping Clusters 1 and 2 in 2010, but with France being more marginal in terms of its relative strength of economic performance when compared to other similar Eurozone countries.

The rest of the analysis tells a different story of divergence rather than convergence. The growth (GDP) of the 2005 Cluster 5 has gone, fragmenting the economic characteristics of these countries in 2010. The more extreme crisis in Greece has pushed it into an outlier position, although in reality it still has some similarities with the other nations it was situated within 2005 (2005 Cluster 2). The other countries that were previously similar to Greece in 2005 are still together in 2010 in Cluster 4 with low savings (gns), low tax revenue (revenue), and negative trade (bop). These are consistent features for those countries in both 2005 and 2010.

Taking these QCA-based variable influences into account, the simplest element of the dendrogram hierarchy in Figure 2 (2010) Cluster Analysis can be reduced to two higher level cluster groups on the right-hand side of the dendrogram figure. First, those in the top half of the dendrogram look economically more similar, and most able to work in a shared currency (Austria, The Netherlands, Germany, Luxembourg, Italy, Slovenia, Belgium, France, Finland, and Estonia). Those in the bottom half of the dendrogram have increasingly struggled to converge and survive during the Financial

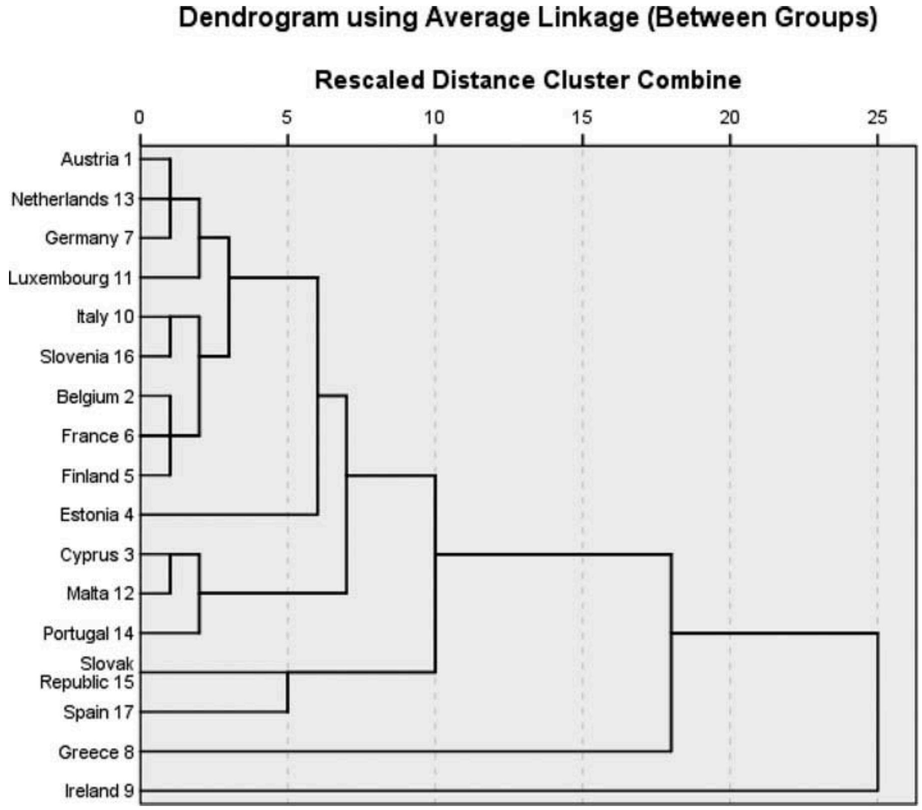

FIGURE 2 Cluster analysis dendrogram: Post-financial crisis 2010 model of Eurozone countries.

TABLE 3
QCA Truth Table for Validation of Post-Crisis 2010 Clusters

GDP	*GNS*	*CPI*	*Unemp*	*Revenue*	*GovExp*	*GovCA*	*BoP*	*Cluster*	*Id*
1	**1**	1	**0**	0	0	1	**1**	1	Luxembourg
1	**1**	0	**0**	1	1	1	**1**	1	Austria
1	**1**	0	**0**	1	1	0	**1**	1	The Netherlands
1	**1**	0	**0**	1	0	1	**1**	1	Germany
1	1	1	0	1	1	1	1	2	Belgium
1	1	0	0	1	1	1	1	2	Finland
1	0	0	0	1	1	1	0	2	Italy
0	1	0	1	1	1	0	0	2	France
0	1	0	0	0	0	0	0	2	Slovenia
1	1	1	1	1	0	1	1	3	Estonia
1	**0**	1	0	**0**	0	1	**0**	4	Malta
0	**0**	1	0	**0**	0	0	**0**	4	Cyprus
0	**0**	0	1	**0**	1	0	**0**	4	Portugal
1	**1**	0	**1**	**0**	0	**0**	0	5	Slovak Republic
0	**1**	1	**1**	**0**	0	**0**	0	5	Spain
0	0	1	1	0	0	0	0	6	Greece
0	0	0	1	0	1	0	1	7	Ireland

Thresholds (1 = threshold or above: 0 = below threshold).
Primary Implicants
Cluster 1 GDP*GNS*unemp*BOP.
Cluster 2 (no primary implicants) – two subsets.
2a GDP*GNS*unemp*REVENUE*GOVEXP*GOVCA*BOP.
2b cpi*bop.
Cluster 3 Outlier.
Cluster 4 gns*revenue*bop.
Cluster 5 GNS*UNEMP*revenue.

Crisis after 2007 (Cyprus, Malta, Portugal, Slovak Republic, Spain, Greece, and Ireland).

CONCLUSION

The research example illustrates the advantages of using Cluster Analysis and QCA as a combined method to study comparative similarities between countries. Cluster Analysis is a method that can be used to search for similarities and patterns amongst countries. It is good method for exploring the data because it uses the full range of interval variable scores available and data do not have to be degraded or recoded into categories. Once exploratory patterns are formed using Cluster Analysis, these groups can be better understand using QCA. QCA allows for theoretical modeling where the groups proposed in the exploratory clusters can be validated, or alternatively rejected as artifacts that have no logical political or economic explanation. The process of theoretical validation during QCA necessitates linking cluster groupings to patterns of variable scores.

Cluster groupings have hard and soft elements. The hard elements are groupings of countries and proximities of country characteristics that remain when modeling is replicated with different mathematical criteria and after using QCA for theoretical validation. When undertaking longitudinal research, as with the example in this article, hardness might also be argued to be present if groups of countries remain together consistently over time. The QCA concept of "Primary Implicants" clarifies "hardness" of linkage in clusters. These hard links are indicated in bold in Table 4.

TABLE 4
Comparison of Cluster Models.

Model 1 2005	
Cluster 1 Core Europe	gdp***REVENUE***GOVEXP
Cluster 2 New Southern	**gns*****revenue***GOVEXP*govca***bop**
Cluster 3 Northern	**GNS***unemp*GOVCA***BOP**
Cluster 4	(linked to 3 by GNS*GOVCA*BOP)
Cluster 5 New growth	GDP*GNS*revenue*govexp*GOVCA*bop
Cluster 6	(linked to 5 by GDP*revenue*govexp*bop)
Model 2 2010	
Cluster 1 Northern plus	GDP***GNS***unemp***BOP**
Cluster 2 Core Europe	(no primary implicants)—two subsets
2a	GDP*GNS*unemp***REVENUE***GOVEXP*GOVCA*BOP
2b	cpi*bop
Cluster 3 Outlier	
Cluster 4 New Southern	**gns*****revenue*****bop**
Cluster 5 Southern	GNS*UNEMP*revenue

Notes

1. Key primary implicants that have influence over similar clusters from 2005 to 2010 are indicated in bold.
2. Computer generated cluster numbers change between 2005 and 2010. For example, "Core Europe" moves from Cluster 1 in 2005 to Cluster 2 in 2010.

Soft elements are country outliers and countries prone to move clusters easily when different mathematical criteria and QCA are used. This is where replication and cross triangulation for validation is difficult and cannot easily validate consistent patterns. However, when examining the political economy of countries over time, softness also illustrates countries that are relatively unstable.

The robustness of the Northern Plus and Core Europe cluster over time (Table 4) is linked to its enduring positive balance of payments (BOP), higher national savings (GNS), and above threshold government revenue (REVENUE).

Across the 17 countries, the reducing homogeneity of clusters illustrates the lack of convergence achieved by the Eurozone single currency countries and suggests that economic patterns will continue to evolve and surprise commentators as the world economy moves through a prolonged crisis and that this will continue to change traditional patterns of economic stability and activity. There is no indication from this data analysis that the policy of sharing the Euro currency will enable European Union countries to achieve a homogeneous economic experience.

The assumption is that the clusters are a holistic representation of the numerous variables entered and that higher abstraction demonstrated by cluster definition is evidence of the combination of variables into a possible synthesis of "political economy type," "economic policy," or "economic performance". However, Cluster Analysis alone provides a weak theoretical basis for such theoretical labeling. With Cluster Analysis alone, it is difficult to understand the microelement of variable effects when these clusters are created. QCA allows the researcher to understand the interrelationship of variable effects with cluster group definition, in terms of which variables are assisting the definition of similarity in particular clusters. Where the robustness of cluster groups remain or change over time, it is also important to remember that the cluster variable characteristics are actually dynamic and changing. The cluster (or a proportion of cluster members) may evolve their variable score characteristics over time. Country cases may remain together, but not necessarily because of the same defining features of variables. Variables that define clusters may change dynamically over time, but the same cluster might remain, even if defined differently by its relationship with variables. Over time, cluster groups of countries might remain together dynamically because the underlying variable influences evolve and influence the countries in a similar way. For example, it can be hypothesized in a financial crisis that a group of countries will experience the same combined negative effects. What is particularly interesting is when one country breaks away from its historical grouping based on some unexpected variable scores. This illustrates the highly dynamic relationship of countries with each other and their changing variable scores over time. The political economy of countries is not static but always evolving. These complex interactions and relationships are best understood by case-based methods

(Byrne & Callaghan, 2013), of which Cluster Analysis and QCA are two examples recently used in public policy and public administration. What is innovative in this article is the demonstration of how these methods can be used concurrently to answer the same research question. Using a combination of the methods of Cluster Analysis and QCA with the added benefit of a longitudinal view better aids the researcher in understanding the complex interaction of country cases with each other and the dynamic movement of underlying variables over time. The patterns between cases and variables depend on mutual interactions rather than the predetermined relationship of variables that always determine the path of others.

REFERENCES

Aghion, P., Howitt, P., & Mayer-Foulkes, D. (2005). The effect of financial development on convergence: Theory and evidence. *Quarterly Journal of Economics*, *120*(1), 173–222.

Aldenderfer, M., & Blashfield, R. (1984). *Cluster analysis*. London, UK: Sage

Bailey, K. (2012). Sociological classification and cluster analysis. In D. Byrne & E. Uprichard (Eds.), *Cluster analysis* (Vol. 2; pp. 83–98). London, UK: Sage.

Berg-Schlosser, D., De Meur, G., Rihoux, B., & Ragin, C. (2009). Qualitative analysis (QCA) as an approach. In B. Rihoux & C. C. Ragin (Eds.), *Configurational comparative methods: Qualitative comparative analysis (QCA) and related techniques* (pp. 1–18). London, UK: Sage.

Blackman, T., Wistow, J., & Byrne, D. (2013). Using qualitative comparative analysis to understand complex policy problems. *Evaluation*, *19*(2), 126–140.

Borsi, M., & Metiu, N. (2013). *The evolution of economic convergence in the European Union*. Discussion Paper. Frankfurt, Germany: Deutshce Bundesbank.

Byrne, D., & Ragin, C.C. (Eds.). (2010). *The Sage handbook of case-based methods*. London, UK: Sage.

Byrne, D., & Callaghan, G. (2013). *Complexity theory and the social sciences: The state of the art*. London, UK: Routledge.

Gerrits, L., & Verweij, S. (2013). Critical realism as a meta-framework for understanding the relationship between complexity and qualitative comparative analysis. *Journal of Critical Realism*, *12*(2), 166–182.

Gullberg, J. (1997). *Mathematics: From the birth of numbers*. London, UK: W.W. Norton.

Haynes, P. (2012). *Public policy: After the financial crisis: An international comparative study*. London, UK: Routledge.

International Monetary Fund (IMF). (2012). *World economic outlook*. Retrieved January 7, 2012 from http://www.imf.org

Kennett, P. (2001). *Comparative social policy: Theory and research*. Buckingham, UK: Open University Press.

Lynn. M. (2011). *Bust: Greece, The euro, and the sovereign debt crisis*. Hoboken, NJ: Bloomberg.

Mahoney, J., & Larkin Terrie, P. (2010). The proper relationship of comparative-historical analysis to statistical analysis: Subordination, integration or separation? In D. Byrne & C. C. Ragin (Eds.), *The Sage handbook of case-based methods* (pp. 410–423). London, UK: Sage.

Norušis, M. J. (2010). *PASW statistics 18 statistical procedures companion*. New York, NY: Prentice Hall.

Pastor, D.A. (2010). Cluster analysis. In G. R. Hancock & R. O. Mueller (Eds.), *The reviewer's guide to quantitative methods in the social sciences*. New York, NY: Routledge.

Ragin, C. (1987). *The comparative method: Moving beyond qualitative and quantitative strategies*. Berkeley, CA: The University of California Press.

Rihoux, B. (2006). Qualitative comparative analysis (QCA) and related systematic comparative methods: Recent advances and remaining challenges for social science research. *International Sociology*, *21*(5), 679–706.

Rihoux, B., & De Meur, G. (2009). Crisp-set qualitative comparative analysis. In B. Rihoux & C. C. Ragin (Eds.), *Configurational comparative methods: Qualitative comparative analysis (QCA) and related techniques*. London, UK: Sage.

Rihoux, B., & Ragin, C. C. (Eds.). (2009). *Configurational comparative methods: Qualitative comparative analysis (QCA) and related techniques*. London, UK: Sage.

Rihoux, B., Rezsöhazy, I., & Bol, D. (2011). Qualitative comparative analysis (QCA) in public policy analysis: An extensive review. *German Policy Studies*, 7(3), 9–82.

Rose, R. (1991). Comparing forms of comparative analysis. *Political Studies*, 39(3), 446–462.

Uprichard, E. (2009). Introducing cluster analysis; what can it teach us about the case? In D. Byrne & C. C.Ragin (Eds.), *The Sage handbook of case-based methods* (pp. 132–147). London, UK: Sage.