A Bi-regional SAMâ€™s clusterization: disposable and primary factor incomeâ€™s dispersions indexes

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This paper aims to perform a clusterization technique to identify the dispersion effects between industriesâ€™ productions and income distribution of Institutional Sectors, considering exogenous shock on disposable income. The methodology used is represented by the bi-regional Social Accounting Matrice (SAM) for the US and Mexico, from which we use a bi-regional extended multisector model (BEMM) (Ciaschini & Socci, 2007). Such methodology is used to identify the structure of direct, indirect, and induced effects that rise in both regions. The BEMM technically describes the income circular flows by each phase: the generation, the allocation, the distribution and the use of income. The clustering technique we develop is based on the correlation and cross-correlation of â€˜impact componentsâ€™. This approach is called Macro Multipliers (MM) analysis (Ciaschini & Socci, 2007), which identifies all the latent structures of exogenous variables and their impact on the endogenous variables. Finding latent structures unable to perform backwards and forward dispersion analysis that aims to represent the structural matrix in bi-dimensional plots, capturing more than 70% of the total variance.
One of the multisectoral analysis and development economics topics is represented by the possibility of identifying â€˜keyâ€™ industries (or groups of them) that are interdependent in an economic system. During the 1950s, Hirschman (1958) introduced the concept of linkages to explore and measure the inter-industrial relations and the multiplicative effects of investment. Rasmussen (1956) proposed the power and sensitive dispersion indexes, the most widely used technique applied to the Leontief inverse matrix. Chenery and Watanabe (1958) proposed a method to rank industries by their multiplier power using the sum of each column of the Leontief technical coefficients matrix. Those classical techniques represent the first attempts to create an index to rank output multipliers by industry to search the key sectors.
After 1960, new alternative techniques were proposed for ranking the industries, for example, the hypothetical extraction method (Strassert, 1968; Schultz, 1977); the total linkage (Cella, 1984) applied to a partitioned SAM; the eigenvector method (Dietzenbacher, 1992); the output-to-final demand elasticity index (Mattas & Shrestha, 1991). However, these techniques have a fundamental criticism: they assume an equi-distributed structure in the exogenous variable (Skolka, 1986), which is unrealistic. Indeed, the structure of the exogenous vector affects results in a way that implies avoiding this assumption (Ciaschini, 1993).
In the 1970s, there was an interest in identifying industrial complexes, groups or clusters in the input-output (IO) framework; for example, the pioneer contribution of Czamanski (1974) proposed an associationâ€™s index to identify industrial clusters. Roepke et al. (1974) use factor analysis to identify industrial complexes with similar transaction patterns; those studies are done on the columns of the technical coefficient matrix; thus, both methods use only the so-called backward linkages. In the late 90s and early 2000s, Sakurai et al. (1997) identified the relevance of ICT industry clusters in ten countries using econometric regressions. Dietzenbacher and Los (2002) modified total and induced forward multipliers for the US economy, clustering the research and development investment effects. Hoen (2002) used diverse cluster-based techniques and pointed out four problems: the clusters are sensitive with respect to the matrix analyzed; different data generally lead to different results; many methods generate a mega cluster without clear relationships; in many cases, the clusters consist only of two industries. Subsequently, Sonis et al. (2008) used the tools of topologic analysis and Q-analysis to identify clusters in an economic inter-industrial input-output table for the Chicago economy.
Finally, in the last decade, papers on industrial clustering have incorporated the use of indicators

from the input-output framework; in some studies, these indicators are mixed with other accounting or statistical frameworks to identify the industrial clusters (Delgado, et al., 2016) or to identify the cluster of the financial industry in China (Khan, et al., 2024). Other contributions use clustering techniques to identify the most carbon-emitting industries in input-output tables (Kanemoto, et al., 2019) or to identify industrial clusters in Germany (Kosfeld & Titze, 2017) or the cluster associated with the construction industry in Russia (Kudryavtseva, et al., 2021). However, most of the papers above identify inter-industrial clusters, leaving out the link with the institutional sectors in the IO framework or even more in the SAM.

In conclusion, the methodology used in this paper is unable to analyze the interaction between institutional sectors and industries since the BEMM makes it possible to perfo