Spatial Lag of Economic Structures: Do They Provide Evidence of Technological Convergence across Countries?

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Regional input-output (IO) analysis is often anchored under national input-output systems. Despite recognizing that regional production recipes differ, researchers assume, without any embarrassment, that national technology prevails everywhere. In a world of limited information, the usual justification considers that the lack of appropriate data at the regional level can be surpassed by the assumption that the available technology for regional firms is given nationally. From a practitioner's perspective, it translates into the assumption of national sectoral technology at the regional level leading to the prevalence of the same input mix for a given sector everywhere with differences only in the degree of interregional dependence on input sources.

Shared technology is a plausible working assumption for practitioners dealing with isolated or integrated subnational systems. Technological convergence in input-output technical coefficients, defined as high similarity between **A** matrices, is more likely to be observed across regions within a country than across different countries, given the existing relative homogeneity in sub-national economic spaces.

Input-output practitioners also face conditions of limited information when dealing with national input-output models for countries with poor statistical institutions. Although many countries produce their supply and use tables (SUT) with different publication frequencies and levels of details, there are still many countries for which SUTs are dated or not available. To circumvent this problem, researchers adjust existing input-output tables from elsewhere to one or various of such countries by estimating or inferring the parts of the system that are undetermined – usually the technical coefficients (**A** matrix) –, or even replicating the structure of a "similar" country.

Different experiences with developing multiregional input-output (MRIO) share the common challenge of estimating individual country IO tables based on a limited set of information. Different versions of the GTAP Project (Hertel, 1997) database develop the concept of representative IO tables as a linear combination of IO tables from regions representing a broad economic and geographic spectrum, for which good quality IO data are available. Representative tables are used for different purposes, including the adaptation of the production structure, intermediate usage, and consumption for sectors that are not split in the original I-O table of a given country. The GTAP database also encompasses the concept of composite regions, constructing for them IO tables based on linear combinations of specific countries' tables, namely those countries which have similar GDP per capita and economic characteristics as the countries that comprise the composite regions (Dimaranan, 2001; Corong, 2020).

The EORA project (Lenzen et al., 2012, 2013) is more ambitious in terms of its geographic coverage focusing on the economic structures of individual countries. Its current database comprises 190 countries, including many for which official SUTs have never been published. Given the uncertainty and low reliability from many parts of the estimated tables, the EORA team provides IO data as values along with their standard deviations so that users can judge any quantitative information concerning its magnitude and reliability.[1] Nevertheless, despite its unreliable local properties, its pursued holistic accuracy (Jensen, 1980) justifies its use in many applications. Other global MRIO models, such as WIOD and OECD, are more conservative in using country-level data, relying mainly on published SUTs, which precludes their geographical coverage[2] in favor of higher local accuracy.

Although not explicitly stated, the underlying hypotheses behind the IO estimation strategies followed in the GTAP and EORA projects relate to the conceptual hypothesis of the fundamental structure of IO tables initially explored in work by Simpson and Tsukui (1965). Accordingly, given that the structure of production of an economic system, represented by the matrix of input-output coefficients, is determined by technology (all feasible transformations of goods and factors), one should expect to discover a productive structure that is common to all economic systems having a like technology. By exploring the concept of geographical regions, the GTAP database also touches on the spatial dimension of fundamental structures, suggesting that geographical proximity may be an important determinant of access to technology.

Some of the underlying mechanisms that may provide the necessary theoretical and empirical support to the seeming *ad hoc* strategies used in the GTAP and EORA projects have been extensively explored in the literature. There are at least three hierarchical dimensions for which space matters for knowledge spillovers and, consequently, potential technological convergence: individual, regional, and country levels.

Boschma (2005) analyzed how geographical proximity between individuals influences interactive learning and innovation. Moreover, other proximity dimensions help foster and improve communication leading to potential innovations: social, relational, institutional, and cognitive proximity. An extensive empirical literature emerged from this conceptual work, producing accurate evaluations of the effect of a particular proximity form. Accordingly, geographical proximity may be seen as a critical proximity dimension that accelerates technological convergence and fosters innovation at the firm level.

Knowledge spillovers also benefit from the geographical proximity of firms and workers at the local level. According to Malecki (1991), there are several forms of learning of new technology. In addition to internal learning and specialization, localized learning can also be thought of in the context of a firm's external environment, benefitting from agglomeration economies. Caragliu and Nijkamp (2016) examined in detail the channels along which knowledge flows in the context of EU NUTS-2 regions and provide a complete picture of knowledge spillovers beyond the pure identification of their existence and an indication of the relevance of distance-decay functions. They reviewed and tested the notions of proximity, identifying five main typologies of space (geographic, relational, social, technological, and cognitive), over which knowledge is expected to travel. Analyzing the determinants of knowledge spillovers from an interregional point of view provided a clearer picture of the mechanisms driving the diffusion of knowledge over long distances. As the authors emphasized, different proximity concepts are

[1] See https://www.worldmrio.com/documentation/EoraConfidence.jsp. For a philosophical discussion on the accuracy of IO estimation process as an underdetermined problem, see Von Morgenstern (1950).
[2] While the latest versions of GTAP and EORA cover, respectively, 121 and 190 individual countries, the WIOD and OECD databases cover only 43 and 66 countries.

expected to act as preconditions for knowledge diffusion; even when actors exchanging knowledge are not co-located.

At the country level, technology transfer is critical to technological convergence. If a nation has been unable to learn technology sufficiently to compete, it can obtain technology through technology transfer (Malecki, 1991). In our context, the term "transfer of technology" refers to the process by which a technology developed for a specific use or sector becomes applicable in a different productive setting. There are various channels of technology and knowledge transfer at the country level, mainly motivated by economic interaction between countries through trade, financial flows, including foreign direct investment (FDI), and the movement of workers, managers, professionals, and academics (UNCTAD, 2014).

Empirical evidence suggests the external environment that affects successful technology transfers practices and strategies also includes public policy developments, regulatory and legal issues, and global trends. Considering different macro, meso, and micro foundational perspectives of technology transfer (Cunningham and O'Reilly, 2018) helps to understand one of their global outcomes, namely the holistic approach taken in this article on geographical spillovers and the productive structure of countries.

We explore in this article the relationship between geographical proximity and technological similarity at the country level. Using a set of national tables extracted from the OECD MRIO database, which provides for each of the 43 countries in the sample a reconciled common sectoral classification, we first identify dimensions of proximity associated with countries' similar technologies. We also check whether contiguity (i.e., sharing a common border) matters for the technological similarity between countries and whether nearby countries are more technologically similar than distant countries. We finally assess the effects of geographical proximity on technological convergence over time.

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