Optimum Currency Areas within the US and Canada: a Data Analysis Approach

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Abstract

Over the last few decades Robert Mundell’s theory (1963) of Optimum Currency Areas (OCA) has attracted significant attention between researchers and policy makers especially after the formation of the European Monetary Union and the debate over whether the eurozone countries actually consist an OCA. In this paper, we take this debate to the area that was originally the subject of Mundell’s motivation: the US and Canada. We employ the methodology of Correspondence Analysis and Hierarchical Cluster Analysis, in a sample of macroeconomic data from the fifty US states and ten Canadian provinces for 2009 in an effort to investigate whether the current currency split between north (Canada) and south (the US) is an OCA or possibly another split may be more appropriate. Our results show that three OCAs are identified within US states and Canadian provinces: one that includes regions of eastern US and Canada, one that includes regions of central-eastern and eastern US and Canada and finally one with regions of western US and Canada.

1. Introduction

During the last decades there have been several attempts from different groups of countries to adopt a common currency. The reason for this is that a monetary integration would eliminate currency risk resulting in favorable conditions for trade and business within the monetary union. This will result in increased efficiency by reducing hedging and uncertainty costs and optimum factor allocation. Generally when the conditions among two or more regions are suitable for creating a monetary union, then these areas are called Optimal Currency Areas (OCA). Robert Mundell developed a theory for OCA in 1963, for which he was awarded the Nobel Prize in
economics for 1999. Not only did Mundell set the background of OCA, but he also proceeded on an empirical study of U.S. and Canadian regions. According to Mundell’s study, these two countries should not be monetarily separated in the way they are today, between the northern and the southern part that use the Canadian and U.S. dollar respectively. Instead he argued that the two regions should be divided into two groups one in the East and one in the West. In other words, one group would include the regions of eastern U.S. and eastern Canada and the other would include the regions of western U.S. and western Canada.

In this paper we use two methodologies of data analysis: Correspondence Analysis and Hierarchical Cluster Analysis in an attempt to group together the U.S. and Canadian states and provinces that may form an OCA with respect to their macroeconomic performance.

2. Methodology

2.1 Correspondence Analysis

Correspondence Analysis (CA) is a method of exploratory data analysis\(^1\) designed to analyze two-way (or multi-way in the case of Multiple Correspondence Analysis - MCA) contingency tables. In a way similar to Principal Component Analysis (PCA), CA aims at representing a data matrix in a single two-dimensional (or even three-dimensional) plot. However, as opposed to PCA, CA a) must be applied to categorical data variables (PCA can be applied to continuous variables), b) is equipped with the \(\chi^2\) metric (instead of the Euclidean metric in PCA) and c) both rows and columns can be represented in the same plot (it is impossible to do so in PCA).

The \(\chi^2\) distances between each row category and each column category\(^2\) (or each row individual and the row categories in the case of MCA) are used to form the initial plot. The data structures and the category relations are maximized by applying axis rotation to the Cartesian system. After this procedure, the first axis is the one describing the maximum information of the dataset, the second one is the next in line, etc.

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1 Exploratory data analysis is a branch of Statistics exploiting the relations on the dataset without a priori assumptions.

2 The total \(\chi^2\) distance between rows and columns in a two-way contingency calculates the distance of the two variables from statistical independence.
MCA can be applied to an indicator matrix\(^3\) or a Burt table. Consider the dataset describing the attributes of \(N\) individuals to \(m\) discrete variables (w.l.o.g. we can assume that every variable has \(k\) categories). An indicator matrix of the described dataset is a matrix with \(N\) rows and \(m \times k\) columns (one column for every category), where each row corresponds to an individual and every column is a binary (dummy) variable representing one category of a variable. The value in every cell describes the absence (with a 0) or presence (with a 1) of the selected category for an individual. The Burt table is the symmetric cross-tabulation matrix between all the categories.

2.2 Hierarchical Cluster Analysis

In Clustering, we aim at grouping a set of data points in groups based on a similarity measure. Hierarchical Cluster Analysis performs the task repetitively, by merging, in each iteration, the two closest points based on the \(X^2\) distance: the pair of the closest points is removed from the dataset, and in their place we put the center of the cluster (i.e. the weighted mean of all points within a class). The procedure is performed until all datapoints are grouped in the same class. The visual output of the method is an hierarchical tree plot showing all the clustering steps as nodes. It is up to the researcher, to set a threshold in the plot that will define the final groups: all the datapoints of a “branch” below the threshold are grouped together in a class.

2.3 Data

\(^3\) Often called “0-1” matrix in Data Analysis jargon.
We collected 8 macroeconomic variables for the 50 U.S. states and the 10 Canadian for the year 2009: GDP, per capita income, government deficit, unemployment rate, inflation, GDP growth, imports, and exports. The initial datamatrix has 60 rows, and 8 columns. All the variables have been separated into three classes except of GDP growth (which has been separated into 2 classes). For the purposes of the survey we applied the MCA to the indicator matrix.

3. Empirical Estimation

3.1 Applying Correspondence Analysis

Applying the Factor Analysis to the data from the U.S. and Canada we get the symmetric plot depicted in Figure 1.

We can observe that two groups emerge from the graphical representation, each group sharing the same features. The group created on the left side of the symmetric plot of Figure 1 consists of 30 regions. These regions are mostly from western and eastern U.S. and Canada. The variables that characterize the group are mostly variables of low level e.g. low per capita income, low GDP, etc. This means that this group consists mainly of low-income regions. On the contrary, the group of regions that is formed on the right side of Figure 1 consists mainly of high-income areas. These U.S. states and Canadian provinces show a high GDP, high per capita income, and high imports and exports.
The resulting groups of states and provinces of Figure 1 are depicted in Map 1. There is a certain pattern in the division of the regions in two groups: a) the first group consists of states and provinces that belong to the east and west side of USA and Canada; b) the second one consists mainly of regions of the central part of both the U.S. and Canada.

One of Factor Analysis’s tools is the COR indicator which helps the researcher reduce the number of data points in the plot to just the ones with higher fidelity. The symmetric plot with the higher COR datapoints is shown in Figure 2.
In the new symmetric plot we observe that the group that was previously on the left side now can be further divided in two new groups, yielding a total of three groups of states and provinces. These groups along with the relevant variables are presented in Table 1.

Table 1 Separated groups of regions

<table>
<thead>
<tr>
<th>States/Provinces</th>
<th>Group 1</th>
<th>Group 2</th>
<th>Group 3</th>
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</thead>
<tbody>
<tr>
<td>Variables</td>
<td>Low GDP, low imports and low exports, low deficit and low</td>
<td>Medium levels of exports, GDP and deficit and low per capita</td>
<td>High GDP, high deficit, high imports, high exports, high per capita income</td>
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</table>
The Groups that are created in this case are three and they are also depicted in Map 2. The first one, marked in blue in Map 2 consists of regions in the central and western part of the U.S. with low income, low GDP, low imports and exports, low deficit and low unemployment. The second group includes the regions marked with red in Map 2 and these regions are characterized by medium middle economic class, middle levels of exports, GDP and deficit and low per capita income. Finally the third group marked with yellow, includes the rich and prosperous regions located on the east side of the US and Canada with high GDP, high deficit, high imports, high exports, high per capita income. The areas in gray color are not studied in this section due to the COR indicator which eliminates the less significant data.
Hierarchical Cluster Analysis

The Hierarchical Cluster Analysis, as stated above, is applied with the help of a hierarchical tree plot. The researcher selects the nodes of greatest interest for the interpretation of data and control which variables characterize them. The tree plot for the U.S. and Canada is the Tree Plot 1.

The nodes that are taken under consideration in the above tree plot are nodes 115, 116 and 117. Therefore the data are separated into three groups, each of which contains the data of these nodes. The groups that are created under the ascending hierarchical classification are those shown in the table 2.

<table>
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<th>Group 1</th>
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<td>States/Provinces</td>
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<td>Idaho, New Mexico, Arkansas, West Virginia, Kentucky, South Carolina, Mississippi, Iowa, Kansas, Missouri, Nebraska, Oklahoma, South Dakota, Alabama, Delaware, Nevada, Maine, Rhode Island, Arizona, Utah, Colorado, Oregon, Nova Scotia, New Brunswick</td>
<td>Absence of high GDP and high per capita income, presence of medium-level and low level of exports per capita income.</td>
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As we can see at the table above, US and Canada are divided into three groups similar to those created earlier by factor analysis. The first group marked with red color includes mainly the eastern U.S. states which belong to a high economic level with high GDP, high imports, high exports but also high deficit. The second group, marked with yellow color, includes (mainly) areas of the West that are characterized by low GDP, exports and deficit, high levels of per capita income. Finally the third one, marked with green color, includes western and central regions that are characterized by absence of high GDP and high per capita income, and presence of medium-level and low level of exports per capita income. These results are shown schematically on the map 3.
With the application of factor analysis and ascending hierarchical classification, we can draw some very important conclusions with respect to regional U.S. and Canada grouping on macroeconomic variables that related to the formation of optimum currency areas. We conclude that the U.S. and Canada with respect to forming an OCA can actually be divided into three parts. The first one includes regions mainly from the East that are industrialized, and characterized by high levels of economic activity as this is measured by the macroeconomic variables used in our analysis. The second part includes regions mainly from western US and Canada with diverse levels of economic activity and prosperity. Finally, a third group of regions can be identified. This group includes a geographically diverse set of regions as it spans from east to west. The common factor though that links these regions is the relatively low level of economic prosperity as it is measured in our study in terms of income, growth, imports, exports, etc. It is important to note, that our study is based on a “tomography” of the economy of the North American regions. In order to make it more accurate we’ll have to enrich our dataset with more economic and financial variables and for larger periods of time.

References


