TRANSFORMATIONS, TRAJECTORIES AND SIMILARITIES OF NATIONAL PRODUCTION STRUCTURES: A COMPARATIVE FINGERPRINTING APPROACH

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Abstract

This article proposes a network-analytical framework for the comparative study of national production structures in global production networks. Conceptualizing such structures as the networks of sectorial flows in nationally delineated components of multiregional input-output tables, the proposed heuristic extracts a structural profile that captures the up- and downstream prominence of economic sectors for a particular country and year. These 'fingerprints' of national - production structures can subsequently be compared on a pairwise basis, providing novel ways to determine and compare the structural similarities, transformations, and trajectories of national economies in the global production regime.

Two case studies exemplify the heuristic. The first applies clustering methods to explore spatiotemporal similarities for 40 countries over the 1995-2011 period. Based on such similarities, an analytically useful classification into 12 structural types is proposed. The second study addresses structural transformations and trajectories during EU's eastern enlargement, finding significant structural change, yet minuscule East-West convergence. (150 words)

Keywords

Production structures, comparative analysis, Interregional input-output data, transnational production, fingerprinting

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1. Introduction

Disrupting the classical and neoclassical narratives of economic globalization, in which commodities produced within singular nations are traded on international markets, recent decades have seen a marked increase in the trans-nationalization of production itself. Gereffi's now decades-old automobile example continues to illustrate this well: a 1994 Ford Escort was produced in 15 countries, spanning three continents, extending the archetypal assembly lines of Fordism across the globe (Gereffi & Korzeniewicz, 1994; also Ferdows, 1997; Nordlund, 2010, p. 154ff). Indeed, the emergence of commodity chains and fragmented production is not a novel phenomenon, having precursors traced back to 'the long 16th century' (e.g., Hopkins & Wallerstein, 1986), but the intensity, scope and systemic nature of this 'second unbundling of globalization' (Baldwin, 2006; Hornok & Koren, 2017) is unprecedented. This contemporary transnational production regime has had, and will undoubtedly continue to have, a profound impact on the developmental trajectories of nations, and thus also on the specific narratives, models and analytical approaches we employ to understand these impacts and dynamics (Antràs & Chor, 2021; e.g. Coe, 2021; Coe & Yeung, 2019; Grossman & Rossi-Hansberg, 2007; Malets, 2017).

To map and compare how national production structures transform and evolve in this transnational production regime, several different analytical approaches are at our disposal, each representing a specific take on how such structures can be conceptualized and operationalized. One recent contribution to this analytical toolbox is the 'economic complexity' framework proposed by Hidalgo and colleagues (2007; 2009). With a stated aim to "quantify the complexity of a country's economy" (Hidalgo & Hausmann, 2009, p. 10570), where the placement and trajectory of a nation in the generated 'production space' "can be used to analyze the evolution of a country's productive structure" (Hidalgo et al., 2007, p. 485), their proposed heuristic and metrics for such analyses are solely based, by design[1], on compositions of national gross exports. Export commodity bundles and their similarities across nations could indeed be interesting (see, e.g., Smith & Nemeth, 1988; De Benedictis & Tajoli, 2007; Timmer et al., 2019, p. 4ff), but the interpretation of transformed country-product bipartite data is arguably more relevant under the assumption that national gross exports have been fully produced within these countries, which is contrary to the defining feature of transnational production (see, e.g., Inomata, 2017; Ahmad, 2013, p. 86ff; Koopman et al., 2014; Timmer et al., 2019, p. 2; Brakman & Marrewijk, 2017; Koch, 2021). Building on these more contemporary ideas about fragmented production, a large body of work has studied the creation and trade in value-added of sectors and nations (e.g. Aslam et al., 2017; Johnson & Noguera, 2012, 2017; Mattoo et al., 2013; Stehrer, 2012; Timmer et al., 2019; for a recent review, see Antràs & Chor, 2021). These studies capture important aspects of the structural trajectories and transformations of nations, as the creation and trade in value-added indeed both shape and are shaped by national production structures. Combining the computational approach of economic complexity's product space with value-added export data, the 'industry space' captures similarities in sectorial value-added exports between national economies (Koch, 2021; Koch & Schwarzbauer, 2021). The industry space approach is, similar to its product space sibling (Hidalgo et al., 2007), aimed at comparing economic structures of nations over time (Koch & Schwarzbauer, 2021, p. 206): economies with similar sectoral distributions of their value-added exports would thus, it is argued, reflect a similarity with respect to the capabilities of national production structures.

Inter-temporal and international comparisons of sectorial and functional distributions and trade in value-added, as well as gross or value-added export compositions, indeed provide key insights on the structure and dynamics of the contemporary transnational production regime and its

[1] "[T]he mix of products exported by a region's industries represents a fingerprint of the region's productive capacities that does not suppress the identity of the economic elements involved" (Hidalgo, 2015, p. 154; also Balland et al., 2022, p. 4ff).

national components. Yet, if the intentions of such analyses are to compare national production structures with each other, such comparisons are at best by proxy. Product- and sectoral-based compositions of both gross and value-added exports might indeed be *associated* with the structures of national production, representing specific aspects and outputs emanating from such structures, but neither of these *are* said production structures. Rather, for more direct analyses and comparisons of the structures that produce such outcomes, we should arguably shift our attention to what goes on “under the hood” (Leontief, 1954, p. 228) of national economies, i.e. the properties of the complex networks of interdependent flows between and within economic sectors.

This paper proposes an input-output-based analytical framework for the comparative study of national production structures within global production networks. Adapting an earlier eigenvector-based approach by Dietzenbacher (1992) for the transnational production regime, here conceptualizing a national production structure as the complex network of economic flows between and within domestic economic sectors that includes foreign intermediate inputs, the proposed heuristic extracts a structural profile in terms of up- and downstream sectorial prominence for a given country and year. Having determined such ‘fingerprints’ of national production, these can subsequently be compared in a way that is theoretically and conceptually grounded, computationally transparent, and, in the context of global production networks, arguably and hopefully demonstrated to be both useful and insightful when studying structural similarities, transformations and trajectories of national economies.

Using national input-output data for 40 countries from the WIOD[2] dataset (Timmer et al., 2015) between 1995-2011, the fingerprinting heuristic is first contrasted with three alternative approaches based on, respectively, gross sectorial exports, gross commodity exports, and an alternative technology- and output-coefficient-based fingerprint approach (cp. Dietzenbacher,

[2] As the 2016 release of WIOD has more missing data than the 2013 release (see Appendix A.3), the latter was chosen for this study.

1992). Comparing their respective pairwise findings reveals that the proposed fingerprint heuristic captures structural features of national economies that are not captured by these other approaches.

The usefulness of the proposed framework is demonstrated through two short case studies. The first case study explores similarity patterns in the full set of fingerprints. Albeit not finding empirical support for a well-defined taxonomy of discrete national economies, an analytically useful classification into 12 structural types is proposed. This classification is contrasted with corresponding and somewhat trivial clustering results based on, respectively, gross sectorial exports and the alternative coefficient-based fingerprints.

The second case study tracks the structural transformation of European economies during EU's eastern expansion. Tying into pertinent questions on divergent developmental pathways of East European nations following their accession (see, e.g., Bruszt & Vukov, 2018), this case study demonstrates longitudinal approaches to comparative fingerprint analysis as means to examine structural transformations and would-be convergences among six Western and ten Central- and East-European countries. Finding significant structural change among these Eastern economies, their developmental trajectories were more of an orbital kind: indeed on the move, yet remaining equidistant to the relatively stable Western production structures.

A project website[3] supplements this article and provides access to the complete set of WIOD-derived fingerprints. The website also hosts implementations of the various analytical tools[4] presented in this article, allowing for additional analyses and explorations not covered here.

The next section provides a brief introduction to national input-output tables, highlighting the segments that arguably correspond to the production structure of an economy. A brief overview of previous approaches for comparing such structures follows, emphasizing their shortcomings in the

[3] The project website is located at https://demesta.com/fingerprinting.

[4] Figures marked with [D3js] were created using the set of interactive components available on the project website.

context of transnational production. The proposed fingerprint heuristic is then specified, exemplified, and compared with findings obtained from three alternative approaches. The two case studies follow, and a short summary and outline for future research conclude this article.

2. Fingerprinting national input-output tables

A national input-output table is an account of economic flows that occur between different parts of a national economy, and to different ends, during a specific time. With early precursors in the work of Quesnay and Walras (and perhaps even Cantillon: see Hewings & Jensen, 1987, p. 295), it was Wassily Leontief's work that popularized the approach (Leontief, 1936, 1941; see Miller & Blair, 2009). In 1951, Walter Isard extended the idea of input-output analysis by combining multiple regional (single-economy) tables together into inter-regional input-output tables (Isard, 1951, p. 321). More recent advances in data processing and the international harmonization of economic statistics have resulted in several Isard-style multi-regional input-output datasets, such as the World Input-Output Database (WIOD).

Representing a typical national input-output table, Table 1 below depicts the structure of a national table in the WIOD dataset (2013 release). The submatrix Z contains the valued directional flows between and within 34[5] different domestic sectors, this being the "largest and, for most empirical analyses, the most important part of the table" (Hoen, 2002, p. 46). In addition to intermediate inputs originating from domestic sectors, such upstream flows can also have foreign origins, the latter represented by submatrix M. The output from domestic sectors is either turned into intermediate domestic inputs within the Z matrix, being consumed or accumulated within the country (DFU), or exported abroad (E), the latter either for final use or as intermediate input to foreign sectors.

[5] As the 35th sector (for households) in WIOD13 contains no data in Z and M, it was here excluded.

<table>
<tr><td></td><td></td><td>Sector
c1 .. c34</td><td>Final use
(Various end uses)</td><td colspan="2">Total</td></tr>
<tr><td rowspan="3">Sector</td><td>c1</td><td rowspan="3">Intermediate use (Z)</td><td rowspan="3">Domestic final use (DFU)</td><td rowspan="3">Exports (E)</td><td rowspan="3">Total output (x)</td></tr>
<tr><td>..</td></tr>
<tr><td>c34</td></tr>
<tr><td rowspan="3">Sector</td><td>c1</td><td rowspan="3">Imports (M)</td><td rowspan="3">Imports final use (IFU)</td><td rowspan="3"></td><td rowspan="3"></td></tr>
<tr><td>..</td></tr>
<tr><td>c34</td></tr>
<tr><td></td><td></td><td>Value added (VA)</td><td></td><td></td><td></td></tr>
<tr><td></td><td></td><td>Total output (x)</td><td></td><td></td><td></td></tr>
</table>

Table 1: The structure of a national input-output table (from WIOD13)

Input-output tables are used in many types of analyses, ranging from impact assessments of investments, demand mechanisms and spillover effects, to environmental analyses, calculating gross domestic products, and regional planning. Many of these analyses focus specifically on the inter-sectorial intermediate submatrices (Z and M), combining these with total sectorial outputs to determine technology coefficients (A) and the Leontief inverse (L), capturing the direct and total requirements to produce one unit of output per sector (see, e.g., Miller & Blair, 2009, p. 16). When full information about the sectorial origins of imports is available, as in Table 1 below, the Z and M matrices are often combined (through addition) when calculating these coefficients (Hoen, 2002, p. 53).

The complex valued directional network of intermediate flows within and between the economic sectors of an economy, where inputs originate both from within (Z) and outside (M) national boundaries, constitutes a core characteristic of the production structure of a national economy at a specific time. Whereas the direct (A) and total requirement (L) matrices have occasionally been described as the ‘production structure’ of a country, and compared as such (see, e.g., Hoen, 2002, pp. 207–215; also see Chenery & Watanabe, 1958, p. 497; Kondo, 2014; Simpson & Tsukui, 1965), it is here argued that the de facto economic flows between and within sectors better represent a national production structure than what the conversion of such flows into the transformation functions of direct and total requirement coefficients do.

2.1 Previous approaches for comparing national input-output networks

A classical approach for capturing characteristic and comparable features of a national production structure involves the triangulation of the inter-sectorial flows of a national input-output table (Chenery & Watanabe, 1958; also Hewings & Jensen, 1987, p. 322ff). By reordering sectors to maximize the sum of elements in the lower triangle of the matrix, the optimal order arguably captures a sectorial hierarchy of production for a particular economy and year, an ordering which subsequently can be compared for those of other countries and years (e.g. Kondo, 2014; Simpson & Tsukui, 1965; Lamel et al., 1972; Östblom, 1997). Several such studies have found high rank order similarities of sectors, also between assumedly different types of economies (e.g. Chenery & Watanabe, 1958, p. 496; Östblom, 1997, p. 116,127), supporting the notion of certain fundamental structures that economies seem to share (Simpson & Tsukui, 1965, p. 442).

Whereas these findings of fundamental structures are interesting, they also point to some general drawbacks with using triangulation for comparative purposes. First, triangulation assumes a linearity of production, in which potentially circular sectorial relations, albeit possibly rare (see Helmstädter, 1969, p. 231), are ignored. Secondly, rank order correlations capture the ordinal sequence of items, while ignoring the finer details and continuous intervals underpinning such sequences (see also Kondo, 2014, p. 4; Östblom, 1997). Third: as reflected by the scarcity of triangulation studies using multiregional input-output data, it remains unclear how triangulation could be adapted to the context of transnational production, i.e. in the presence of both domestic and foreign intermediate inputs.

Other studies take a more network-analytical approach to map and compare networks of national production. Many of these extract structural metrics at the nodal (sectorial) level, typically various kinds of centrality indices (e.g. Blöchl et al., 2011; McNerney, 2009; Montresor & Marzetti, 2009) but there are also studies looking at other kinds of nodal and dyadic metrics (e.g. Bosma et al., 2005; Defourny & Thorbecke, 1984). Although not explicitly framed as such, the proposal by Dietzenbacher (1991) does reflect a network-analytical approach to the study of national production structures. Building on Hirschman's ideas on unbalanced growth and the importance of industrial backward and forward linkages, Dietzenbacher suggested an eigenvector-based approach to capture such linkages. The dominant[6] left-hand eigenvector of the direct requirement matrix (A) is here operationalizing the magnitude of sectorial backward linkages. Correspondingly, sectorial forward linkages are captured by the dominant right-hand eigenvector on the 'output matrix' (B), the latter containing the shares of one unit of output from a sector that flow as intermediate input to the other sectors (Dietzenbacher, 1992, p. 421). Using 1948-1984 data for the Netherlands, Dietzenbacher concludes that his proposed eigenvector-based approach is more useful when tracking structural change of an economy than previous alternative approaches, even though the average sectorial rankings remained surprisingly static over the 1948-1984 period (see Dietzenbacher, 1992, p. 430).

The above approaches indeed look under the Leontiefian hoods, providing means to map and compare the complex networks of inter-sectorial flows that occur within national economies. However, with the increasing shares of sectorial intermediate input that flow across national borders, where the domestic intermediate sectorial flows of the Z matrix are supplemented with the foreign intermediate inputs of the M matrix, such hoods are increasingly less autarkic. Yet, whereas the inclusion of imported intermediate input makes sense when operationalizing sectorial backward/upstream linkages (and for determining technology coefficients), it is not immediately clear whether a corresponding operationalization of sectorial forward/downstream linkages of a national economy also should include such intermediate flows *from* foreign sectors. Additionally, the

[6] I.e. the corresponding eigenvector for the highest eigenvalue, also known as the leading or primary eigenvector, or the Perron vector (Dietzenbacher, 1992, p. 420), which corresponds to the 'eigencentrality' measure in network science/analysis (Bonacich, 2007).

choice between either comparing the networks of intra- and inter-sectorial transaction flows, or the technology- and output-coefficients derived from such transactions, is not an arbitrary choice, even though triangulation of either type of data might lead to the same hierarchy. Two economies sharing similar technology and output coefficients could indeed have very different economies in terms of inter-sectorial transactions.[7]

Addressing the shortcomings of the comparative approaches above, the next section will propose and specify a novel network-analytical heuristic for the mapping and comparison of national production structures in a transnational production regime.

2.2 Specifying the proposed fingerprinting heuristic

Following Dietzenbacher (1992), the heuristic proposed in this article uses directional left- and right-hand eigenvectors to extract structural fingerprints of economies, each capturing the prominence of up- and downstream linkages for each economic sector in an economy for a specific year. However, the fingerprinting heuristic departs from the 1992 approach in two ways. First, instead of determining sectorial backward and forward linkages using the direct technology and output coefficient matrices, respectively, the fingerprint heuristic uses the sectorial flow networks to determine up- and downstream sectorial prominence. The aim here is thus not to capture the coefficients of sectorial production functions of a specific country and year, but rather the specific intersectoral flow patterns that characterize its economic activities and production structure.

Second, whereas the proposed heuristic measures sectorial upstream prominence using the combined intermediate sectorial inputs from both domestic and foreign sources, the downstream prominence metrics are determined based on domestic sectorial intermediate output alone. Specifically, as given in Equation 1 and 2 below, the downstream prominence vector d is here operationalized as the dominant right-hand eigenvector of the Z matrix, whereas corresponding

[7] This will be demonstrated in the specification of the approach as well as in the first case study.

prominence of upstream flows *u* is captured by the dominant left-hand eigenvector of the summed Z and M matrices (T representing the element-wise summed together Z and M matrices).

$$Zd = \lambda_{\mathrm{max,d}} d \qquad \text{(Eq. 1)}$$

$$uT = \lambda_{max,u} u \qquad \text{(Eq. 2)}$$

Underpinning the motivation for this specific operationalization, a visual representation of domestic (Z) and foreign (M) intermediate flows of a 4-sector toy economy is given in Figure 1 below. As the aim of the heuristic is to capture structural properties of a domestic production structure, it arguably makes sense to include both foreign and domestic sectorial inputs (i.e. the T matrix) when capturing the upstream properties of a domestic economy, i.e. mimicking how technology coefficients typically are calculated from multi-regional input-output data. These domestic and foreign upstream flows correspond to the inbound black and gray solid arrows in Figure 1 below. For the downstream properties of domestic sectors, it is however reasonable to *exclude* sectorial outputs of the foreign sectors, so that the downstream profile of sectors thus only captures sectorial prominence and embeddedness with respect to the domestic economy (i.e. the Z matrix alone, as given by the outbound black arrows in Figure 1 below). If instead both Z and M were included in Equation 1 above, the downstream sectorial prominence vector would then be based on *both* the domestic intermediate output to the domestic economy *and* the corresponding intermediate output of all foreign sectors to domestic sectors.

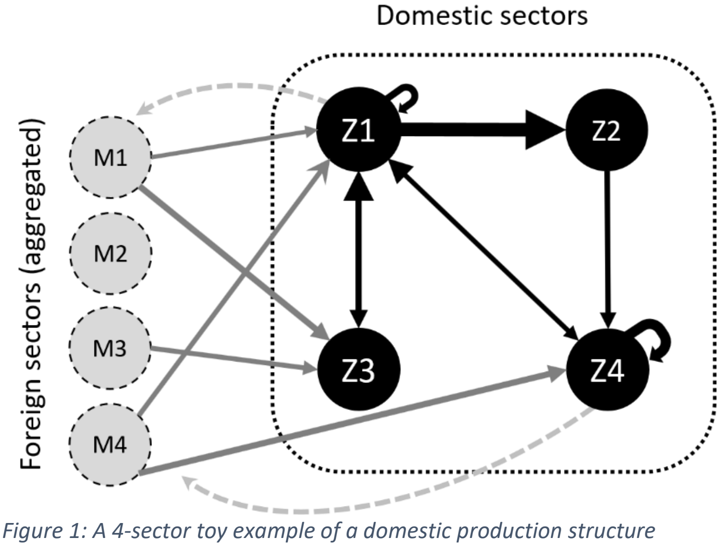

Figure 1: A 4-sector toy example of a domestic production structure

Figure 2 below depicts[8] the WIOD13-derived fingerprint of the production structure of Denmark in 1995. A notable feature of the Danish economy in 1995 is the prominent upstream linkages of its Food sector, a sector whose output is more likely to end up for final use than as intermediate input to other sectors. The up- and downstream prominence of the Business and Finance sectors are somewhat reversed, where the prominence of their domestic downstream linkages reflect their common role of serving other sectors of the domestic economy.

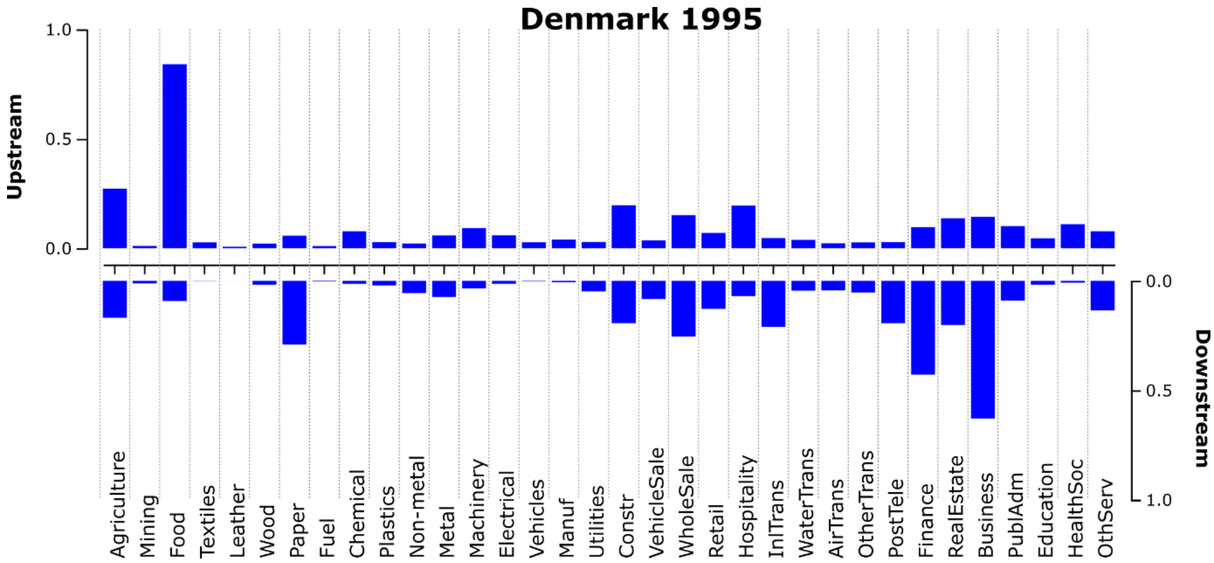

Figure 2: Fingerprint of the Danish production structure in 1995 [D3js] (see Appendix A.2 for sector details and the WIOD mapping to ISIC rev.3). Eigenvalue diagnostics(DNK_1995)[9]: $u_{\%}$=27%, u_{1vs2}=1.38, $d_{\%}$=36%, d_{1vs2}=1.45

The solid dots in Figure 3 below represent the average up- and downstream sectorial prominences for all 40 countries for the period 1995-2011, with lighter bars capturing spread (as one standard deviation from the means). An ocular comparison with the Danish fingerprint for 1995 hints at a more pronounced upstream prominence for the Danish Food sector and a somewhat higher downstream prominence for its Business, Finance, and Paper sectors, compared to the average fingerprint.

[8] For up- and downstream prominence values for individual fingerprints, see the D3js versions of this figure: https://demesta.com/fingerprinting/single.php?country=DNK&year=1995

[9] The eigenvalue diagnostics are explained in Section 2.4.

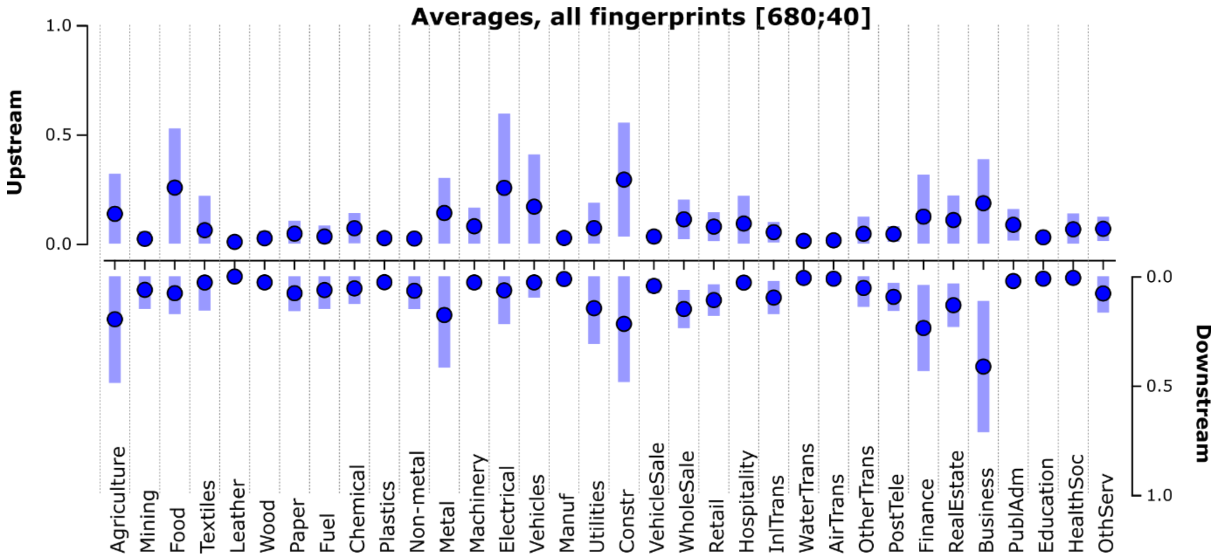

Figure 3: Average fingerprint of the production structures for 40 countries in the 1995-2011 period [D3js]

How does the Danish production structure for 1995 differ from its north-eastern neighbor Sweden in the same year? Figure 4 below depicts the fingerprint of both these production structures – Denmark 1995 (green dots) and Sweden 1995 (red dots) – with the colored bars indicating the relative difference in the up- and downstream prominence of each sector in its respective economy. The upstream prominence of the Danish Food sector is noticeably larger than that of its Swedish counterpart, whereas the upstream prominences of the Swedish manufacturing sectors are somewhat larger than in Denmark for this year.

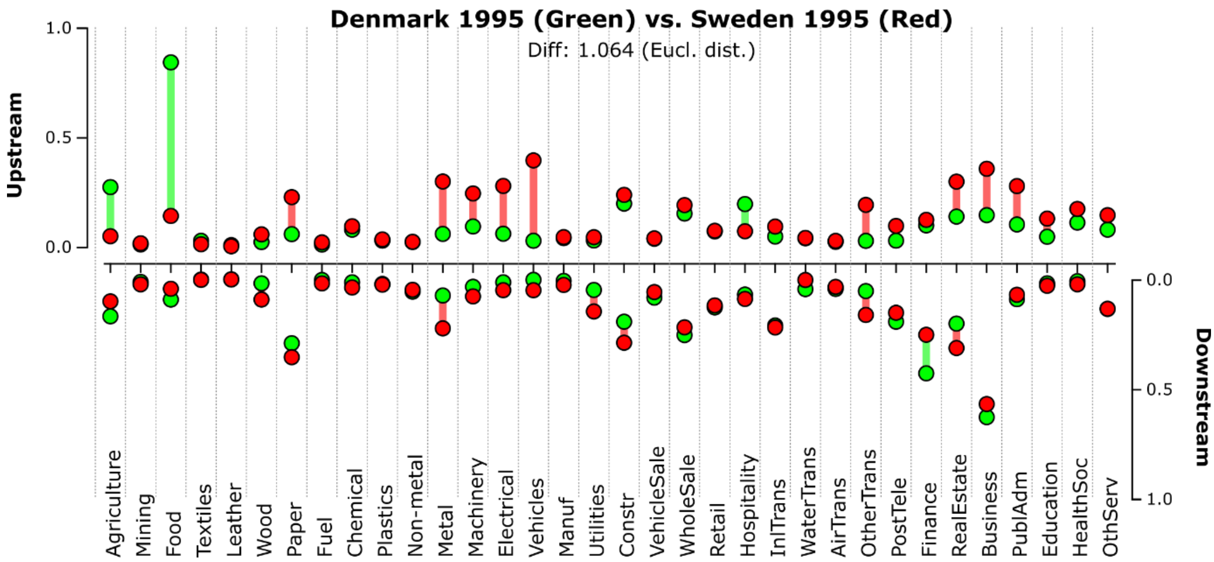

Figure 4: Comparing fingerprints: Denmark 1995 vs. Sweden 1995 [D3js]. Eigenvalue diagnostics(SWE_1995): $u_{\%}$=23%, u_{1vs2}=1.56, $d_{\%}$=28%, d_{1vs2}=2.12

With each fingerprint corresponding to a point in a 68-dimensional hypercube, the pairwise measure of dissimilarity proposed here constitutes the Euclidean distance between two such points.

In the case of the two Nordic economies in Figure 4 above, the dissimilarity between the Swedish and Danish structural fingerprints in 1995 is 1.06. This is lower than the average pairwise dissimilarity measure for all 780 country-pairs in 1995 (1.41), yet far from as similar as what is the case for the Romanian and Lithuanian fingerprints of 1995 (0.15). For the complete set of 230,860 pairwise dissimilarity measures for all countries and years in the WIOD13 dataset, the left-skewed distribution has a mean and median of 1.43 and 1.50 respectively (see Figure 5).

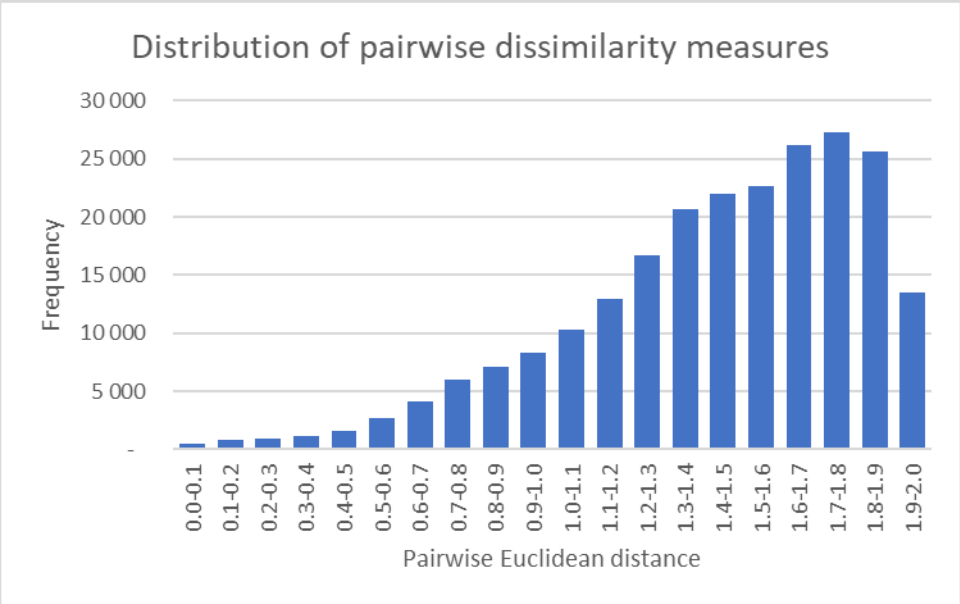

Figure 5: Distribution of all pairwise Euclidean dissimilarities for the whole set of 680 fingerprints

2.3 Comparative fingerprinting vis-à-vis export- and coefficient-based alternatives

To what degree does the fingerprinting heuristic capture aspects of production structure that cannot be captured by gross exports and technology coefficients? To evaluate this, the WIOD13-based pairwise dissimilarity measures of the proposed fingerprint approach are compared with corresponding measures obtained from three alternative approaches based on, respectively, sectorial exports, commodity exports, and technology- and output coefficients.[10]

[10] Country-year data for these alternative metrics (including their dissimilarity matrices) are available for download on the project website. The website also provides tools for visualizing and comparing coefficient-based fingerprints.

For gross sectorial exports, the E vectors from the national input-output tables in WIOD13 (see Table 1) were first normalized and pairwise dissimilarity measures (Euclidean distances) between vectors were determined. For the second alternative approach, that of pairwise similarities of gross commodity exports[11], export vectors consisting of 97 different commodities were used, similarly normalized, and subsequently compared on a pairwise basis using Euclidean distances.

Inspired by Dietzenbacher (1991), the third alternative approach applies the proposed fingerprinting heuristic to the technology and output-based coefficients derived from the WIOD13 data, yielding what is here labeled as 'coefficient-based fingerprints' for each country and year. Contrary to Dietzenbacher's approach, instead following the previous reasoning underlying the previous specification of the proposed (i.e. 'flow-based') fingerprinting heuristic, the coefficient-based backward linkages are determined from the technology coefficients stemming from the T matrices, whereas sectorial forward linkages are determined from the output coefficients using the Z matrix alone. Specifically, with $\hat{x}$ being the diagonalized version of the total output vector *x*, technology coefficients $A = (Z + M)\hat{x}^{-1} = T\hat{x}^{-1}$ and output coefficients $B = \hat{x}^{-1}Z$, the forward (*f*) and backward (*b*) sectorial vectors are determined using Equation 3 and 4 below.

$$\hat{x}^{-1}Zf = \lambda_{max,f}f \qquad \text{(Eq. 3)}$$

$$bT\hat{x}^{-1} = \lambda_{max,b}b \qquad \text{(Eq. 4)}$$

Concatenating these coefficient-based backward (b) and forward (f) sectorial vectors for each country and year, pairwise dissimilarity metrics for this third alternative approach were subsequently determined using Euclidean distances in a similar 68-dimensional hypercube.

With pairwise dissimilarity measures for 642 country-years available[12] for the fingerprinting heuristic and the three alternative approaches, it is possible to compare how pairwise fingerprint

[11] Gross commodity export data obtained from the BACI database (Gaulier & Zignago, 2010)

[12] Commodity export data was missing for Taiwan in the 1995-2011 period (17 years) and reported commodity export data for Belgium in 1995-1998 is merged with that of Luxembourg. Additionally, extracting the

dissimilarities associate with corresponding dissimilarities for the alternative metrics – see Figure 6.

A permutation-based Mantel/QAP test was also conducted, confirming all associations as statistically significant.[13]

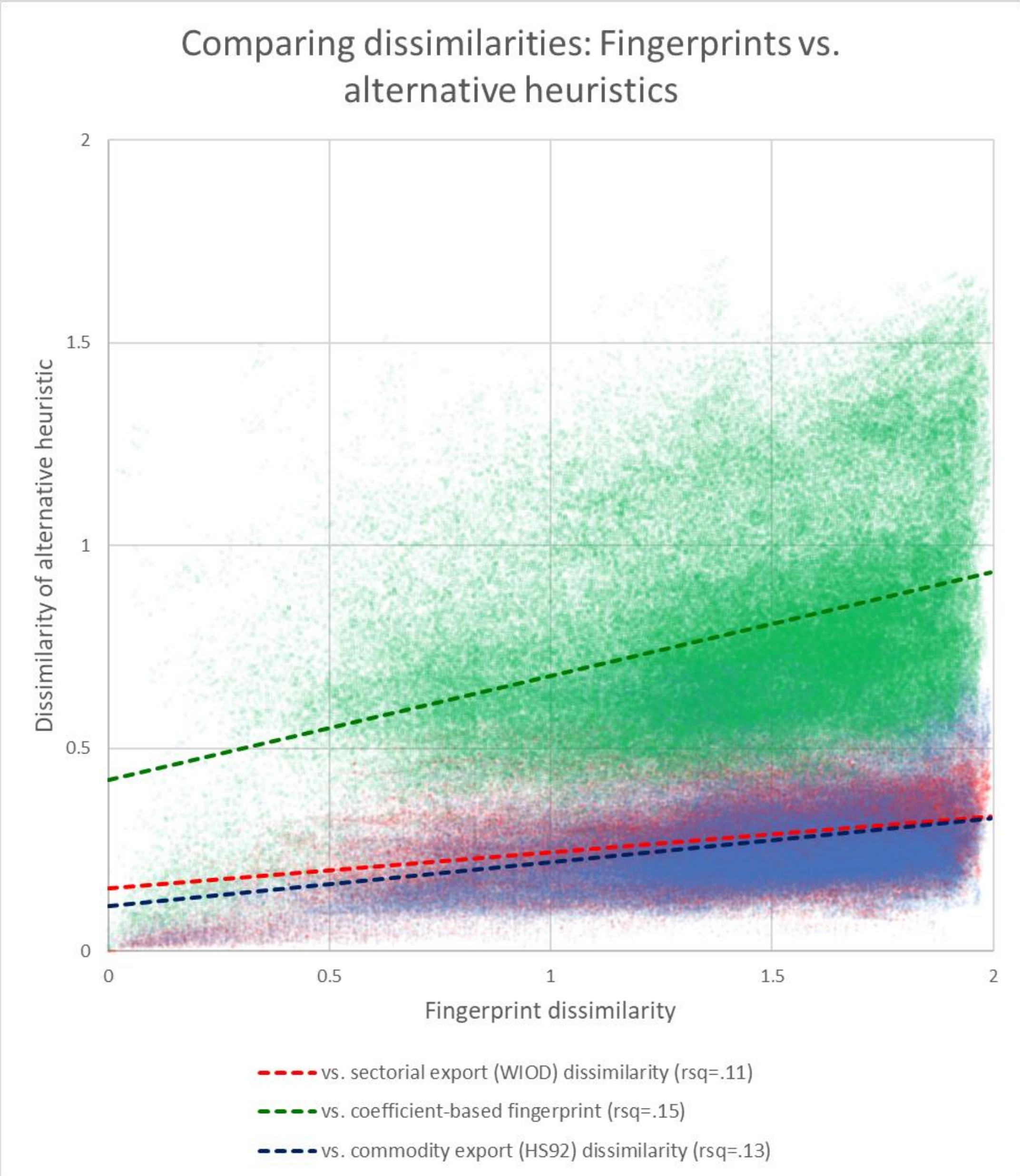

Figure 6: Comparing pairwise fingerprint dissimilarity measures with corresponding dissimilarity measures of three alternative heuristics

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eigenvectors for Luxembourg's output coefficients turned out to be problematic, leading to the removal of all its 17 years in this comparison.

[13] The expected correlations between each pair of metrics (with 10,000 permutations) were 0.00, with all p-values <0.00. As expected, the correlation between gross sectorial and gross commodity exports was high (0.74).

Whereas economies with very similar flow-based fingerprints also have very similar sectorial and commodity-based gross export compositions, the reverse associations do not hold. Rather, countries with similar gross exports could have very different domestic production structures. This tendency is even more pronounced with respect to the coefficient-based alternative metric: although the correlation between the default and coefficient-based fingerprinting dissimilarities is slightly higher, two economies with similar coefficient-based fingerprints could either have very similar or very dissimilar production structures in terms of actual intra- and inter-sectorial flows.

This difference between flow- and coefficient-based fingerprinting is exemplified by an inter-temporal comparison of Bulgaria. Comparing its 2004 fingerprint with that of 2011 – see Figure 7 below – Bulgaria seemingly transitioned from a predominantly agricultural economy to one with more prominent metal and construction sectors, a transformation corresponding to a structural dissimilarity of 1.74. However, a comparison of the coefficient-based fingerprints of Bulgaria in 2004 and 2011 reveals that they are almost identical – see Figure 8 below – with a dissimilarity of only 0.25[14]. Thus, whereas the technology- and output coefficients might give the impression of structural stability, the fingerprinting heuristic points to significant structural transformations in Bulgaria during this period.

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[14] Measured in terms of Euclidean distances, the composition of Bulgarian gross sectorial export in 2004 is also very similar to its 2011 composition (0.06), which also is the case when comparing the gross commodity export of Bulgaria for these years (0.13).

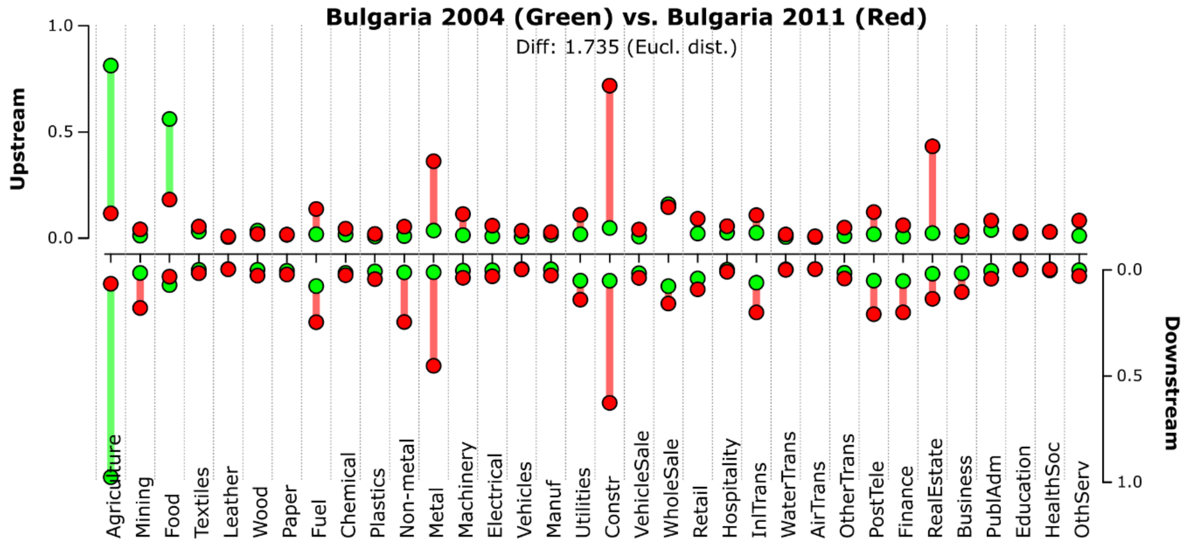

Figure 7: Comparing fingerprints: Bulgaria 2004 vs. 2011 [D3js]. Eigenvalue diagnostics(BGR_2004): $u_{\%}$=0.29, u_{1vs2}=1.70, $d_{\%}$=0.36, d_{1vs2}=1.99; Eigenvalue diagnostics(BGR_2011): $u_{\%}$=0.23, u_{1vs2}=1.92, $d_{\%}$=0.26, d_{1vs2}=2.03

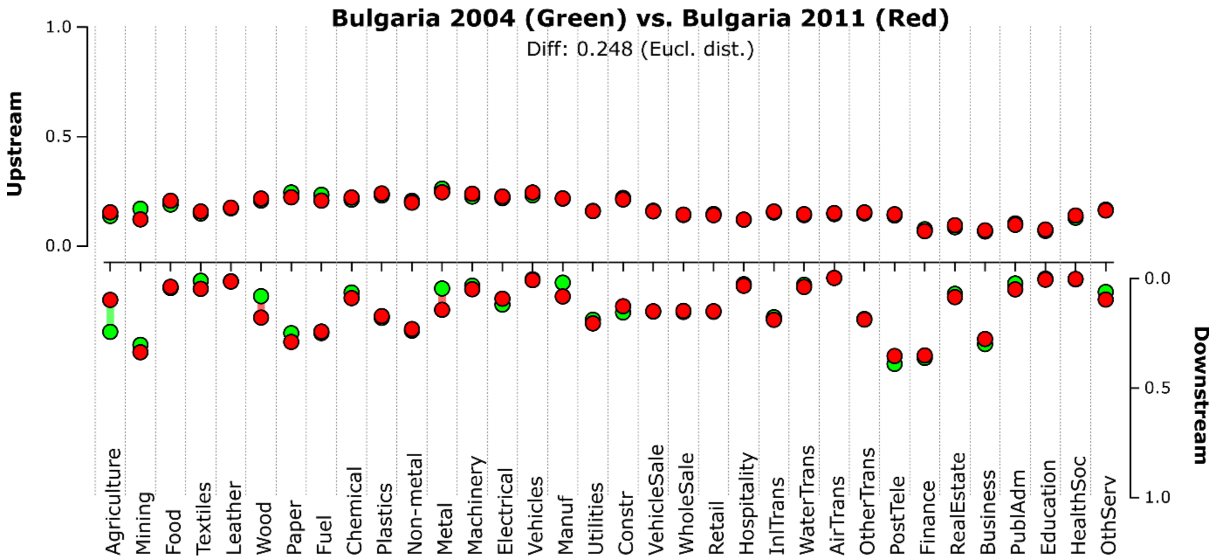

Figure 8: Comparing alternative coefficient-based fingerprints: Bulgaria 2004 vs. 2011 [D3js]

Figure 9 below captures the average coefficient-based fingerprint. Compared to the corresponding figure for the (flow-based) fingerprinting heuristic proposed in this article (Figure 3), the coefficient-based fingerprints are notably more similar to each other than what is the case for the 'default' fingerprints. This does lend support to existing findings on production function similarities of economies (e.g. Korte & Oberhofer, 1971; Drabek, 1984, p. 297 note 12), which in a well-integrated transnational production setting with extensive capital mobility perhaps is to be expected, but it also obfuscates the variety of production structures that evidently exists and which, it can be theorized, could explain this emergence of global integration of production.

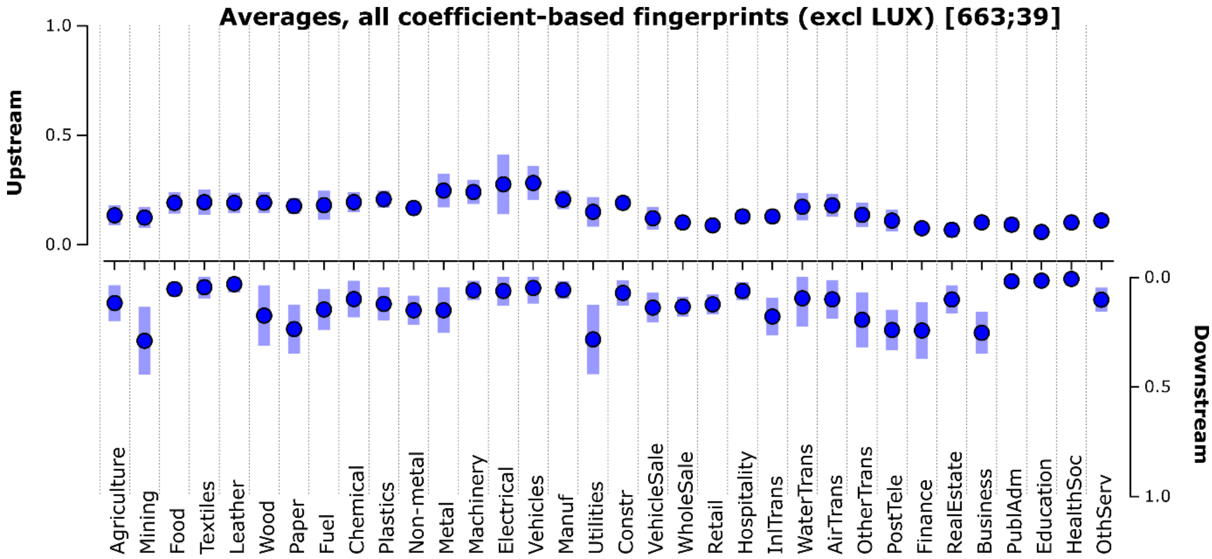

Figure 9: Average coefficient-based fingerprint of the production structures for 39 countries in the 1995-2011 period [D3js]

2.4 The eigenvalues of WIOD13-based fingerprints[15]

A common way to evaluate how well extracted eigenvectors manage to capture latent features of more complex data involves examining the eigenvalues corresponding to these eigenvectors. As each fingerprint consists of two dominant eigenvectors derived from slightly different matrices (T vs. Z), each of these have their own set of decreasing eigenvalues. The size of these dominant eigenvalues with respect of remaining eigenvalues could thus provide insight on how well the complexity of these networks can be expressed in terms of these measures of sectorial prominence.

Two diagnostic measures were calculated for each dominant eigenvector. The first measure ($u_{\%}$ and $d_{\%}$) captures the size of the dominant eigenvalue as a percentage of the sum of all eigenvalues, and the second measure (u_{1vs2} and d_{1vs2}) captures the ratio between the dominant and second-largest eigenvalue. A statistical summary of these four eigenvalue diagnostics for all 680 fingerprints in the WIOD13 database is given in Table 2 below.

[15] See Appendix D.1 for a full specification, discussions and more analyses of the eigenvalue diagnostics.

Table 2: Statistics on the eigenvalue diagnostics derived from the 680 WIOD13 fingerprints

	Upstream vectors (Z+M)		**Downstream vectors (Z)**	
	1st share ($u_{\%}$)	**1st/2nd ratio (u_{1vs2})**	**1st share ($d_{\%}$)**	**1st/2nd ratio (d_{1vs2})**
Mean	0.27	2.05	0.29	2.04
Median	0.24	1.54	0.27	1.66
Range	0.16 – 0.87	1.08 – 18.81	0.18 – 0.89	1.11 – 19.24

Although the mean and median diagnostics are satisfactory, several fingerprints do have eigenvectors whose eigenvalue diagnostics preferably would be larger. Few, however, have low values for *both* of their eigenvalue diagnostics. Still, whereas one should be careful when interpreting the individual fingerprints with relatively poor eigenvalue diagnostics, the dominant eigenvectors do reveal a significant structural consistency over time. Thus, even though occurrences of low eigenvalue diagnostics could reflect structural dynamics that are not properly caught by the dominant eigenvectors, such dips do not seem to be associated with spurious transformations and transitions between types (see Appendix D.1).

3. Case study 1: Distinct types and classifications of national production structures

Reminiscent of the classical discrete-vs.-continuous debate on the properties and functions of the core, semiperiphery, and periphery in the modern world-system (Chase-Dunn, 1989, p. 214; Wallerstein, 1974, p. 403, 1979, p. 69) and also the idea of determining a taxonomy of national economies (cp. Hewings & Jensen, 1987, p. 324; Hewings et al., 1989): to what extent can discrete types of national production structures be observed in the WIOD13 data? Can we derive analytically useful classifications of nations based on similarities among their production fingerprints? To explore the first question, complete-link hierarchical clustering[16] was applied to the full set of pairwise fingerprint dissimilarity measures. Since subsequent cluster adequacy tests indicate little support for the existence of any such discrete and reasonably "crisp" set of types, the strictness of the complete-

[16] For an introduction to hierarchical clustering, see Murtagh & Contreras (2012)

link clustering was replaced by an (unweighted) average-link-based cluster analysis, yielding a slightly different hierarchical clustering structure. From this, two nested partitions, at the 7- and 12-cluster levels, are explored as potential classifications of national production structures. Contrasting these findings, corresponding cluster analyses using, respectively, the coefficient-based fingerprint alternative heuristic and gross sectorial exports reveal rather trivial and less insightful partitions.

3.1 Evaluating the existence of discrete types of national production structures

The radial dendrogram in Figure 10 depicts the clustering structure resulting from complete-link[17] agglomerative clustering of the full set of 680 national fingerprints. Informed by a cluster adequacy test (see Figure 11 and subsequent discussion), the dendrogram in Figure 10 is labeled and color-coded based on the partition that yields nine clusters.[18]

[17] In complete-link clustering, new cluster distances are determined based on the largest distance between the items in two clusters, resulting in relatively “tight” clusters in which the maximum within-cluster distances are kept low.

[18] For supplementary data on this partition, see Appendix B.1-2 (cluster membership and average fingerprint; also project website), and Appendix C.1 (Table 1 and 2: average within- and between-cluster distances).

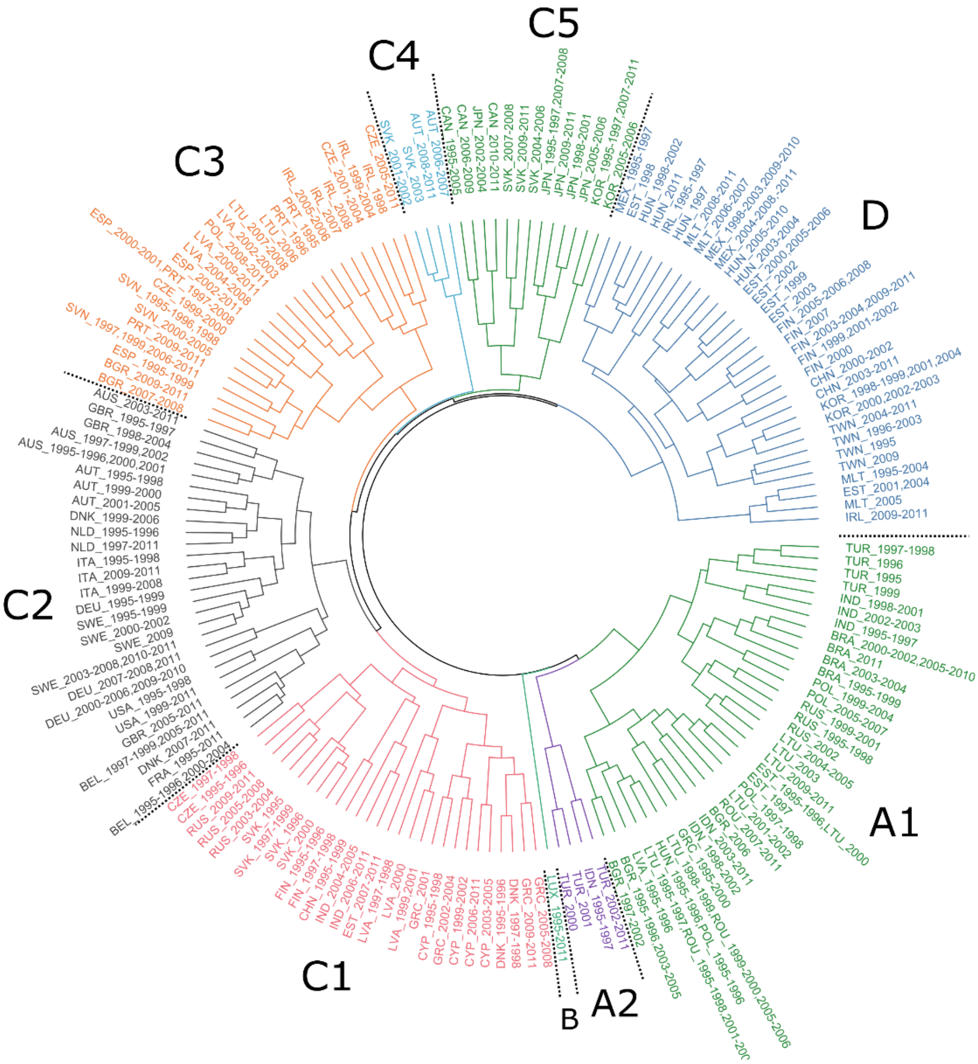

Figure 10: Dendrogram of complete-link hierarchical clustering of 680 fingerprints (visualized from the 170-cluster partition), highlighting the 9-cluster partition (countries and years given by [ISO3]_[years]; see Appendix A.1 for the ISO3-to-country table, and Appendix B.1-2 for cluster memberships and average cluster fingerprints)

Two cluster adequacy metrics were applied to all partitions between two and 50 clusters – see Figure 11. The Calinski-Harabasz (CH) metric captures the ratio between high between-cluster dispersal and low within-cluster dispersal, while the within-cluster sum-of-squares (WCSS) metric captures the latter, i.e. within-cluster dispersal. A distinct peak in the CH measures, combined with a notable drop in the WCSS metric, could thus indicate that a particular partition corresponds to a set of clusters that, in the Wallersteinian functional sense, are more distinct than the partitions surrounding it.

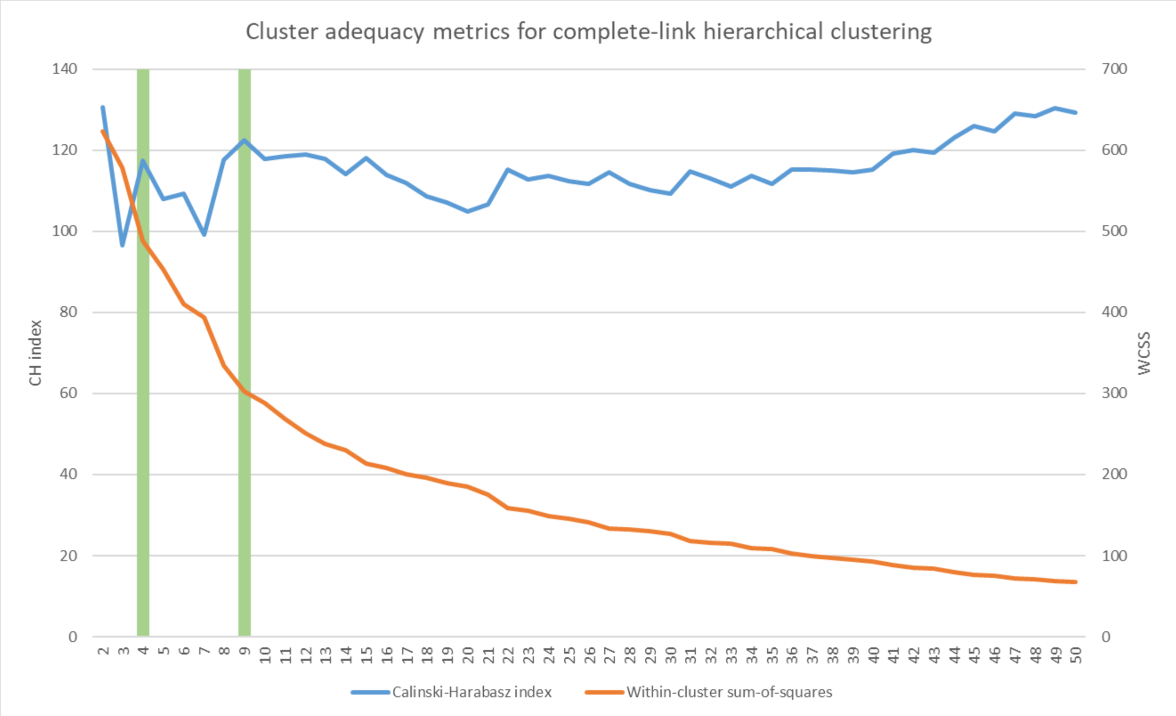

Figure 11: Cluster adequacy analysis for the complete-link hierarchical clustering of 680 fingerprints

The first notable peak occurs at the 4-cluster partition. Luxembourg, with its unique finance-dominated structural fingerprints, forms its own cluster, whereas remaining fingerprints split up into three broad clusters.[19] However, the WCSS metric is notably high at this partition and with within-cluster distances[20] almost at par with those between clusters, it is only the Luxembourg subset that can be considered a discrete type.

Although the CH index reaches a local maximum at the 9-cluster[21] partition, this hardly constitutes a peak. Rather, the index remains high beyond this partition, eventually exceeding this value at the 44-cluster partition. The conclusion is thus that there is no support for treating *this* specific 9-cluster partition, nor *any* other potential partition in this dataset, as corresponding to a set of *discrete* and functionally distinct types of national production structures in the contemporary global production network. Any classification of structural types derived from these data should

[19] For cluster membership and characteristic fingerprints, see project website or appendix B.1.

[20] For supplementary cluster statistics, see appendix C.1-2.

[21] For information about these clusters, see the project website and Appendix B.2.

instead preferably be seen as “a shorthand” for a more complex continuum (Chase-Dunn, 1989, p. 214).

3.2 A 12-type classification of national production structures

For analytically more useful classifications, (unweighted) average-link[22] hierarchical clustering was applied to the same full set of distances. Figure 12 below tracks cluster adequacy metrics for partitions in the 2-to-50 cluster range. Corresponding to the maximum peak value, the 12-cluster partition was selected for further analysis, but the 7- and 21-cluster partitions were also included as reference. A sunburst chart for these three partitions is presented in Figure 13 below, with clusters named according to the prominent economic sectors characteristic of each cluster subset (e.g. Figure 14).

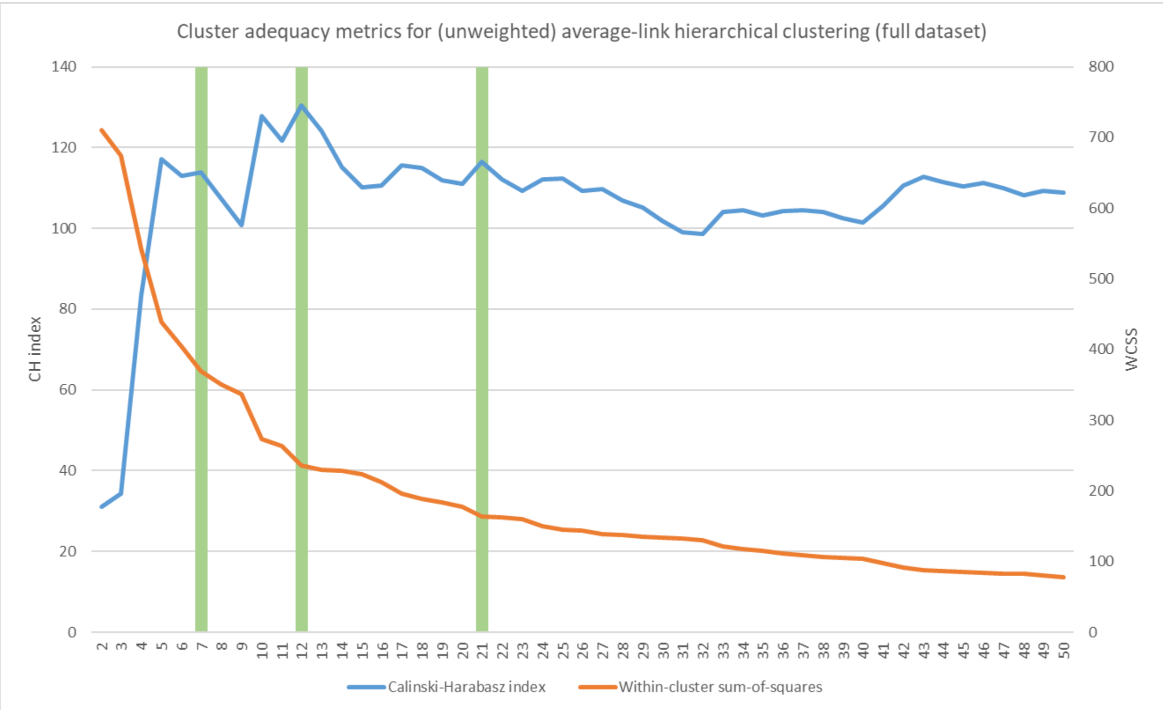

Figure 12: Cluster adequacy analysis for the (unweighted) average-link hierarchical clustering of 680 fingerprints

[22] In agglomerative hierarchical clustering using the unweighted average-link (UPGMA) method, new cluster distances between two recently merged clusters and all other clusters are determined based on the unweighted average distance between items in the two clusters.

*Figure 13: Sunburst chart of the 7-, 12- and 21-cluster[23] partitions from (unweighted) average-link clustering of 680 fingerprints. *: Excludes Estonia in 2001 and 2004.*

The 7-cluster partition is dominated by the Business & Construction cluster, containing more than half of all countries (see Figure 14:A). Notably, this cluster contains the full temporal sets for almost all West- and South-European countries, as well as Australia and USA. Slovenia is in this cluster for the whole 1995-2011 period, whereas Poland, Czech Republic and the Baltic states are

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[23] Turkey 1999 constitutes its own agricultural cluster at the 21-cluster partition but is here placed together with its preceding 4 years in the diversified Agricultural cluster. Also note that Estonia in 2001 and 2004 is categorized as an Electrical (embedded) type, not the Electrical & Agriculture type.

here intermittently. This cluster is followed by two clusters characterized by Metal & Electrical (Figure 14:B), and Agriculture & Food (Figure 14:C). Four smaller clusters follow, capturing specializations in, respectively, vehicle production, textiles, utilities/fuel, and the unique financial profile of Luxembourg.

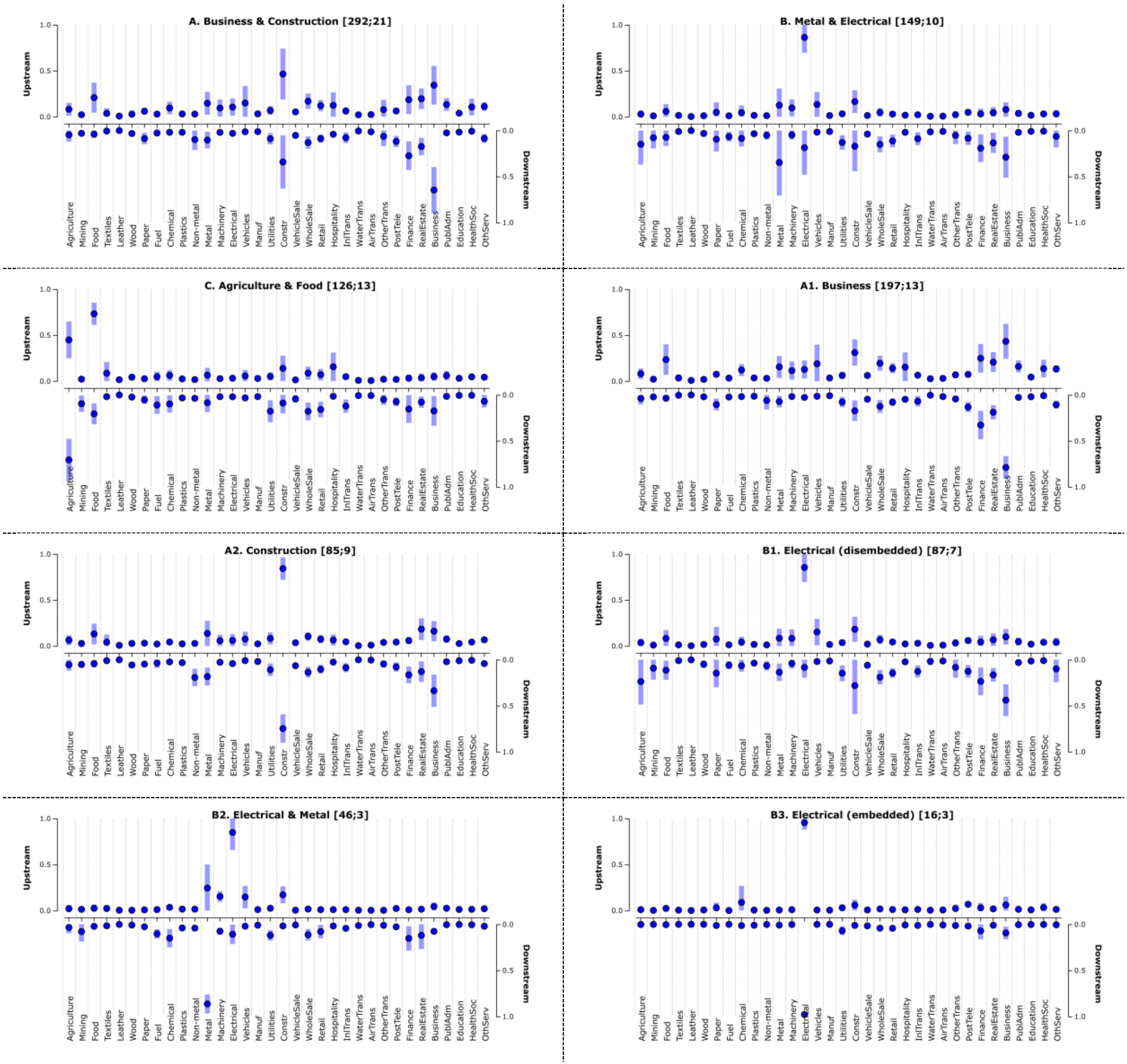

Figure 14: Major fingerprint types in the 7- and 12-cluster partitions [D3js]

Whereas the size of the Business & Construction cluster might undermine the analytical usefulness of this partition, it is interesting that these production structures are so similar. Thus, in terms of domestic production structures, there seems to be support for a 'European economy' moniker at this level of detail – and indeed also a corresponding 'Western developed economy' moniker at the 12- and 21-cluster partitions.

The Agriculture & Food subset remains the same at the 7- and 12-cluster partitions, but the other two major subsets of the 7-cluster partition split into more specialized types. Business & Construction emerge as two distinct economic types, broadly separating the business-oriented core[24] European countries (Figure 14:A1) from its more construction-focused southern and eastern neighbors (Figure 14:A2). Latvia (1997-2001) and Estonia (2007-2011) form a separate cluster: with prominent Other transport sectors, its high average within-cluster distance (0.68)[25] combined with its small size indicates that this is more of a residual 'type'.

The Electrical & Metal cluster also separates into three subsets at the 12-cluster partition (Figure 14:B1-3), all sharing prominent Electrical upstream flows with different secondary specialization. Taiwan, South Korea and China (2000-2011) share domestically well-embedded Metal sectors (Figure 14:B2), which the other Electrical sector-oriented economies lack (Figure 14:B1). A smaller and fairly distinct cluster with Malta (1995-2005), end-period Ireland, and two Estonian fingerprints have Electrical sectors that are notably well-embedded in their domestic economies (Figure 14:B3).

Providing an overview of longitudinal change and transitions between structural types, the sequence index plot in Figure 15 below represents an alternative way to visualize the 12-cluster partition. Of the 12 countries classified as Agricultural- & Food-oriented in 1995, only Lithuania, Romania and Brazil remained so in 2011. Contrasting this, most countries in the Business and Construction types remained so during the whole 1995-2011 period. Several country-specific transitions between types associate with specific economic-historical events. For example: Greece's 2001 transition to the Business-oriented structural type coincides with its adoption of the Euro; Malta's 2006 shift to a domestically dis-embedded electronics industry coincides with both a general

[24] Greece (2002-2011) and Cyprus (all years) are here found in the Business type but join early-period Denmark in a Hospitality- and Food-oriented category at a higher clustering resolution.

[25] Average within- and between-cluster distances for all partitions can be found in Appendix C.

deceleration of industrial value added growth rates (Grech, 2016, p. 17), economic policy adjustments following its 2004 EU membership, and a major restructuring[26] of Malta's main electronics industry; and Russia's structural transformation from Agriculture & Food to Metal & Fuel in 2003 coincides with a drastic increase in international oil prices (e.g. Tabata, 2006). Although not conclusive in any way, these kinds of substantive observations, along with the overall structure and country memberships of these 12 clusters, indicate that this partition could function as an analytically useful classification of national production structures.

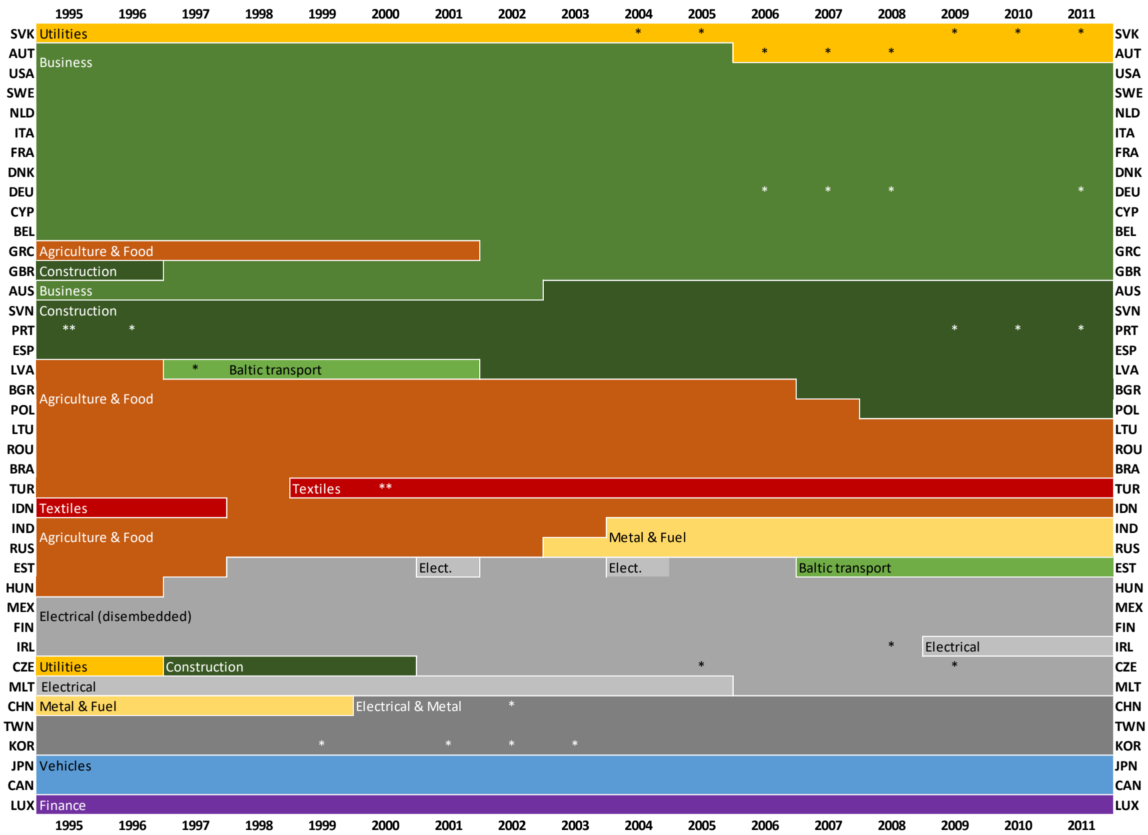

*Figure 15: Longitudinal transformations of national production structures: a sequence index plot of the 12-cluster partition. (Country-year fingerprints marked with * and ** indicate potentially problematic diagnostics for either one or both of the directional eigenvectors of a fingerprint; see section 2.4 and Appendix D.1)*

[26] https://www.design-reuse.com/news/10376/stmicroelectronics-additional-restructuring-efforts.html

3.3 Cluster analyses based on gross sectorial exports and coefficient-based fingerprints

To what extent do the clustering results above compare with corresponding clustering structures using the alternative metrics previously introduced? To test this, corresponding (unweighted average-link) cluster analyses were performed on, respectively, gross sectorial exports and the coefficient-based[27] fingerprints (see Appendix D.1 and C.2 for details). Although cluster adequacy tests were ambiguous, a 16- and 15-cluster partition was chosen for, respectively, the gross sectorial export clustering (Figure 16) and coefficient-based fingerprints (Figure 17) to approximately match the size of the proposed 12-cluster classification.

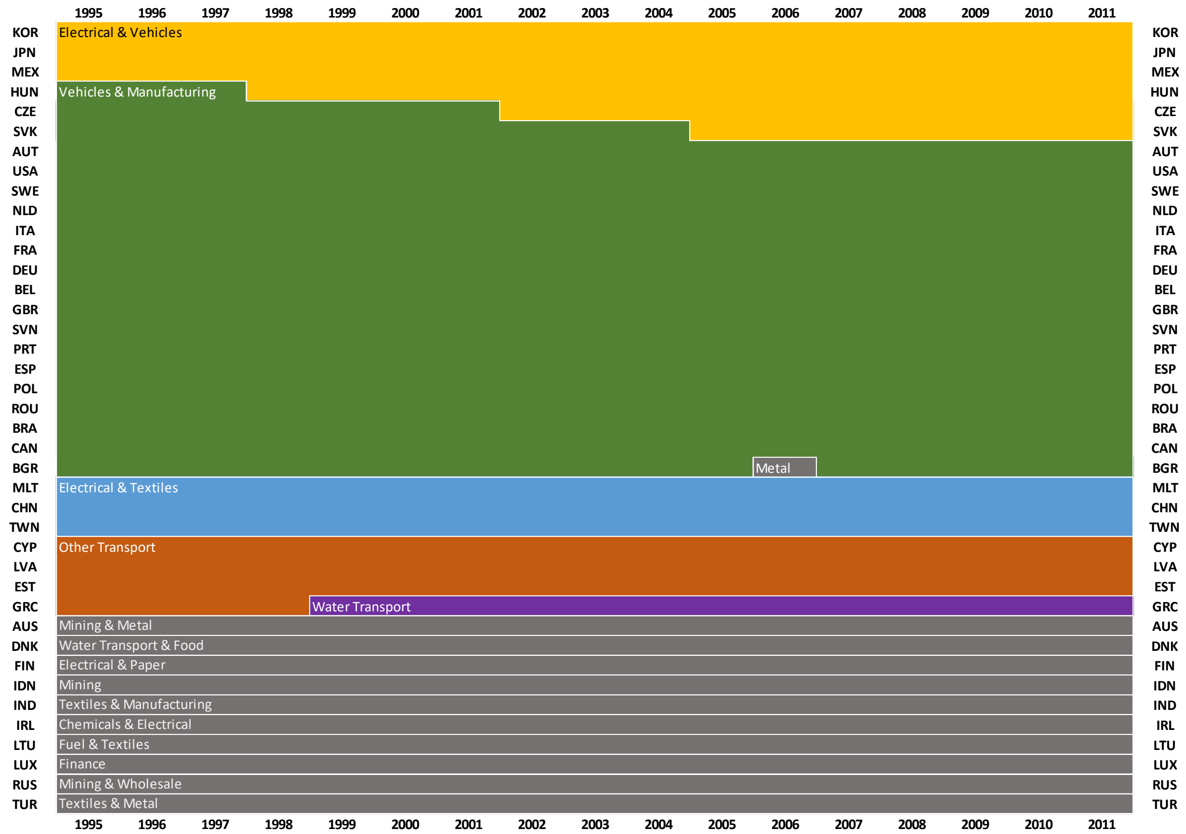

Figure 16: Sequence index plot: 16-cluster partition of gross sectorial export dissimilarities (alternative metric)

[27] As in the previous analysis, Luxembourg is not included in the coefficient-based fingerprint dissimilarity data.

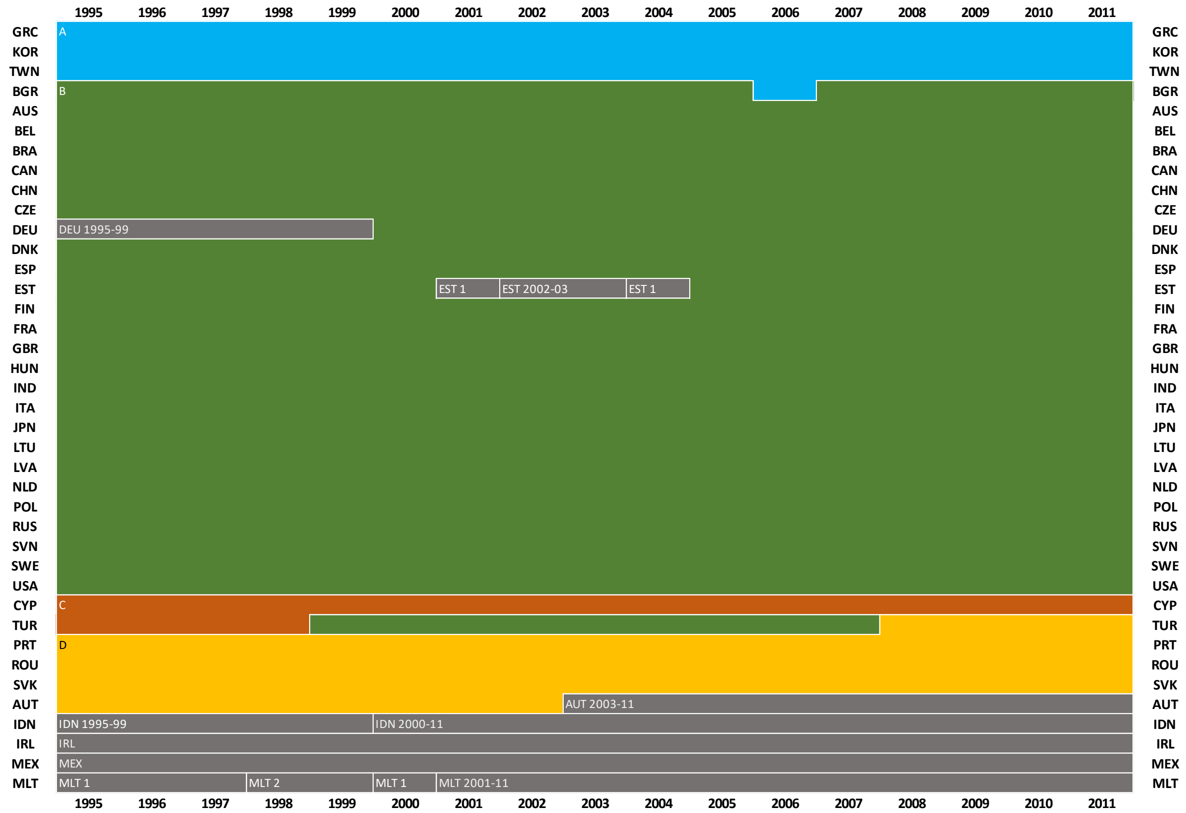

Figure 17: Sequence index plot: 15-cluster partition of coefficient-based fingerprinting dissimilarities (alternative metric)

Compared with the 12-cluster partition using the proposed (default) fingerprinting heuristic (Figure 15), the alternative metrics produce results that seems to be analytically less interesting. Gross sectorial export profiles are to a large degree both static and country-specific: 10 out of the 16 clusters contain all years for individual countries. The few clusters with multiple countries are seemingly non-intuitive, with Korea, Japan and Mexico forming a cluster, and Malta, China and Taiwan forming another. Transitions are also somewhat rare: only four countries shift from one type to another during the 1995-2011 period.

The 15-cluster partition of the coefficient-based fingerprinting dissimilarities is even less intuitive and arguably less interesting. Most countries and country-years form a huge cluster, and the three remaining multi-country clusters are somewhat non-intuitive: Greece, Korea and Taiwan form a cluster (along with Bulgaria 2006), Portugal, Romania, Slovakia and, partly, Turkey and Austria form a second cluster. Inherently difficult to interpret and label these clusters, this reflecting the poor separation between clusters (see Appendix C.2), these findings indeed support the notion of fundamental production structures in terms of technology- and output coefficients (e.g. Simpson &

Tsukui, 1965), especially for the more developed and European economies. Compared to the clustering obtained from the proposed (flow-based) fingerprinting heuristic, the analytical usefulness of tracking similarities in gross exports and technology-coefficients is arguably lower.

4. Case study: regional structural transformations during the Eastern expansion of the European Union

This second case study addresses the Central-Eastern enlargement of the European Union (e.g. Bohle & Greskovits, 2012; Bruszt & Vukov, 2018; Podkaminer, 2013; Sapir, 2011; Shields, 2014), which has been viewed as a natural experiment (e.g. Hornok, 2010; Martínez-Zarzoso et al., 2020) for testing theories of market integration and trade (e.g. Balassa, 1961, 1963; Krugman, 1991; Krugman & Venables, 1990). Specifically, this case study tracks the production-structural trajectories of the set of 'Eastern'[28] countries that joined the EU in 2004 – the so-called 'A8' countries consisting of Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Slovakia, and Slovenia – and also Bulgaria and Romania, both joining three years later. Contrasting these, the West-European region is represented by five[29] of the six founding members of the EU: Belgium, France, Germany, Italy, and the Netherlands, labeled here as the 'Core 5' group.

Viewed through the lens of the proposed fingerprinting heuristic: how did the structural transformation of national economies look like in the East and the West respectively in the period 1995-2011? Did these transformations result in a diversification of national production structures within each region? Of particular relevance for theories on integration and economic specialization: did the national production structures of respective region converge or diverge during this period?

[28] For simplicity, this subset of 10 Central- and East-European countries is here labelled 'East', even though the standard UNSD classification of regions (M49) categorizes the Baltic states as Northern European and Slovenia as Southern European.

[29] Due to its seemingly unique and stable production structure, Luxembourg was excluded here. If included, the average structural transformation for the Western set would be even lower.

Figure 18 captures the cumulative annual structural change in each country from 1995 to 2011. With the exception of Slovenia and Germany, the Eastern economies experienced more aggregate structural transformation than their Western counterparts during this period. Confirming what was noted in the previous case study (see Figure 15), the fingerprinting heuristic suggests that it is specifically Estonia's production structure that transforms the most during this period. The dramatic transformations of the Eastern economies seem unrelated to their year of accession; and indeed, this 'great transformation' of the Central-East European economies began long before their formal accession to the European Union (e.g. Andor, 2019).

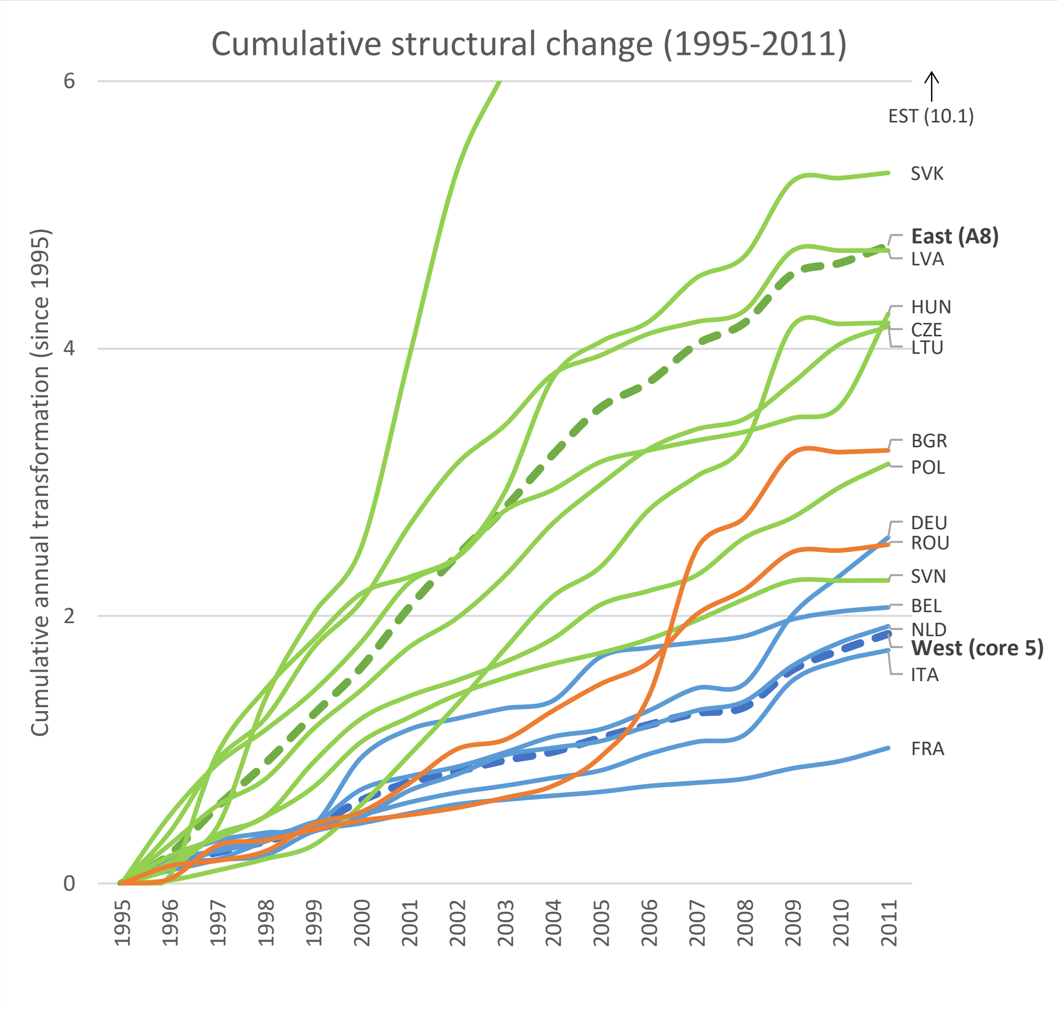

Figure 18: Cumulative annual structural change of 10 Eastern and 5 Western economies over the 1995-2011 period

What did these annual transformations imply for the overall trajectories of the national production structures? By setting 1995 as the index year to which we compare subsequent annual fingerprints, Figure 19 below captures a similar story: whereas the Western production structures in

2011 were not that different from their 1995 versions, the Eastern production structures anno 2011 were indeed quite different from their historical counterparts. Similar trajectories emerge when indexing from 2004 (see Figure 20), where the Eastern production structures (and particularly those of Estonia and Bulgaria) anno 2011 being quite different from their 2004 counterparts, while the Western structures on average remained relatively similar. The continuous transformations of the Eastern national production structures that occurred over the period 1995-2011 were thus not merely oscillations around country-specific structural types but represented more fundamental movements along new structural trajectories.

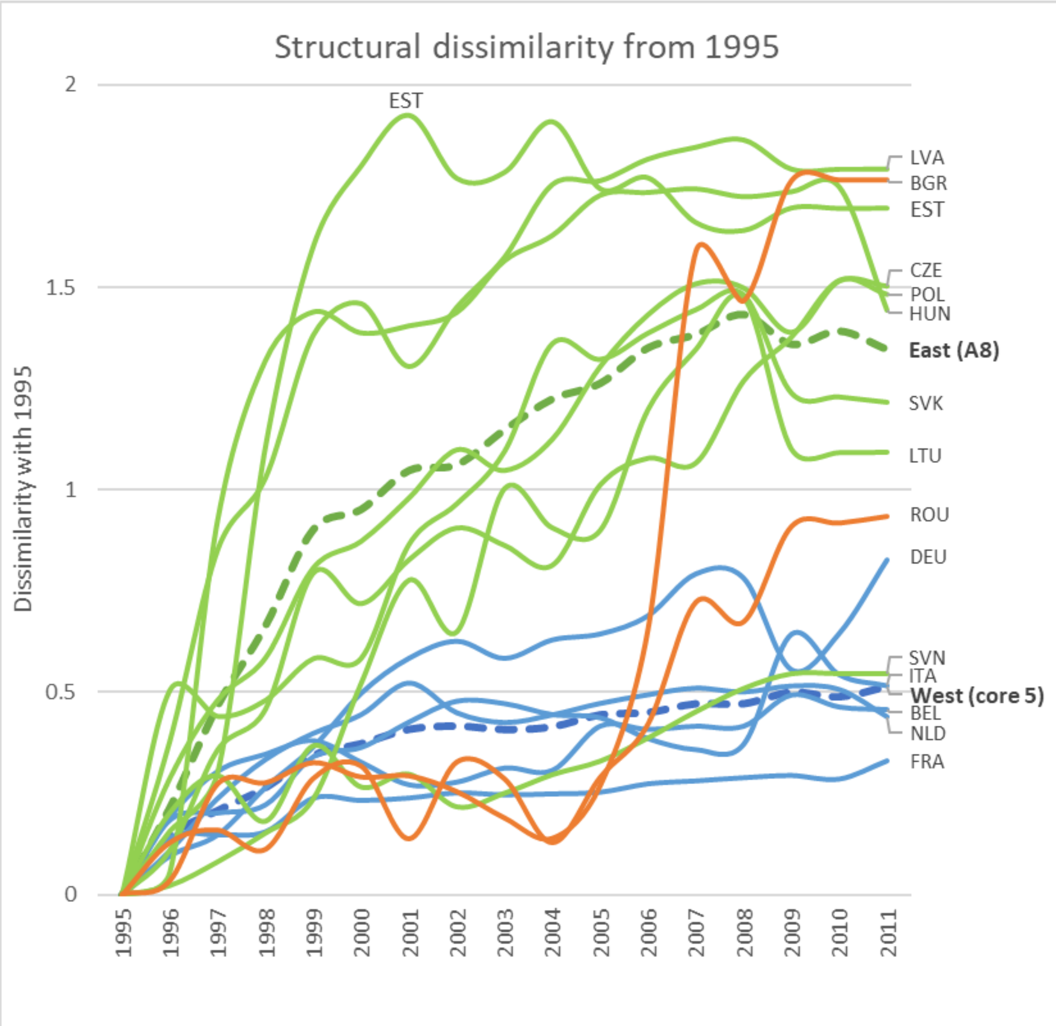

Figure 19: Structural transformation of 8 Eastern and 5 Western economies during the period 1995-2011, as compared to their structural fingerprints in 1995

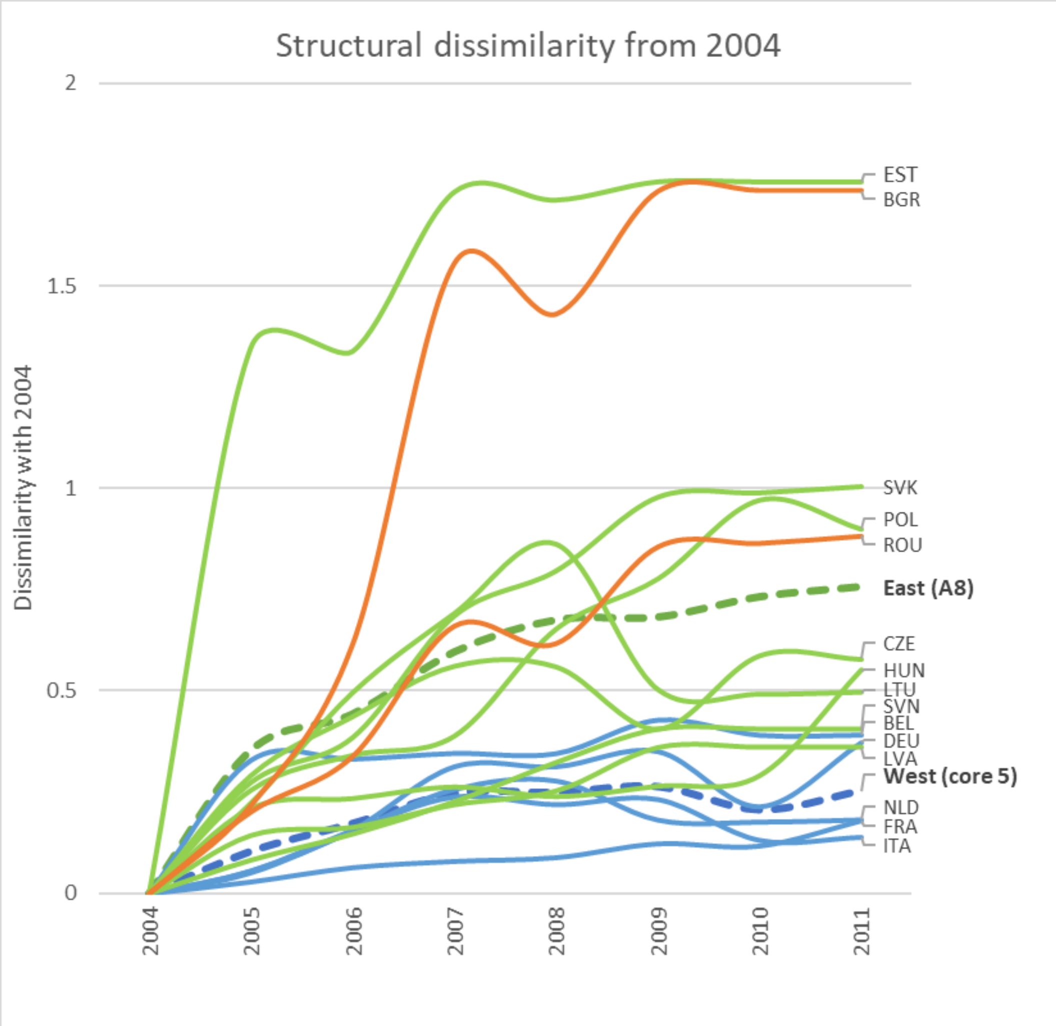

Figure 20: Structural transformation of 8 Eastern and 5 Wester economies during the period 2004-2011, as compared to their structural fingerprints in 2004

What did these national transformations mean for the structural diversity of respective regions? We operationalize the latter by tracking the pairwise structural dissimilarities for the countries within each region over time. Among the A8 countries, the relatively high mean dissimilarity in 1995 (1.10) increased even further (1.34) – see green solid line in Figure 21. It is particularly noteworthy that the internal pairwise dissimilarity variance decreased at the same time (green dotted lines). Thus, production structures that might have been relatively similar in 1995, such as those of Poland and Hungary (0.30), and Latvia and Lithuania (0.34), ended up being quite dissimilar in 2011 (1.53 and 1.46, respectively). The corresponding trends in structural diversity among the 5 Western economies differ from their Eastern counterparts, where both the average pairwise dissimilarity (solid blue line in Figure 21) and the intra-Western structural variance (dashed blue lines) remain low in comparison.

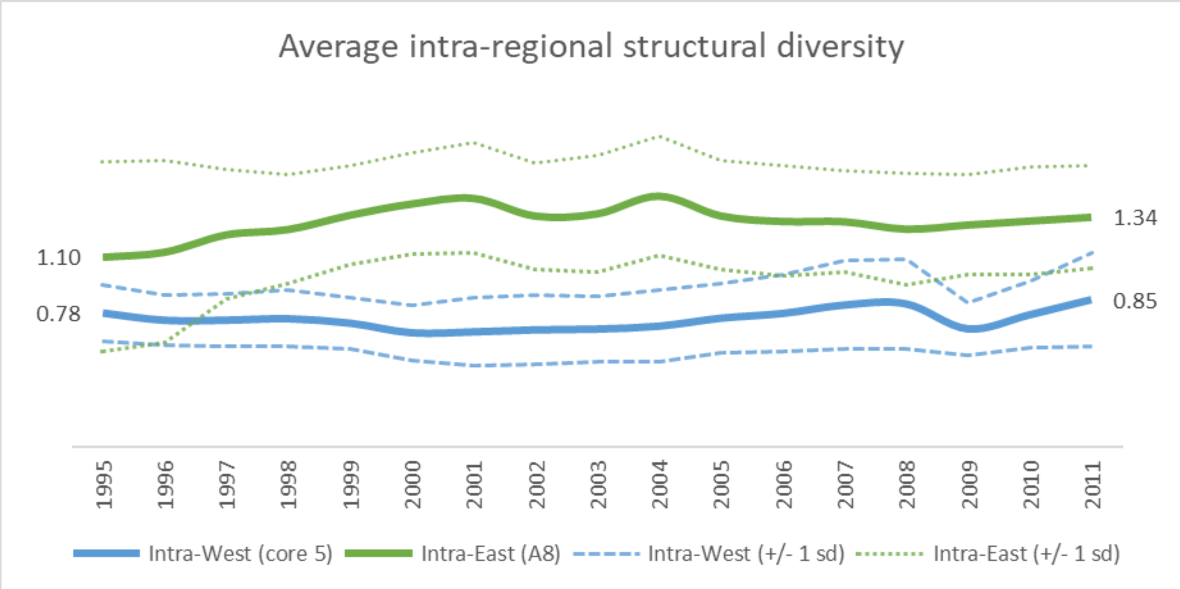

Figure 21: Average within-group fingerprint dissimilarity among 8 Eastern and 5 Western economies over the period 1995-2011

To what extent did the Eastern structural transformation lead to a convergence or divergence with respect to the archetypal Western production structures? Examining the average pairwise dissimilarities between all Eastern and Western production structures, the average regional dissimilarity decreased only marginally from 1.49 to 1.38 – see solid orange line in Figure 22 below. At the same time, the distance between the most similar cross-regional economies increased, from 0.79 in 1995 (Netherlands and Slovenia) to 1.11 (Italy and Poland). The structural trajectories of the Eastern economies thus seem most akin to an orbital trajectory: indeed on the move, yet remaining structurally equidistant from the seemingly stationary state of Western production structures.[30]

[30] A supplementary analysis and visualization using multi-dimensional scaling on this set of EU countries in 1995-2011 – see Appendix D.2 – yields similar orbital findings.

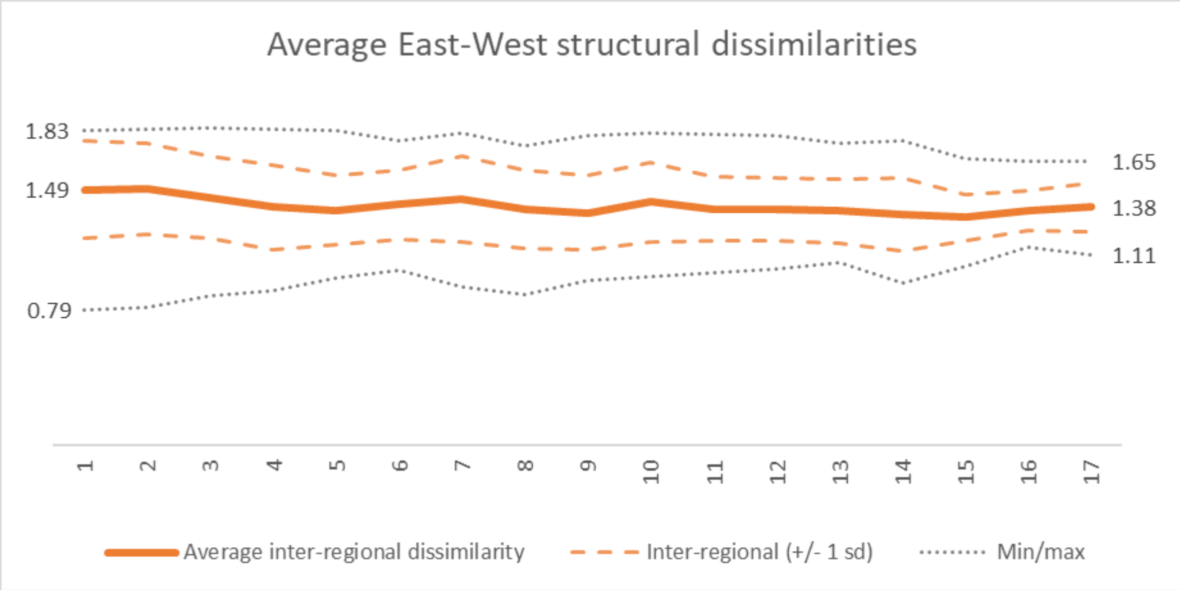

Figure 22:Average fingerprint dissimilarity between the Eastern and Western countries over the period 1995-2011

5. Summary and conclusion

This paper has proposed an eigenvector-based analytical framework for the comparative study of national production structures in the contemporary world of transnational production. Conceptualizing such structures as the complex networks of intra- and inter-sectorial flows between the domestic sectors of a national economy, including intermediate input originating from foreign sectors, the proposed heuristic utilizes both the national and international components of multiregional input-output data to extract characteristic fingerprints of the production structures of countries. This allows for several novel types of spatiotemporal comparative analyses of the similarities, transformations, and trajectories of national economies in contemporary networks of global production.

Using the national input-output tables from WIOD (2013 release), covering 40 countries over 17 years, two case studies demonstrated the practical utility of the fingerprinting heuristic. The first case study explored similarity patterns in the full set of fingerprints using hierarchical clustering. Although not finding support for the existence of discrete types of national production structures in this dataset, a 12-cluster partition was proposed as an analytically useful classification. Viewed longitudinally, several country-specific transitions between these types seem to coincide with specific economic-historical events and policy shifts of respective country, supporting the potential usefulness of this classification and the fingerprint heuristic at large. Corresponding cluster analyses using gross sectorial exports and coefficient-based fingerprints produced rather trivial partitions.

The second case study addressed East-West regional differences with regards to structural transformations and trajectories in the European Union in the period 1995-2011, contrasting a Western set of five founding EU members with ten Central- and East-European countries that joined in 2004 and 2007. Finding significant structural transformation in the East during this period, the Western production structures hardly changed at all. However, these large transformations of the Eastern economies had only a marginal effect on East-West production-structural convergence.

Despite the substantive findings from the two case studies, a certain degree of interpretational humility is warranted until the proposed approach has been validated and explored further. First, although the heuristic arguably produces feasible and seemingly rigorous findings, the eigenvalue diagnostics for several of the WIOD13-derived fingerprints are somewhat low. Although seemingly having little to no impact on obtained cluster-analytical results, interpretations of individual fingerprints with relatively poor eigenvalue diagnostics should be done with care. Second, whereas the heuristic has been tested here using the WIOD dataset (2013 release), it is imperative to also test the heuristic using other MRIO-type datasets and, specifically, compare the findings between these different datasets. Third, it is imperative that future evaluations of the fingerprinting heuristic should not only be conducted within the quantitative and computational domains, but more importantly within the qualitative and conceptual domains, to verify that the heuristic indeed captures features of relevance for the comparative study of national production structures in a transnational production regime. “Conceptions”, as the saying goes, should indeed “precede and govern measurements” (Wallerstein, 1974, p. 36).

Finally, regardless of potential methodological improvements, it is imperative to view the proposed fingerprinting heuristic for what it is: a heuristic for the comparative analysis of national production structures. While it is arguably relevant and useful for understanding the structural transformations and trajectories of national economies in global production networks, the approach constitutes merely one of a plethora of different ways of conceptualizing what is meant by a 'production structure', both within and outside the realms of input-output data and quantitative analysis. Our contemporary global economy is indeed "an immensely complex, interdependent and dynamic system [and] our attempts to comprehend it analytically are always partial, provisional and incomplete" (Coe, 2021, p. 152; see also Coe et al., 2008, p. 273) – it is hoped that the fingerprinting heuristic can provide yet another incomplete, partial, and complementary way of understanding this complexity.

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Declarations of interest

Declarations of interest: none

References

Ahmad, N. (2013). Estimating trade in value-added: Why and how. *Global Value Chains in a Changing World*, 85–133.

Andor, L. (2019). Fifteen years of convergence: East-West Imbalance and what the EU should do about It. *Intereconomics*, *54*(1), 18–23.

Antràs, P., & Chor, D. (2021). *Global Value Chains* (Working Paper No. 28549; Working Paper Series). National Bureau of Economic Research. https://doi.org/10.3386/w28549

Aslam, A., Novta, N., & Rodrigues-Bastos, F. (2017). *Calculating Trade in Value Added*. International Monetary Fund.

Balassa, B. (1961). *The Theory of Economic Integration*. R.D. Irwin.

Balassa, B. (1963). European Integration: Problems and Issues. *The American Economic Review*, *53*(2), 175–184.

Baldwin, R. E. (2006). *Globalisation: The great unbundling (s)*. Economic council of Finland.

Balland, P.-A., Broekel, T., Diodato, D., Giuliani, E., Hausmann, R., O'Clery, N., & Rigby, D. (2022). The new paradigm of economic complexity. *Research Policy*, *51*(3), 104450. https://doi.org/10.1016/j.respol.2021.104450

Blöchl, F., Theis, F. J., Vega-Redondo, F., & Fisher, E. O. (2011). Vertex centralities in input-output networks reveal the structure of modern economies. *Physical Review E*, *83*(4), 046127. https://doi.org/10.1103/PhysRevE.83.046127

Bohle, D., & Greskovits, B. (2012). Capitalist Diversity on Europe's Periphery. In *Capitalist Diversity on Europe's Periphery*. Cornell University Press. https://doi.org/10.7591/9780801465666

Bonacich, P. (2007). Some unique properties of eigenvector centrality. *Social Networks*, *29*(4), 555–564.

Bosma, N. S., Romero Luna, I., & Dietzenbacher, E. (2005). Using average propagation lengths to identify production chains in the Andalusian economy. *Estudios de Economía Aplicada, 23 (2), 405-422.*

Brakman, S., & Marrewijk, C. V. (2017). A closer look at revealed comparative advantage: Gross-versus value-added trade flows. *Papers in Regional Science*, *96*(1), 61–92. https://doi.org/10.1111/pirs.12208

Bruszt, L., & Vukov, V. (2018). Governing Market Integration and Development—Lessons from Europe's Eastern and Southern Peripheries: Introduction to the Special Issue. *Studies in Comparative International Development*, *53*(2), 153–168. https://doi.org/10.1007/s12116-018-9264-3

Chase-Dunn, C. K. (1989). *Global Formation: Structures of the World-economy*. Basil Blackwell Ltd.

Chenery, H. B., & Watanabe, T. (1958). International comparisons of the structure of production. *Econometrica: Journal of the Econometric Society*, 487–521.

Coe, N. M. (2021). *Advanced Introduction to Global Production Networks*. Edward Elgar Publishing.

Coe, N. M., Dicken, P., & Hess, M. (2008). Global production networks: Realizing the potential. *Journal of Economic Geography*, *8*(3), 271–295.

Coe, N. M., & Yeung, H. W. (2019). Global production networks: Mapping recent conceptual developments. *Journal of Economic Geography*, *19*(4), 775–801. https://doi.org/10.1093/jeg/lbz018

De Benedictis, L., & Tajoli, L. (2007). Openness, similarity in export composition, and income dynamics. *The Journal of International Trade & Economic Development*, *16*(1), 93–116. https://doi.org/10.1080/09638190601165798

Defourny, J., & Thorbecke, E. (1984). Structural Path Analysis and Multiplier Decomposition within a Social Accounting Matrix Framework. *The Economic Journal*, *94*(373), 111–136. https://doi.org/10.2307/2232220

Dietzenbacher, E. (1992). The measurement of interindustry linkages: Key sectors in the Netherlands. *Economic Modelling*, *9*(4), 419–437. https://doi.org/10.1016/0264-9993(92)90022-T

Drabek, Z. (1984). A comparison of technology in centrally-planned and market-type economies. *European Economic Review*, *25*(3), 293–318. https://doi.org/10.1016/0014-2921(84)90048-5

Ferdows, K. (1997). Made in the World: The Global Spread of Production. *Production and Operations Management*, *6*(2), 102–109. https://doi.org/10.1111/j.1937-5956.1997.tb00418.x

Gaulier, G., & Zignago, S. (2010). *Baci: International trade database at the product-level (the 1994-2007 version)*.

Gereffi, G., & Korzeniewicz, M. (1994). *Commodity Chains and Global Capitalism*. ABC-CLIO.

Grech, A. G. (Ed.). (2016). *Understanding the Maltese economy*. Central Bank of Malta. https://www.centralbankmalta.org/file.aspx?f=31385

Grossman, G. M., & Rossi-Hansberg, E. (2007). The rise of offshoring: It's not wine for cloth anymore. In *The new economic geography: Effects and policy implications* (pp. 59–102). Federal Reserve Bank of Kansas City. https://www.princeton.edu/~erossi/RO.pdf

Helmstädter, E. (1969). The hierarchical structure of interindustrial transaction. In *International comparisons of interindustry data*. United Nations.

Hewings, G. J. D., & Jensen, R. C. (1987). Regional, interregional and multiregional input-output analysis. In *Handbook of regional and urban economics* (Vol. 1, pp. 295–355). Elsevier.

Hewings, G. J. D., Jensen, R. C., West, G. R., Sonis, M., & Jackson, R. W. (1989). The spatial organization of production: An input-output perspective. *Socio-Economic Planning Sciences*, *23*(1), 67–86. https://doi.org/10.1016/0038-0121(89)90048-7

Hidalgo, C. A. (2015). *Why Information grows; The evolution of order, from atoms to economies*. Hachette UK.

Hidalgo, C. A., & Hausmann, R. (2009). The building blocks of economic complexity. *Proceedings of the National Academy of Sciences*, *106*(26), 10570–10575.

Hidalgo, C. A., Klinger, B., Barabási, A.-L., & Hausmann, R. (2007). The product space conditions the development of nations. *Science*, *317*(5837), 482–487.

Hoen, A. R. (2002). *An Input-Output Analysis of European Integration*. Elsevier.

Hopkins, T. K., & Wallerstein, I. (1986). Commodity Chains in the World-Economy Prior to 1800. *Review (Fernand Braudel Center)*, *10*(1), 157–170.

Hornok, C. (2010). Trade-Enhancing EU Enlargement and the Resurgence of East-East Trade. In *Focus on European Economic Integration* (pp. 79–94). Vienna: OeNB.

Hornok, C., & Koren, M. (2017, April). *Winners and Losers of Globalization: Sixteen Challenges for Measurement and Theory*. Economics without Borders: Economic Research for European Policy Challenges; Cambridge University Press. https://doi.org/10.1017/9781316636404.008

Inomata, S. (2017). Analytical frameworks for global value chains: An overview. *Global Value Chain Development Report*.

Isard, W. (1951). Interregional and regional input-output analysis: A model of a space-economy. *The Review of Economics and Statistics*, *33*(4), 318–328.

Johnson, R. C., & Noguera, G. (2012). Accounting for intermediates: Production sharing and trade in value added. *Journal of International Economics*, *86*(2), 224–236. https://doi.org/10.1016/j.jinteco.2011.10.003

Johnson, R. C., & Noguera, G. (2017). A portrait of trade in value-added over four decades. *Review of Economics and Statistics*, *99*(5), 896–911.

Koch, P. (2021). Economic complexity and growth: Can value-added exports better explain the link? *Economics Letters*, *198*, 109682. https://doi.org/10.1016/j.econlet.2020.109682

Koch, P., & Schwarzbauer, W. (2021). Yet another space: Why the Industry Space adds value to the understanding of structural change and economic development. *Structural Change and Economic Dynamics*, *59*, 198–213. https://doi.org/10.1016/j.strueco.2021.08.019

Kondo, Y. (2014). Triangulation of Input–Output Tables Based on Mixed Integer Programs for Inter-temporal and Inter-regional Comparison of Production Structures. *Journal of Economic Structures*, *3*(1), 2. https://doi.org/10.1186/2193-2409-3-2

Koopman, R., Wang, Z., & Wei, S.-J. (2014). Tracing value-added and double counting in gross exports. *American Economic Review*, *104*(2), 459–494.

Korte, B., & Oberhofer, W. (1971). Triangularizing input-output matrices and the structure of production. *European Economic Review*, *2*(4), 493–522. https://doi.org/10.1016/0014-2921(71)90024-9

Krugman, P. (1991). *Geography and Trade*. MIT press.

Krugman, P., & Venables, A. J. (1990). Integration and the Competitiveness of Peripheral Industry. In *CEPR Discussion Papers* (No. 363; CEPR Discussion Papers). C.E.P.R. Discussion Papers. https://ideas.repec.org/p/cpr/ceprdp/363.html

Lamel, J., Richter, J., & Teufelsbauer, W. (1972). Patterns of industrial structure and economic development: Triangulation of input-output tables of ECE countries. *European Economic Review*, *3*(1), 47–63. https://doi.org/10.1016/0014-2921(72)90023-2

Leontief, W. (1936). Quantitative input and output relations in the economic systems of the United States. *The Review of Economic Statistics*, 105–125.

Leontief, W. (1941). *The Structure of American Economy, 1919-1929: An Empirical Application of Equilibrium Analysis*. Harvard University Press.

Leontief, W. (1954). Mathematics in economics. *Bulletin of the American Mathematical Society*, *60*(3), 215–233.

Malets, O. (2017). Globalization, governance and the nation-state: An overview. *Economic Sociology_the European Electronic Newsletter*, *18*(2), 16–24.

Martínez-Zarzoso, I., Voicu, A. M., & Vidovic, M. (2020). Production networks in Europe: A natural experiment of the European Union enlargement to the east. *Review of International Economics*, *28*(5), 1143–1163. https://doi.org/10.1111/roie.12484

Mattoo, A., Wang, Z., & Wei, S.-J. (2013). *Trade in value added: Developing new measures of cross-border trade*. London: Centre for Economic Policy Research and the World Bank.

McNerney, J. (2009, January). *Network Properties of Economic Input-Output Networks* [Monograph]. IR-09-003. http://pure.iiasa.ac.at/id/eprint/9145/

Miller, R. E., & Blair, P. D. (2009). *Input-Output Analysis: Foundations and Extensions*. Cambridge University Press.

Montresor, S., & Marzetti, G. V. (2009). Applying Social Network Analysis to Input-Output based Innovation Matrices: An Illustrative Application to Six OECD Technological Systems for the Middle 1990s. *Economic Systems Research*, *21*(2), 129–149. https://doi.org/10.1080/09535310902940228

Murtagh, F., & Contreras, P. (2012). Algorithms for hierarchical clustering: An overview. *WIREs Data Mining and Knowledge Discovery*, *2*(1), 86–97. https://doi.org/10.1002/widm.53

Nordlund, C. (2010). *Social Ecography: International Trade, Network Analysis, and an Emmanuelian Conceptualization of Ecological Unequal Exchange*. Human Ecology Division, Lund University. https://portal.research.lu.se/en/publications/social-ecography-international-trade-network-analysis-and-an-emma

Östblom, G. (1997). Use of the convergence condition for triangularizing input-output matrices and the similarity of production structures among Nordic countries 1970, 1980 and 1985. *Structural Change and Economic Dynamics*, *8*(1), 115–128.

Podkaminer, L. (2013). *Development Patterns of Central and East European Countries (in the course of transition and following EU accession)* (Research Report No. 388). Vienna Institute for International Economic Studies (wiiw). https://www.econstor.eu/handle/10419/204160

Sapir, A. (2011). European Integration at the Crossroads: A Review Essay on the 50th Anniversary of Bela Balassa's 'Theory of Economic Integration'. *Journal of Economic Literature*, *49*(4), 1200–1229.

Shields, S. (2014). *The International Political Economy of Transition: Neoliberal hegemony and Eastern Central Europe's transformation*. Routledge. https://doi.org/10.4324/9780203086063

Simpson, D., & Tsukui, J. (1965). The Fundamental Structure of Input-Output Tables, An International Comparison. *The Review of Economics and Statistics*, *47*(4), 434–446. https://doi.org/10.2307/1927773

Smith, D. A., & Nemeth, R. J. (1988). An empirical analysis of commodity exchange in the international economy: 1965–80. *International Studies Quarterly*, *32*(2), 227–240.

Stehrer, R. (2012). *Trade in value added and the valued added in trade*. wiiw Working paper.

Tabata, S. (2006). Observations on the Influence of High Oil Prices on Russia's GDP Growth. *Eurasian Geography and Economics*, *47*(1), 95–111. https://doi.org/10.2747/1538-7216.47.1.95

Timmer, M. P., Dietzenbacher, E., Los, B., Stehrer, R., & Vries, G. J. de. (2015). An Illustrated User Guide to the World Input–Output Database: The Case of Global Automotive Production. *Review of International Economics*, *23*(3), 575–605. https://doi.org/10.1111/roie.12178

Timmer, M. P., Miroudot, S., & de Vries, G. J. (2019). Functional specialisation in trade. *Journal of Economic Geography*, *19*(1), 1–30. https://doi.org/10.1093/jeg/lby056

Wallerstein, I. (1974). The rise and future demise of the world capitalist system: Concepts for comparative analysis. *Comparative Studies in Society and History*, *16*(4), 387–415.

Wallerstein, I. (1979). *The Capitalist World-Economy*. Cambridge University Press.

Appendixes: Transformations, trajectories and similarities of national production structures

Contents

Appendix A: Tables and metadata

A.1 ISO3-to-country table

ISO3	Country name	ISO3	Country name
AUS	Australia	IRL	Ireland
AUT	Austria	ITA	Italy
BEL	Belgium	JPN	Japan
BGR	Bulgaria	KOR	South Korea
BRA	Brazil	LTU	Lithuania
CAN	Canada	LUX	Luxembourg
CHN	China	LVA	Latvia
CYP	Cyprus	MEX	Mexico
CZE	Czech Republic	MLT	Malta
DEU	Germany	NLD	The Netherlands
DNK	Denmark	POL	Poland
ESP	Spain	PRT	Portugal
EST	Estonia	ROU	Romania
FIN	Finland	RUS	Russia
FRA	France	SVK	Slovakia
GBR	Great Britain	SVN	Slovenia
GRC	Greece	SWE	Sweden
HUN	Hungary	TUR	Turkey
IDN	Indonesia	TWN	Taiwan
IND	India	USA	United States of America

A.2 Economic sectors

Sectorial label	ISIC3's	WIOD sector description
Agriculture	A, B	Agriculture, Hunting, Forestry and Fishing
Mining	C	Mining and Quarrying
Food	15, 16	Food, Beverages and Tobacco
Textiles	17, 18	Textiles and Textile Products
Leather	19	Leather, Leather and Footwear
Wood	20	Wood and Products of Wood and Cork
Paper	21, 22	Pulp, Paper, Paper , Printing and Publishing
Fuel	23	Coke, Refined Petroleum and Nuclear Fuel
Chemicals	24	Chemicals and Chemical Products
Plastics	25	Rubber and Plastics
Non-metal	26	Other Non-Metallic Mineral
Metal	27, 28	Basic Metals and Fabricated Metal
Machinery	29	Machinery, n.e.c.
Electrical	30-33	Electrical and Optical Equipment
Vehicles	34, 35	Transport Equipment
Manuf	36, 37	Manufacturing, n.e.c.; Recycling
Utilities	E	Electricity, Gas and Water Supply
Constr	F	Construction
VehicleSale	50	Sale, Maintenance and Repair of Motor Vehicles and Motorcycles; Retail Sale of Fuel
WholeSale	51	Wholesale Trade and Commission Trade, Except of Motor Vehicles and Motorcycles
Retail	52	Retail Trade, Except of Motor Vehicles and Motorcycles; Repair of Household Goods
Hospitality	H	Hotels and Restaurants
InlTrans	60	Inland Transport
WaterTrans	61	Water Transport
AirTrans	62	Air Transport
OtherTrans	63	Other Supporting and Auxiliary Transport Activities; Activities of Travel Agencies
PostTele	64	Post and Telecommunications
Finance	J	Financial Intermediation
RealEstate	70	Real Estate Activities
Business	71-74	Renting of M&Eq and Other Business Activities
PublAdm	L	Public Admin and Defence; Compulsory Social Security
Education	M	Education
HealthSoc	N	Health and Social Work
OthServ	O	Other Community, Social and Personal Services

A.3 Data coverage in WIOD13

Examining the national Input-Output tables in WIOD (2013 release) for all countries and years, the following 7 country-sectors have zero reported inputs for all years in the 1995-2011 period. This corresponds to 0.5% of all sectorial time-series in WIOD13, with 30 out of 34 sectors (88%) having complete data for all countries and years. Although these definitely constitute missing data, these were nevertheless treated as zero values when determining the pair-wise dissimilarity between two fingerprints.

Country	**Sector (ISIC3)**
China	VehicleSale (50)
Cyprus	Fuel (23)
Indonesia	VehicleSale (50)
India	PublAdm (L)
Luxembourg	Leather (19)
Luxembourg	Fuel (23)
Malta	Fuel (23)

Contrasting these 7 sectorial gaps in WIOD13, the WIOD 2016 release has a total of 169 sectorial time-series with zero reported inputs for all years in the 2000-2014 period. This corresponds to 7% of all sectorial time-series in WIOD16, with only 28 of the 56 sectors (i.e. half) having complete data for all countries and years. This relatively higher data coverage in WIOD13 than in WIOD16 motivates the former is used throughout this study.

Appendix B: Cluster memberships

See project website[31] to visualize and download the detailed average fingerprints (sectorial up- and downstream means and standard deviations) of respective subset. n_{FP} is the number of total fingerprints in a cluster, and n_C is the number of countries represented among these. For the 21-cluster partition using average-link (UPGMA), see the project website.

B.1 Complete-link 4-cluster partition

A. Agriculture, Food & Textiles (n_{FP}=137, n_C=13)
[The union set of A1 and A2 below]

B. Finance (n_{FP}=15, n_C=2)
[Same at set B below]

C. Business & Construction (n_{FP}=413, n_C=31)
[The union set of C1-C5 below]

D. Electrical & Metal (n_{FP}=113, n_C=9)
[Same as set D below]

B.2 Complete-link 9-cluster partition

A1. Agriculture (n_{FP}=122, n_C=13)
Bulgaria 1995-2006, Brazil 1995-2011, Estonia 1995-1997, Greece 1995-2000, Hungary 1995-1996, Indonesia 1998-2011, India 1995-2003, Lithuania 1995-2005, 2009-2011, Latvia 1995-1996, Poland 1995-2007, Romania 1995-2011, Russia 1995-2002, Turkey 1995-1999

A2. Textiles (n_{FP}=15, n_C=2)
Indonesia 1995-1997, Turkey 2000-2011

B. Finance (n_{FP}=17, n_C=1)
Luxembourg 1995-2011

C1. Metal & Business (n_{FP}=78, n_C=11)
China 1995-1999, Cyprus 1995-2011, Czech Rep. 1995-1998, Denmark 1995-1998, Estonia 2007-2011, Finland 1995-1998, Greece 2001-2011, India 2004-2011, Latvia 1997-2001, Russia 2003-2011, Slovakia 1995-2000

C2. Business (n_{FP}=177, n_C=11)
Australia 1995-2011, Austria 1995-2005, Belgium 1995-2011, Germany 1995-2011, Denmark 1999-2011, France 1995-2011, Great Britain 1995-2011, Italy 1995-2011, Netherlands 1995-2011, Sweden 1995-2011, USA 1995-2011

C3. Construction (n_{FP}=97, n_C=9)
Bulgaria 2007-2011, Czech Rep. 1999-2011, Spain 1995-2011, Ireland 1998-2008, Lithuania 2006-2008, Latvia 2002-2011, Poland 2008-2011, Portugal 1995-2011, Slovenia 1995-2011

C4. Utilities (n_{FP}=9, n_C=2)
Austria 2006-2011, Slovakia 2001-2003

[31] www.demesta.com/fingerprinting

C5. Vehicles & Metal (n_{FP}=52, n_C=4)
Canada 1995-2011, Japan 1995-2011, South Korea 1995-1997, 2005-2011, Slovakia 2004-2011

D. Electrical & Metal (n_{FP}=113, n_C=9)
China 2000-2011, Estonia 1998-2006, Finland 1999-2011, Hungary 1997-2011, Ireland 1995-1997, 2009-2011, South Korea 1998-2004, Mexico 1995-2011, Malta 1995-2011, Taiwan 1995-2011

B.3 Average-link (UPMGA) 7-cluster partitions

A. Business & Construction
Australia 1995-2011, Austria 1995-2005, Belgium 1995-2011, Bulgaria 2007-2011, Cyprus 1995-2011, Czech Rep. 1997-2000, Germany 1995-2011, Denmark 1995-2011, Spain 1995-2011, Estonia 2007-2011, France 1995-2011, Great Britain 1995-2011, Greece 2002-2011, Italy 1995-2011, Latvia 1997-2011, The Netherlands 1995-2011, Poland 2008-2011, Portugal 1995-2011, Slovenia 1995-2011, Sweden 1995-2011, USA_1995-2011

B. Metal & Electrical
China 2000-2011, Czech Rep. 2001-2011, Estonia 1998-2006, Finland 1995-2011, Hungary 1997-2011, Ireland 1995-2011, South Korea 1995-2011, Mexico 1995-2011, Malta 1995-2011, Taiwan 1995-2011

C. Agriculture & Food
Bulgaria 1995-2006, Brazil 1995-2011, Estonia 1995-1997, Greece 1995-2001, Hungary 1995-1996, Indonesia 1998-2011, India 1995-2003, Lithuania 1995-2011, Latvia 1995-1996, Poland 1995-2007, Romania 1995-2011, Russia 1995-2002, Turkey 1995-1999

D. Utilities & Fuel
Austria 2006-2011, China 1995-1999, Czech Rep. 1995-1996, India 2004-2011, Russia 2003-2011, Slovakia 1995-2011

E. Vehicles
Canada 1995-2011, Japan 1995-2011

F. Finance (Luxembourg)
Luxembourg 1995-2011

G. Textiles
Indonesia 1995-1997, Turkey 2000-2011

B.4 Average-link (UPMGA) 12-cluster partitions

A1. Business
Australia 1995-2002, Austria 1995-2005, Belgium 1995-2011, Cyprus 1995-2011, Germany 1995-2011, Denmark 1995-2011, France 1995-2011, Great Britain 1997-2011, Greece 2002-2011, Italy 1995-2011, The Netherlands 1995-2011, Sweden 1995-2011, USA_1995-2011

A2. Construction
Australia 2003-2011, Bulgaria 2007-2011, Czech Rep. 1997-2000, Spain 1995-2011, Great Britain 1995-1996, Latvia 2002-2011, Poland 2008-2011, Portugal 1995-2011, Slovenia 1995-2011

A3. Baltic transport
Estonia 2007-2011, Latvia 1997-2001

B1. Electrical
Czech Rep. 2001-2011, Estonia 1998-2000,2002-2003,2005-2006, Finland 1995-2011, Hungary 1997-2011, Ireland 1995-2008, Mexico 1995-2011, Malta 2006-2011

B2. Electrical & Metal
China 2000-2011, South Korea 1995-2011, Taiwan 1995-2011

B3. Electrical (embedded)
Estonia 2001,2004, Ireland 2009-2011, Malta 1995-2005

C. Agriculture & Food
Bulgaria 1995-2006, Brazil 1995-2011, Estonia 1995-1997, Greece 1995-2001, Hungary 1995-1996, Indonesia 1998-2011, India 1995-2003, Lithuania 1995-2011, Latvia 1995-1996, Poland 1995-2007, Romania 1995-2011, Russia 1995-2002, Turkey 1995-1999

D1. Utilities
Austria 2006-2011, Czech Rep. 1995-1996, Slovakia 1995-2011

D2. Metal & Fuel
China 1995-1999, India 2004-2011, Russia 2003-2011

E. Vehicles
Canada 1995-2011, Japan 1995-2011

F. Finance
Luxembourg 1995-2011

G. Textiles
Indonesia 1995-1997, Turkey 2000-2011

Appendix C: Additional tables and figures

Section C.1 contains the average pair-wise distances within and between clusters for the mentioned clustering solutions using the default (flow-based) fingerprinting heuristic. Section C.2 explores these within- and between-cluster pair-wise distances in more detail, here also including clustering solutions for the alternative clustering analyses of dissimilarities based on, respectively, sectorial gross exports and coefficient-based fingerprinting.

C.1 Average cluster distances

Total number of national fingerprints for each cluster given by N_{FP}; number of countries represented in each cluster given by N_C. See Appendix B1 for cluster membership tables.

Table 3: Average within- and between-cluster distance for the 4-cluster partition derived from the complete-link hierarchical clustering

Cluster name [N_{FP}; N_C]	*A*	*B*	*C*	*D*
A. Agriculture, Food & Textiles [137;13]	1.00			
B. Finance [17;1]	1.89	0.06		
C. Business & Construction [413;31]	1.62	1.73	1.23	
D. Electrical & Metal [113;9]	1.70	1.85	1.54	1.05

Table 4: Average within- and between-cluster distance for the 9-cluster partition derived from the complete-link hierarchical clustering

Cluster name [N_{FP}; N_C]	*A1*	*A2*	*B*	*C1*	*C2*	*C3*	*C4*	*C5*	*D*
A1. Agriculture [122;13]	0.82								
A2. Textiles [15;2]	1.76	0.38							
B. Finance [17;1]	1.88	1.91	0.06						
C1. Electrical & Metal [78;11]	1.36	1.81	1.79	1.16					
C2. Business [177;11]	1.61	1.85	1.59	1.26	0.77				
C3. Construction [97;9]	1.64	1.88	1.85	1.36	1.32	0.84			
C4. Utilities [9;2]	1.74	1.91	1.93	1.54	1.63	1.68	0.48		
C5. Vehicles & Metal [52;4]	1.72	1.88	1.84	1.51	1.45	1.56	1.66	1.03	
D. Electrical & Metal [113;9]	1.68	1.87	1.85	1.54	1.53	1.55	1.76	1.51	1.05

Table 5: Average within- and between-cluster distances for the 7-cluster partition derived from the (unweighted) average-link hierarchical clustering

Cluster name [N_{FP}; N_C]	*A*	*B*	*C*	*D*	*E*	*F*	*G*
A. Business & Construction [292;21]	1.03						
B. Metal & Electrical [149;10]	1.54	1.13					
C. Agriculture & Food [126;13]	1.56	1.69	0.83				
D. Utilities & Fuel [47;6]	1.48	1.56	1.53	1.13			
E. Vehicles [34;2]	1.43	1.51	1.68	1.45	0.75		
F. Finance [17;1]	1.68	1.85	1.88	1.91	1.78	0.06	
G. Textiles [15;2]	1.85	1.88	1.76	1.83	1.86	1.91	0.38

Table 6: Average within- and between-cluster distances for the 12-cluster partition derived from the (unweighted) average-link hierarchical clustering

Cluster name [N_{FP}; N_C]	A1	A2	A3	B1	B2	B3	C	D1	D2	E	F	G
A1. Business [197;13]	0.83											
A2. Construction [85;9]	1.29	0.67										
A3. Baltic transport [10;2]	1.29	1.39	0.68									
B1. Electrical [87;7]	1.38	1.46	1.51	0.98								
B2. Electrical & Metal [46;3]	1.69	1.67	1.79	1.28	0.65							
B3. Electrical (embedded) [16;3]	1.80	1.86	1.87	1.38	1.41	0.34						
C. Agriculture & Food [126;13]	1.54	1.62	1.40	1.60	1.79	1.91	0.83					
D1. Utilities [25;3]	1.54	1.46	1.58	1.59	1.69	1.85	1.66	0.94				
D2. Metal & Fuel [22;3]	1.44	1.39	1.47	1.48	1.32	1.80	1.38	1.38	0.77			
E. Vehicles [34;2]	1.36	1.56	1.60	1.48	1.47	1.84	1.68	1.49	1.39	0.75		
F. Finance [17;1]	1.60	1.84	1.85	1.81	1.90	1.94	1.88	1.93	1.89	1.78	0.06	
G. Textiles [15;2]	1.85	1.87	1.81	1.85	1.90	1.96	1.76	1.89	1.77	1.86	1.91	0.38

C.2 Within- and between-cluster distance distributions

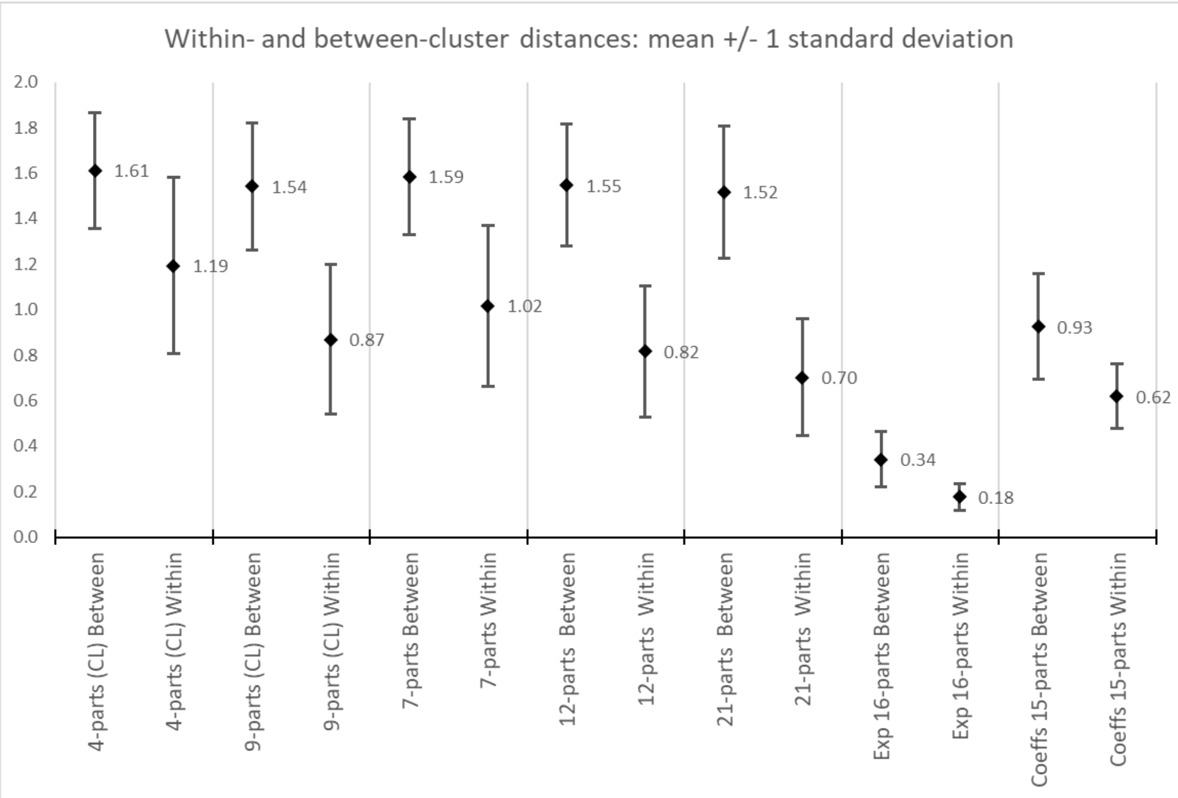

Figure 23: Within- and between-cluster distances: mean and standard deviations, all cluster analyses

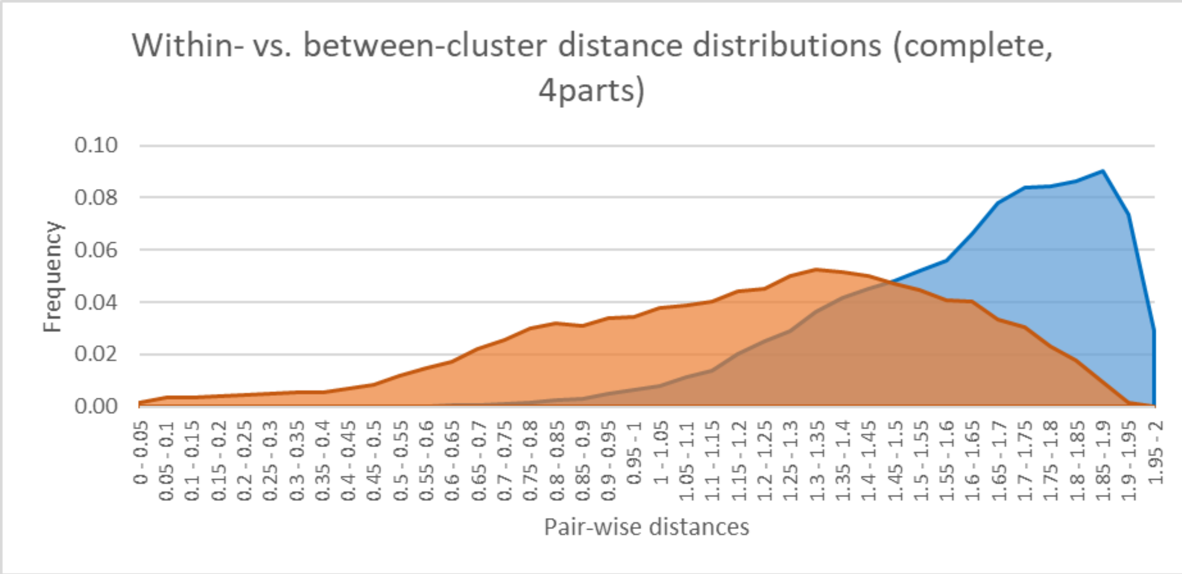

Figure 24: Within- and between-cluster distance distributions: complete-link, 4-cluster partition

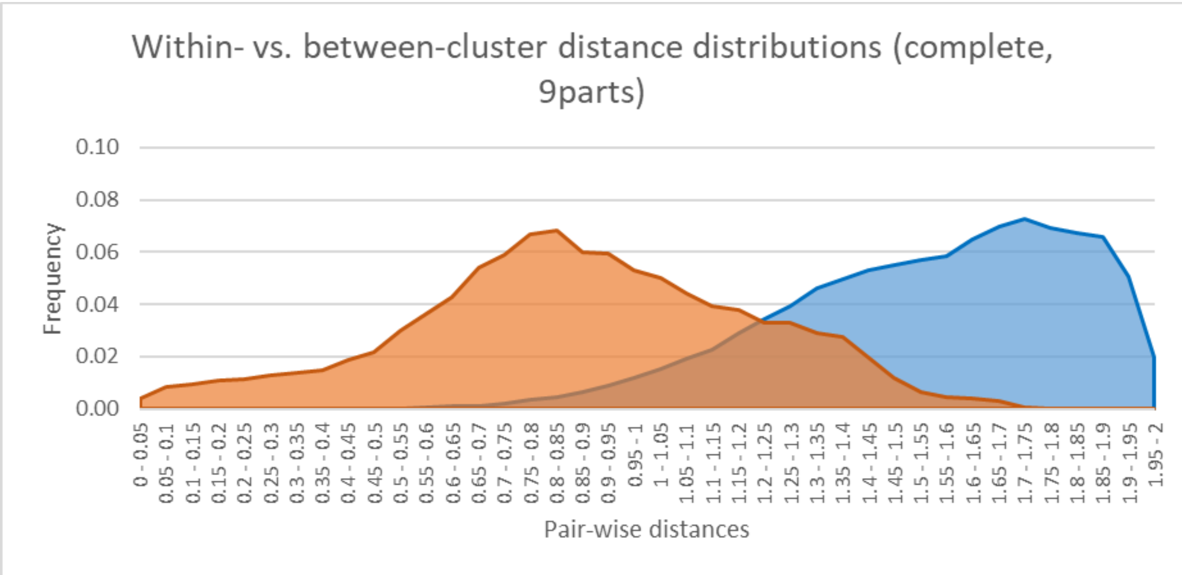

Figure 25: Within- and between-cluster distance distributions: complete-link, 4-cluster partition

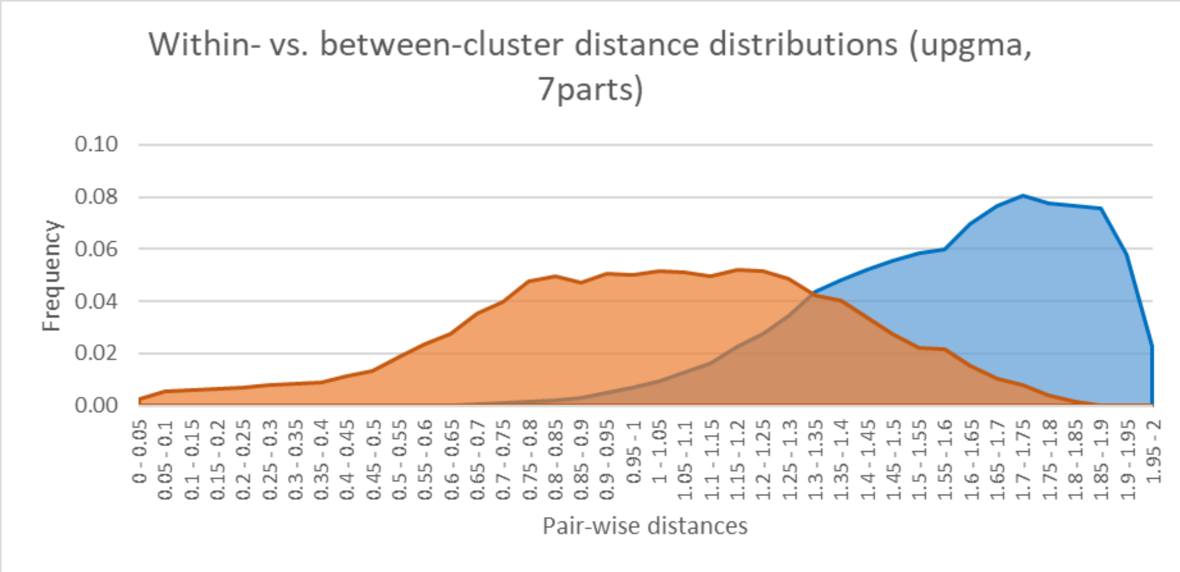

Figure 26: Within- and between-cluster distance distributions: (unweighted) average-link, 7-cluster partition

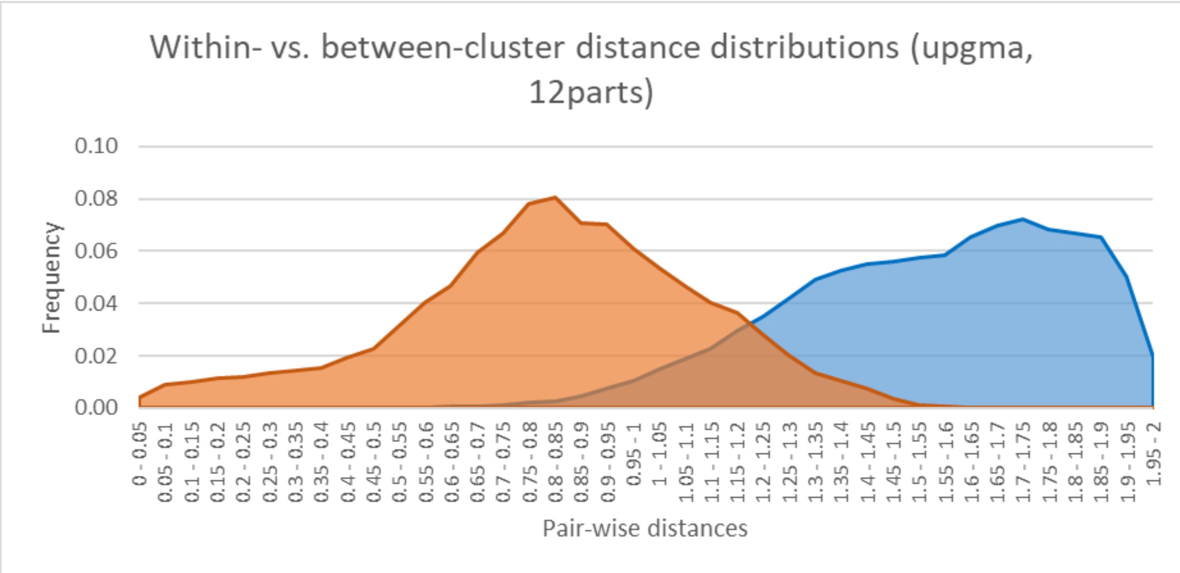

Figure 27: Within- and between-cluster distance distributions: (unweighted) average-link, 12-cluster partition

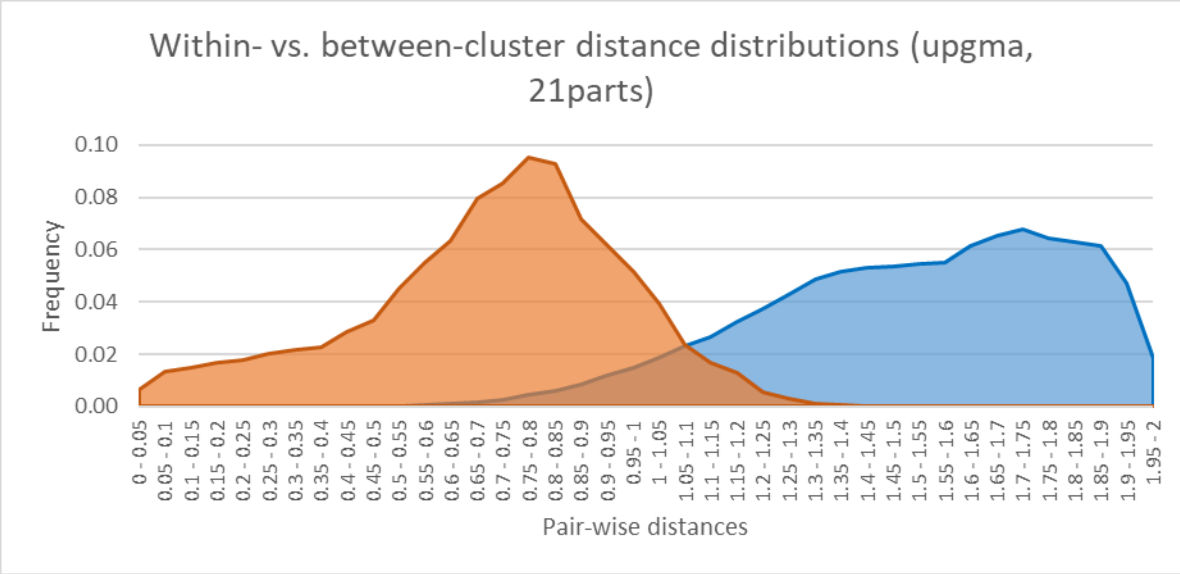

Figure 28: Within- and between-cluster distance distributions: (unweighted) average-link, 21-cluster partition

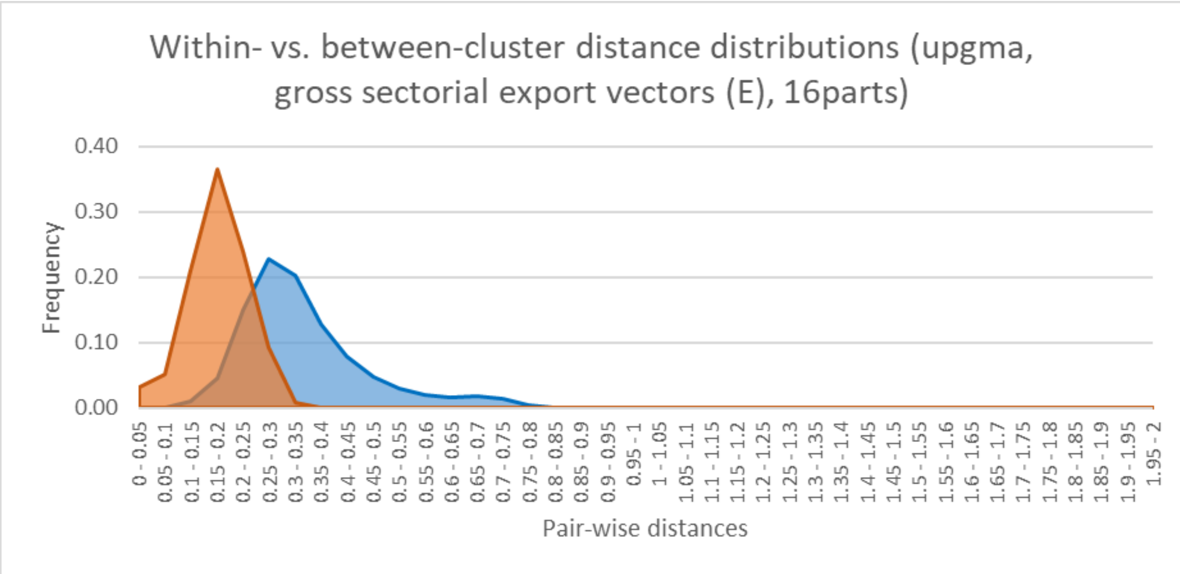

Figure 29: Within- and between-cluster distance distribution: (unweighted) average-link, gross sectorial export vectors (E), 16-cluster partition

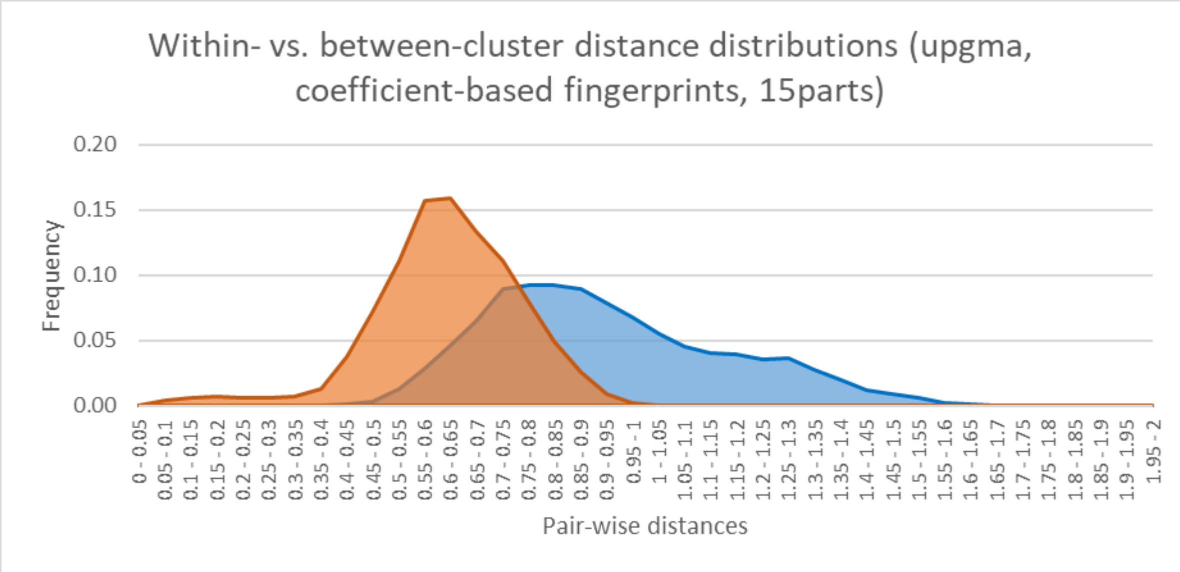

Figure 30: Within- and between-cluster distance distributions: (unweighted) average-link, coefficient-based fingerprints, 15-cluster partition

Appendix D: Additional analyses

D.1 Dominant eigenvalues of WIOD13 fingerprints

A fingerprint for a specific national economy at a specific year consists of two parts, capturing the sectorial prominence of up- and downstream flows, respectively. As specified in the manuscript (see Eq. 1 and 2), upstream prominence is operationalized as the left-hand dominant eigenvector of the added Z and M matrices (labeled as the T matrix), and downstream prominence is operationalized as the right-hand dominant eigenvector of the Z matrix alone. What makes these vectors 'dominant' is that their corresponding eigenvalues are the largest (i.e. λ_{max} in Eq. 1-2) among the set of all eigenvalues. As the up- and downstream vectors are extracted from somewhat different matrices (i.e. T and Z), each fingerprint has two sets of ordered lambda values, for up- and downstream prominences, respectively.

Analogous to the calculation of explained variance in factor analysis, the size of the largest eigenvalue relative to the remaining set of eigenvalues could be indicative of how well the dominant eigenvector captures the main features of the matrix. Two diagnostic measures are used to evaluate the size of dominant eigenvalues. The first measure – *1st share* – captures the share of the dominant eigenvalue with respect to the sum of all eigenvalues. The second measure – 1st/2nd ratio – captures the ratio between the dominant and the second-largest eigenvalue. As a single country-year fingerprint consists of two separate sets of eigenvalues and eigenvectors, for up- and downstream prominence respectively, four eigenvalue diagnostics were calculated for each fingerprint[32].

	1st EV % share of sum	**Ratio 1st/2nd EVs**
Upstream eigenvalues (T)	$u_{\%}$	u_{1vs2}
Downstream eigenvalues (Z)	$d_{\%}$	d_{1vs2}

As the sum of all eigenvalues for a matrix A corresponds to the sum of the diagonal values in A (i.e. the trace of A), the eigenvalues of the various Input-Output matrices (Z and T) depend on the relative sizes of the different economies. To allow for a more direct comparison of the dominant eigenvalues for the upstream (i.e. based on Z) and downstream (i.e. based on T) components, these matrices were first normalized so that the sums of their diagonals were fixed at the size of the matrices (i.e. 34):

$$A_{tracenorm} = 34 \cdot \frac{A}{tr(A)}$$

(where A is either the matrix Z or T, tr(A) is the sum of the diagonal of A, 34 is the size of matrix A, and $A_{tracenorm}$ is the trace-normalized version of matrix A where the sum of the diagonal equals 34)

The extracted left- and right-hand eigenvectors of such a trace-normalized version of the Z and T matrices are identical to those of their non-normalized versions, but the corresponding set of eigenvalues now sums up to the number of sectors in the WIOD13 dataset. This allows for a more

[32] Complete tables with eigenvalue diagnostics for all 680 WIOD13-derived fingerprints are available on the project website: www.demesta.com/fingerprinting. When inspecting a singular fingerprint, the eigenvalue diagnostics are shown below. Eigenvalue diagnostics for the coefficient-based alternative fingerprints are also available for visualization and download.

direct comparison of the relative magnitudes of 1st and 2nd eigenvalues for the up- and downstream vectors for each country and year.

Using these trace-normalized matrices, the statistics for the first (dominant) eigenvalues for the up- and downstream vectors in each fingerprint for the set of 40 countries and 17 years in the WIOD13 dataset is given in *Table 7* below, with the frequency distribution of the first eigenvalues given in *Figure 31* below. Percentages in brackets indicate the 1st share eigenvalue diagnostics: on average, $u_{\%}$ and $d_{\%}$ are 27 and 29 percent respectively, with their medians being slightly lower.

Table 7: Statistics on sizes and shares of dominant eigenvalues for up- and downstream eigenvectors

	Upstream (using T)	**Downstream (using Z)**
Mean	9.09 (27%)	10.00 (29%)
Median	8.15 (24%)	9.17 (27%)
Min-max	5.27 – 29.69 (16 – 87%)	6.22 – 30.41 (18 – 89%)

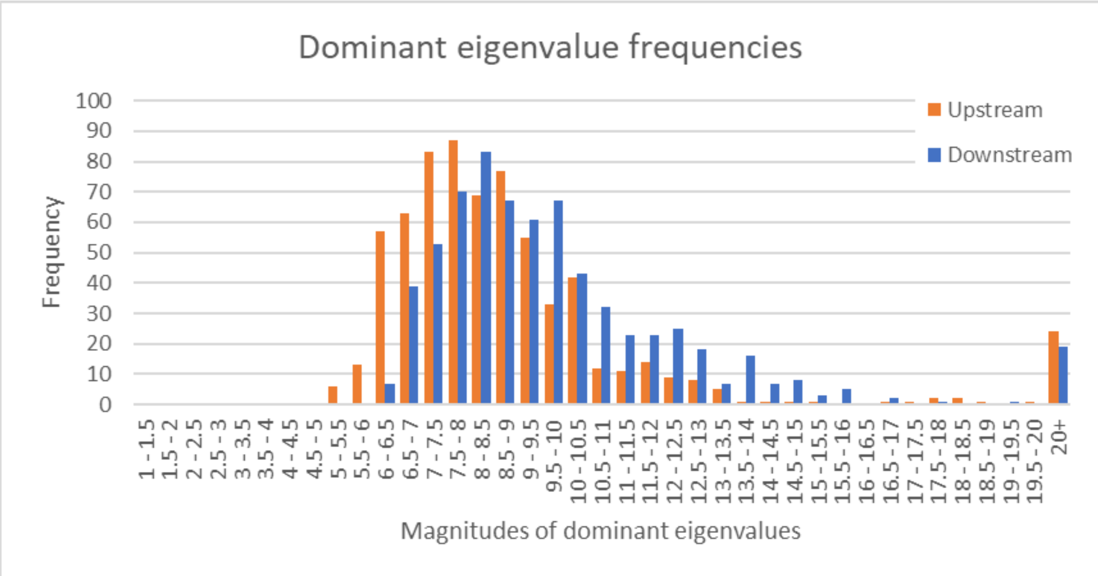

Figure 31: Distribution of dominant eigenvalues for up- and downstream eigenvectors

By dividing the dominant eigenvalues with the second-largest eigenvalues for each of the up- and downstream eigenvectors, we obtain the second eigenvalue diagnostics for up- and downstream eigenvectors: u_{1vs2} and d_{1vs2}. Mean, median and value ranges for these diagnostics are given in *Table 8*, with their distributions given in *Figure 32*.

Table 8: Statistics on ratio between dominant and second-largest eigenvalues for up- and downstream eigenvectors

	Upstream (using T)	**Downstream (using Z)**
Mean	2.05	2.04
Median	1.54	1.66
Min-max	1.08 – 18.81	1.11 – 19.24

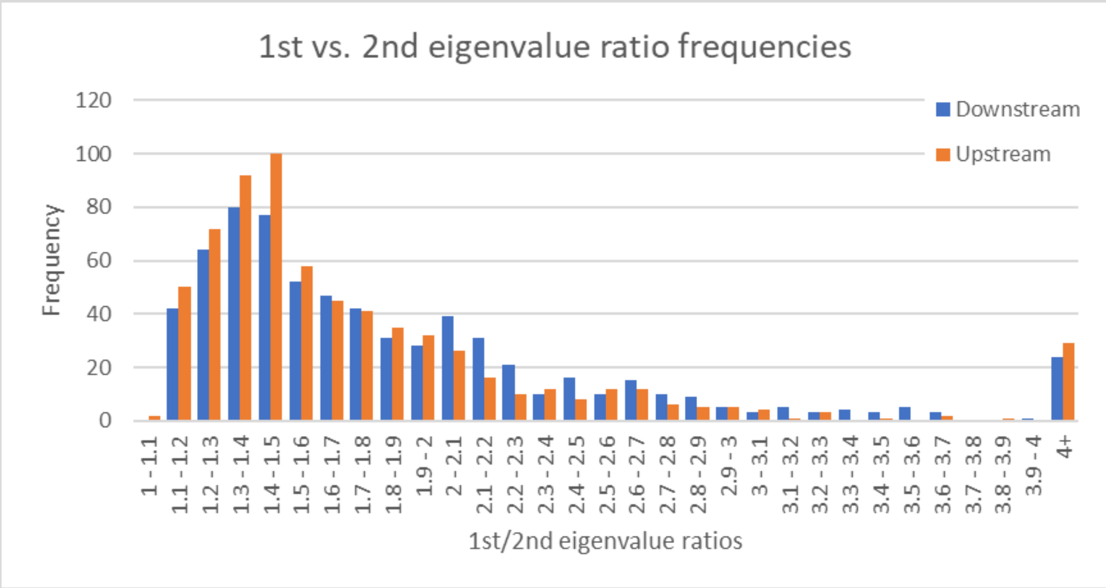

Figure 32: Distribution of 1st vs. 2nd eigenvalue ratios for up- and downstream eigenvectors

The mean and median eigenvalue diagnostics are relatively good, but there are indeed several fingerprints where either one or both of its eigenvectors have corresponding eigenvalue diagnostics that are low.[33] For those where both of the dominant eigenvectors have low diagnostics, Portugal's 1995 fingerprint has the objectively worst diagnostics ($u_{\%}$=15.5%; u_{1vs2}=1.13; $d_{\%}$=18.5; d_{1vs2}=1.20), with Turkey 2000 as a good contender for the second worst ($u_{\%}$=17.9%; u_{1vs2}=1.21; $d_{\%}$=18.3; d_{1vs2}=1.17).

Portugal 1995 and Turkey 2000 stick out with both their diagnostic measures being very low, which is not the case for the vast majority of fingerprints. If we set an acceptable threshold for the 1st share diagnostic measures (i.e. $u_{\%}$ and $d_{\%}$) to 20% and a corresponding threshold for the 1st vs. 2nd ratio diagnostic measure(i.e. u_{1vs2} and d_{1vs2}) to 1.25, the number of fingerprints with combinations of acceptable diagnostic measures for their up- and downstream components are as given in *Table 9* below.

Table 9: Frequency table for acceptable eigenvalue diagnostic measures

	$\|u_{1vs2} > 1.25\|$	**$\|u_{1vs2} < 1.25\|$**	**∑**
$\|u_{\%} > 0.20\|$	502 (74%)	67 (10%)	569 (84%)
$\|u_{\%} < 0.20\|$	90 (13%)	21 (3%)	111 (16%)
∑	592 (87%)	88 (13%)	
	$\|d_{1vs2} > 1.25\|$	$\|d_{1vs2} < 1.25\|$	∑
$\|d_{\%} > 0.20\|$	588 (86%)	64 (9%)	652 (96%)
$\|d_{\%} < 0.20\|$	20 (3%)	8 (1%)	28 (4%)
∑	608 (89%)	72 (11%)	

With Portugal 1995 and Turkey 2000 being part of both the 21 fingerprints with sub-par upstream diagnostics and the 8 with sub-par downstream diagnostics, there are a total of 27 fingerprints with

[33] For the coefficient-based fingerprints, all statistics (mean, median, range etc.) of the four eigenvalue diagnostics are consistently lower than those for the standard (flow-based) fingerprints in Table 5 and 6.

potentially problematic eigenvector components. These particular fingerprints should thus be interpreted with particular care. Yet, if we accept dominant eigenvectors where at least one of their two related eigenvalue diagnostics are above the acceptable threshold, this corresponds to a total of 653 fingerprints, i.e. 96 percent of the total 680 fingerprints.

These thresholds could be criticized as being too liberal, with the implication that one should be even more careful in interpreting the dominant eigenvectors and the obtained fingerprints of up- and downstream sectorial prominence for a larger set of fingerprints. Still, even with sporadically low eigenvalue diagnostic measures for particular fingerprints, these do not seem to interfere much with results from comparative fingerprinting analysis. The case in point is the cluster analysis done in this study (see Section 3.2 in manuscript, particularly Figure 13): although specific fingerprints indeed have rather poor diagnostic measures for their dominant eigenvalues, these fingerprints nevertheless seem to capture enough structural features of their economies to result in longitudinally consistent clusters that make sense.

When tracking longitudinal transformation over time, it could be that relatively lower eigenvalue diagnostics correspond to “turbulence” when measuring annual change between years. *Figure 33* and *Figure 34* below simultaneously tracks the amount of structural transformation between years and the 1st vs. 2nd ratio diagnostics for these fingerprints for Portugal and Turkey, respectively.

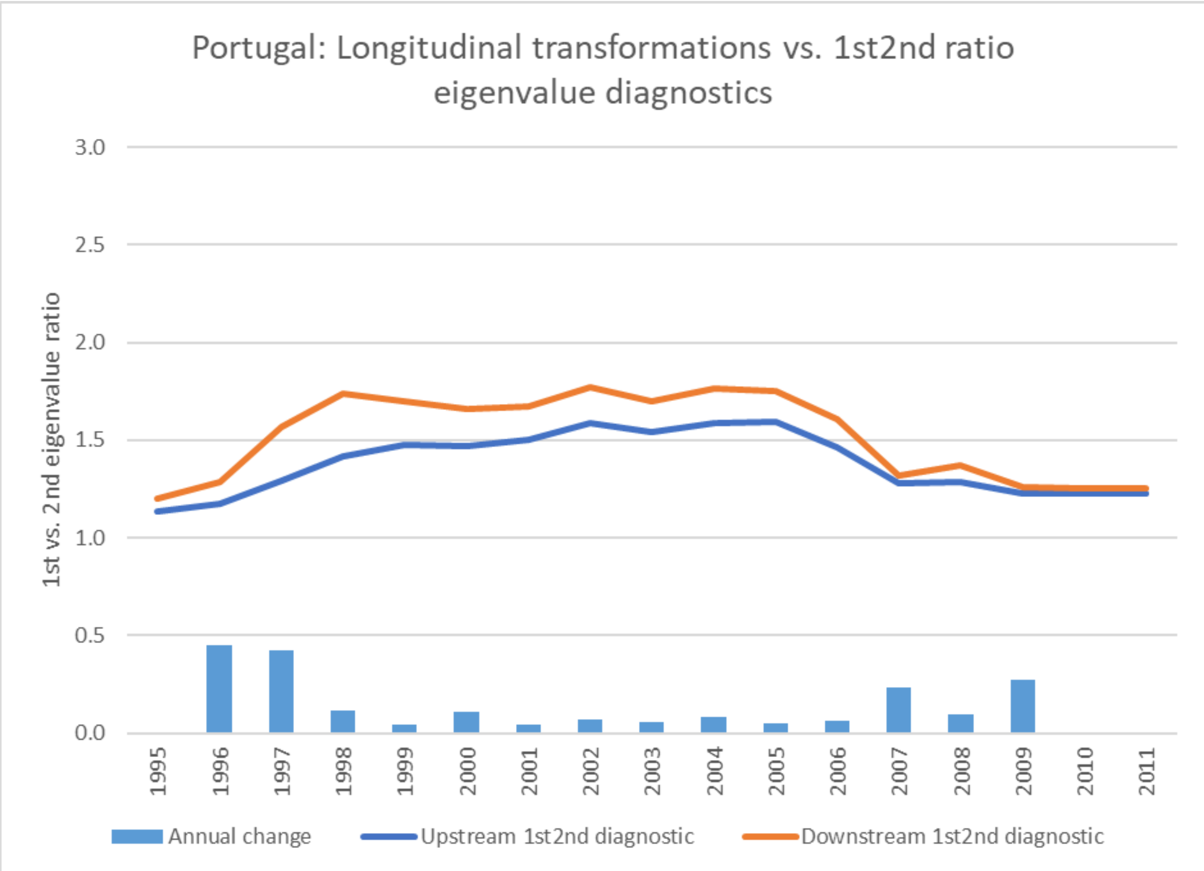

Figure 33: Annual structural transformation and eigenvalue diagnostics for Portugal

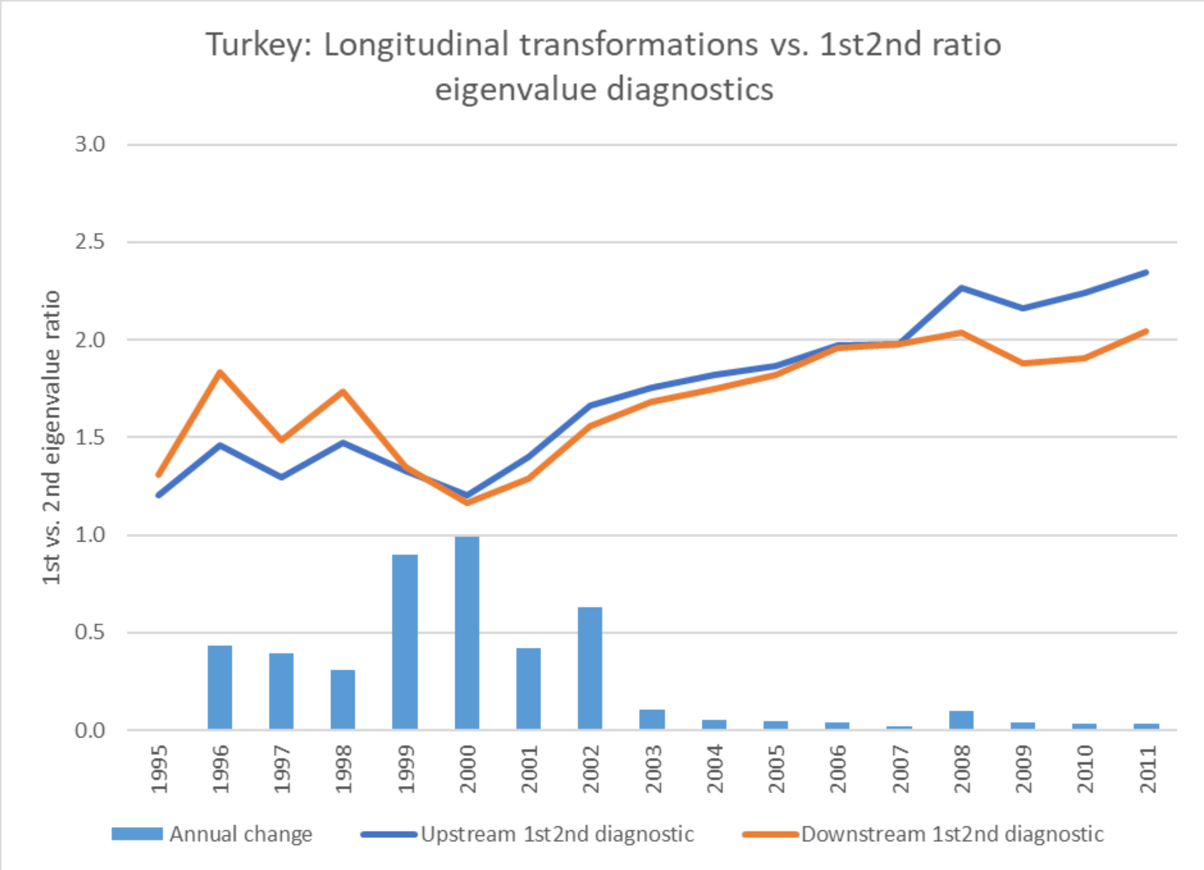

Figure 34: Annual structural transformation and eigenvalue diagnostics for Turkey

For both Portugal and Turkey, the amount of annual structural transformation seem to coincide with low values of the $1^{st}2^{nd}$ ratio eigenvalue diagnostic. This could indicate that the annual structural transformation derived for some of these years might more be an artifact of dominant eigenvectors that are less representative of the structural features of this economy than those for corresponding eigenvectors for adjacent years.

A possible analytical strategy would thus be to exclude all fingerprints with eigenvalue diagnostics deemed as insufficiently large. That could indeed make sense when plotting longitudinal transformations for individual countries, such as annual and cumulative change, and when comparing dissimilarities with an index year. Still, these potential low points evidently have little effect on results from the clustering analysis. Whereas Turkey indeed shifts between the Agriculture & Food and the Textiles types between 1998-99, i.e. where the two eigenvalue diagnostics do take a dive, Turkey remains stable in its two types both before and after this transition (which also applies at the much higher 21-cluster partition; see Figure 13 in manuscript). Despite Portugal's poor eigenvalue diagnostics, it remains steadily within the Construction type throughout the whole 1995-2011 period.

Finally, it is well worth exploring the eigenvalue diagnostics for a country that in both case studies exhibit significant structural transformations during the 1995-2011 period. The annual transformation of Estonia and the corresponding $1^{st}2^{nd}$ ratio eigenvalue diagnostics are given in *Figure 35* below. With eigenvalue diagnostics remaining relatively high for most years, but so do its annual transformations. The first dip in the $1^{st}2^{nd}$ ratio diagnostics occurs in 1998, this being when Estonia transitions from the Agriculture & Food-type to a dis-embedded Electrical-type of production structure. With significant annual transformations for most years in the 1998-2007 period, temporarily classified as an embedded Electrical-type economy in 2001 and 2004, these transformations and transitions seem independent of the ratio diagnostics that overall remain large. This reinforces the conclusion that Estonia indeed is somewhat tricky to categorize, thus indeed shifting between these two Electrical-type economies before, in 2007, turning into the residual Other transport type of economy (see Section 3.2 in manuscript). Estonia's annual transformations and its classification issues is thus not associated with poor eigenvalue diagnostics and, through this, misrepresenting dominant eigenvectors.

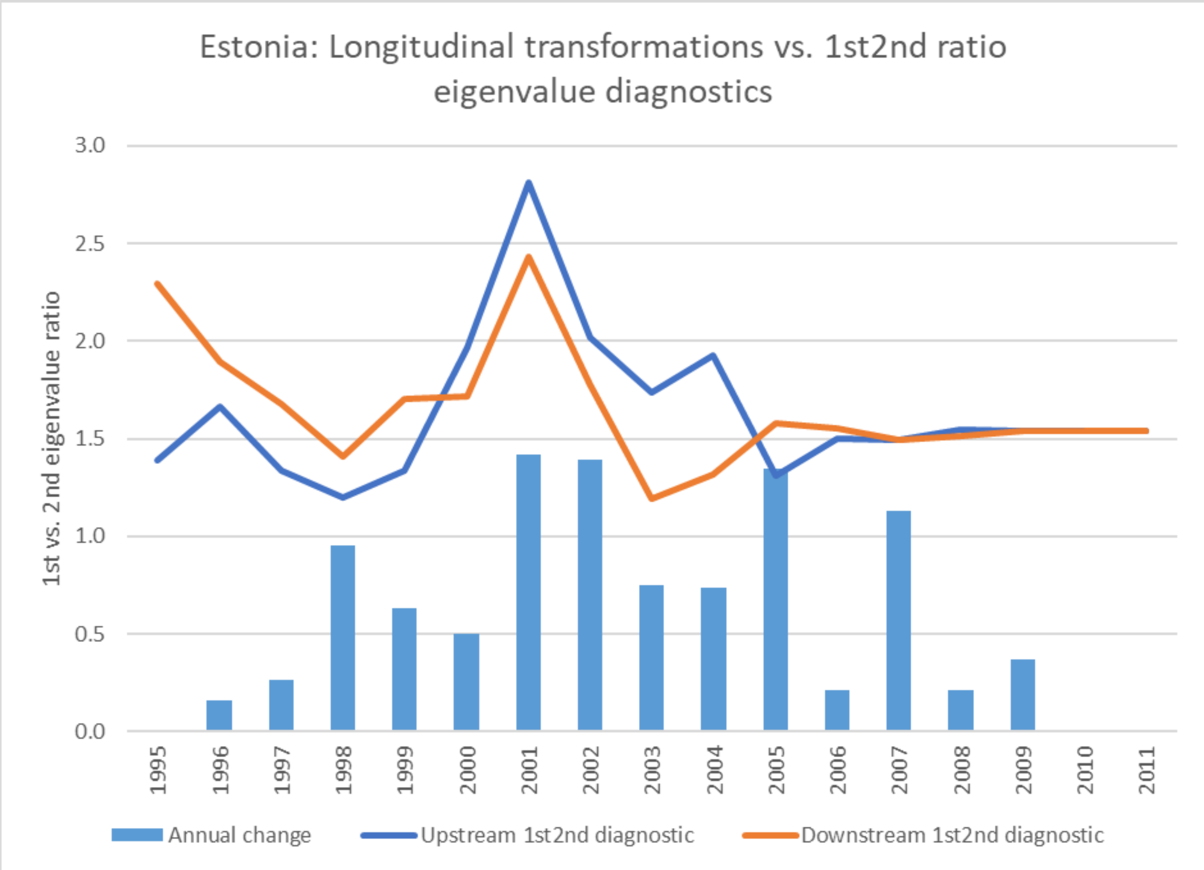

Figure 35: Annual structural transformation and eigenvalue diagnostics for Estonia

D.2 Additional hierarchical clustering analyses: gross sectorial exports, and coefficient-based fingerprinting

Supplementing the hierarchical clustering analyses done on the proposed fingerprint heuristic (i.e. using actual Input-Output flows in the Z and M matrices), this additional study conducts corresponding hierarchical clustering analyses on two of the alternative metrics mentioned in the paper: gross sectorial exports, and the coefficient-based fingerprint approach (see section 2.3). For gross sectorial exports, the E vectors were taken from each of the 680 country-year-specific national Input-Output tables in WIOD1, subsequently marginal-normalized, and a dissimilarity matrix of Euclidean distances between each pair of gross sectorial exports were generated. For coefficient-based fingerprints, technology- and output coefficients were calculated for 663 country-year data points (here excluding Luxembourg due to issues with calculating some of its eigenvectors), also from WIOD13. Back- and forward linkages were determined (see Eq 3-4 in section 2.3) and Euclidean distances between all pairs of these alternative fingerprints generated the coefficient-based dissimilarity matrix.

Unweighted average-link clustering was applied to the two dissimilarity matrices, using the Calinski-Harabasz (CH) and the within-cluster sum-of-squares (WCSS) metrics to search for suitable partitions – see *Figure 36* below. The within-cluster sum-of-squares remains quite low for all partitions, and as there are no distinct peaks in the overall increasing CH measures, the choice of suitable partitions is not obvious. Remaining close to the 12-cluster partition chosen for the default (flow-based) fingerprints, the choice was made to partition the sectorial export- and coefficient-based dissimilarity data into, respectively, 15 and 16 clusters. However, the separation between within- and between-cluster distances in both these partitions are indeed not ideal (see C.2: *Figure 23*, *Figure 29* and *Figure 30* above).

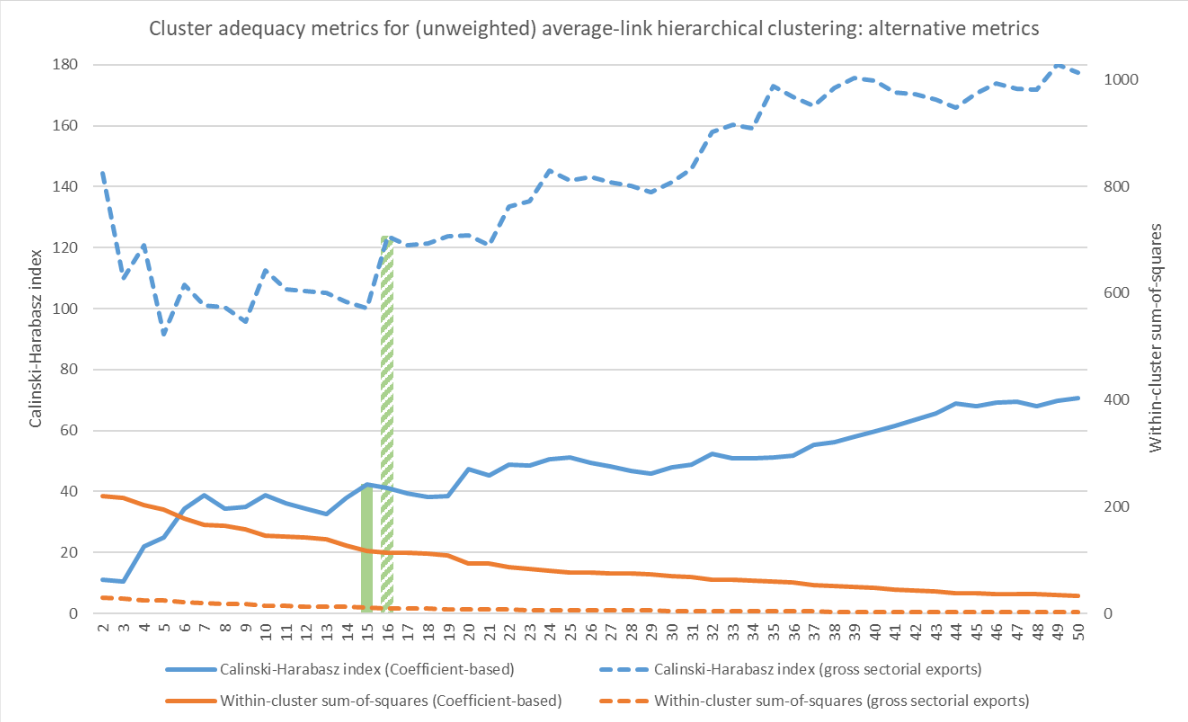

Figure 36: Cluster adequacy analysis for the average-link hierarchical clustering of alternative metrics

The 16-cluster partition for the sectorial gross export dissimilarities is in *Figure 37* below. Ten of these 16 clusters are country-specific, each containing all 17 years for respective country. These static national export profiles are not surprising: Australia with Mining and Metal, Luxembourg with Finance, Finland with Electrical and Paper etc. The Bulgarian sectorial exports of 2006 evidently warrants its own singleton type, and Greece between 1999-2011 equally emerges as a country-specific cluster. Of the 4 multi-country clusters, an Electrical- and Vehicles-exporting cluster emerges with Czech Republic, Hungary, Japan, Korea, Mexico and Slovakia, all sharing somewhat similar export profiles. China, Malta and Taiwan (all years) constitute a second Electrical-exporting cluster, whereas Estonia, Latvia, Cyprus and early-period Greece form a slightly larger cluster characterized by gross exports from their Other Transport sectors. The last cluster, characterized by a gross sectorial export mix of Vehicles, Electrical, Metal and Chemicals, contains 304 country-years (out of 680 in the WIOD13 dataset) for 20 countries (with 17 for the full 1995-2011 period). Apart from Greece's 1998-99 transition from Other transport to Water Transport sectorial exports, the only other transitions occurring in the sectorial gross export clustering are Hungary, Czech Republic, and Slovakia going from this large 304-item cluster to join Korea, Japan and Mexico in the Electrical & Vehicles category.

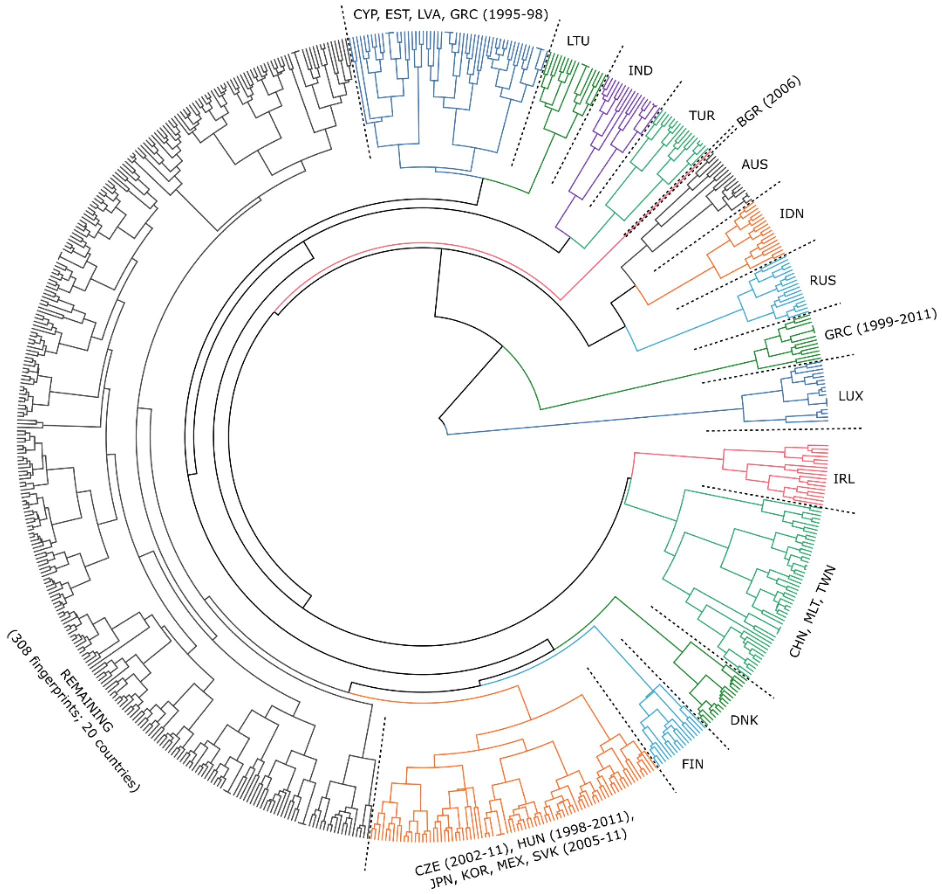

Figure 37: 16-cluster partition of gross sectorial export dissimilarities

The 15-cluster partition based on coefficient-based fingerprint dissimilarities is given in *Figure 38* below. Contrary to the sectorial export clustering above, this one only contains two country-specific clusters that covers their whole periods – for Ireland and Mexico – but there are several other country-specific clusters for particular years. Indonesia has two country-specific clusters for respective millennia, Malta has three, and Germany, Estonia and Austria have periodical country-specific types when not part of a larger multi-country cluster. Greece, Korea and Taiwan – as well as Bulgaria in 2006 – constitute a specific cluster, Portugal, Romania, Slovakia and, partially, Austria constitute another cluster, and Cyprus and early-period Turkey form a third multi-country cluster.

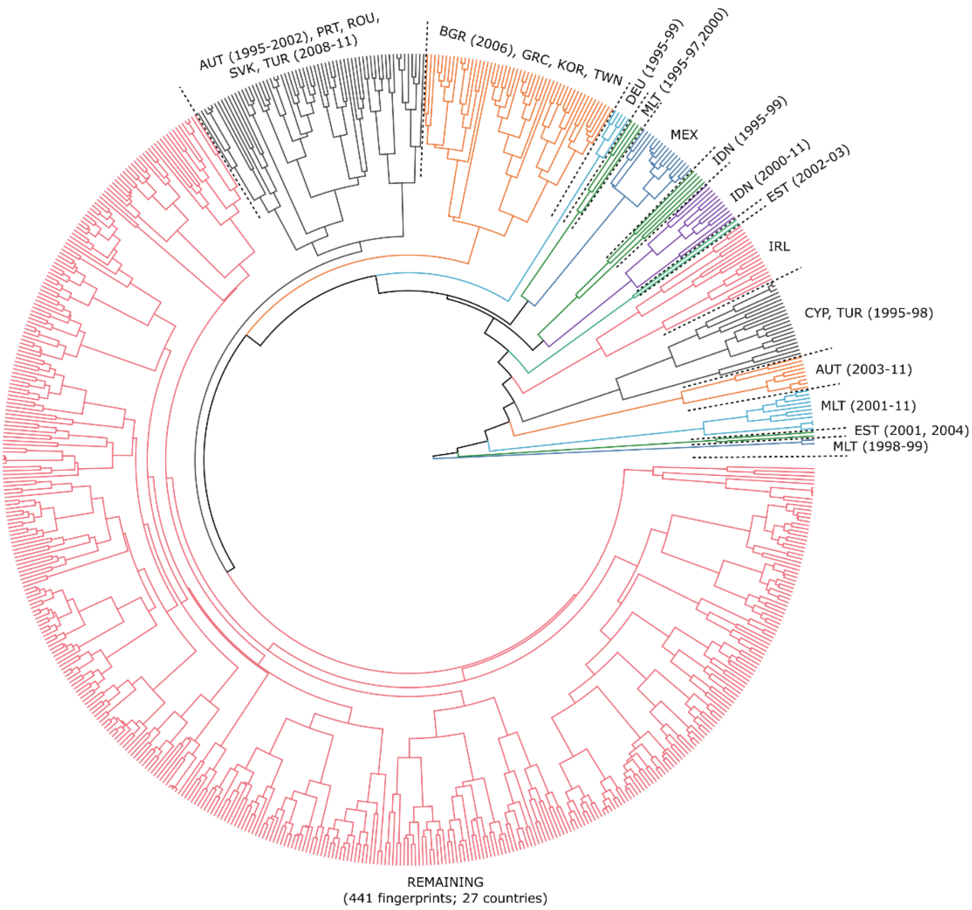

Figure 38: 15-cluster partition of coefficient-based fingerprint dissimilarities

Dominating the clustering structure for the coefficient-based fingerprints is the large cluster containing a majority of countries (27 out of 39) and country-years (441 out of 663). Inspecting the average coefficient-based fingerprint of this particular cluster (see *Figure 39*), it is difficult to label this cluster in terms of particularly prominent sectors. It is evidently also very similar to the average coefficient-based fingerprint for all 663 country-years (see Section 2.3 of article), and it is indeed equally difficult to label the other 14 clusters emerging from the coefficient-based fingerprint dissimilarity matrix. Combined with the poor general separation of clusters for the alternative coefficient-based fingerprinting dissimilarities, this indicates strong support for the notion of a shared fundamental structure in terms of the output- and technology-coefficients of their corresponding national Input-Output tables.

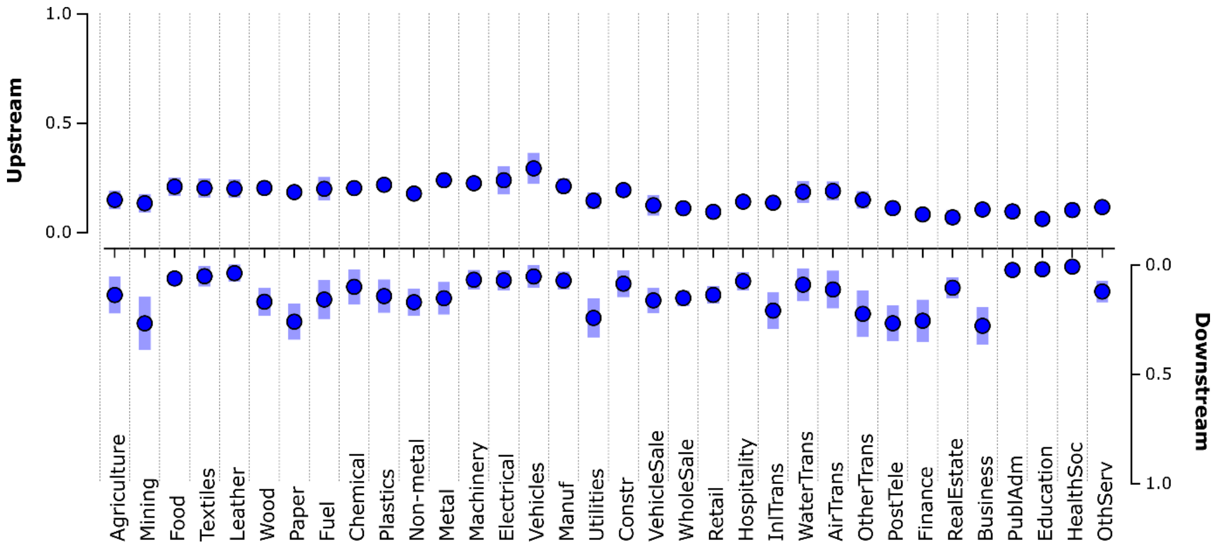

Figure 39: Average coefficient-based fingerprint for the largest cluster (27 countries, 441 country-years) in the 15-cluster partition

6. D.3 Analyzing structural trajectories using multidimensional scaling: the case of the European Union 1995-2011

Given a set of fingerprints and their pairwise dissimilarity/distance metrics, the first case study in the article demonstrates how such a matrix could be analyzed using hierarchical clustering. Whereas this approach provides a way to separate entities into discrete, nominal subsets, such distance data could also be approached using the family of techniques for dimensionality reduction, which maps dissimilarity/distance data into (typically) two or three dimensions. Classical multidimensional scaling (MDS; also known as principal *coordinates* analysis) constitutes one such alternative tool for mapping out similarity patterns and potential latent variables, as well as tracking the developmental trajectories of such structures over time, in a more continuous, non-categorical way.

Building on the second case study in the article, concerning the Eastern enlargement of the European Union, all ten Central- and East-European countries were initially included (i.e. Bulgaria, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovakia, and Slovenia), together with five of the six founding members of the European Union (i.e. Belgium, France, Germany, Italy, and the Netherlands). Covering 15 countries over 17 years, Euclidean distances for each pair of these 255 country-year fingerprints were calculated. Classical metric multidimensional scaling (MDS) was applied to this dissimilarity matrix to extract both 2- and 3-dimensional solutions. Evaluating these solutions with the Kruskal stress index, the 2-dimensional solution resulted in a high stress of 0.51, dropping to 0.31 for the 3-dimensional solution. Further exploration revealed that it was particularly Estonia's inclusion that contributed to this stress. Redoing the MDS with Estonia excluded, i.e. with a total of 14 countries and 238 country-year fingerprints, the Kruskal stress went down to 0.46 for the 2-dimensional solution and 0.27 for the 3-dimensional solution. As the 3-dimensional solution lies below the generally acceptable threshold (0.3), this solution was chosen for further exploration.

Calculating 3-year simple-moving-average coordinates for all years (using 2-year averages for 1995 and 2011, respectively), *Figure 40* depicts the first two dimensions of the 3-dimensional MDS solution. Whereas this figure can be perceived as looking at the 3-dimensional solution from the side (like the side of a cube), the supplementary figure (*Figure 41*) looks at the same data but from "above" (like you are leaning forward into the paper surface and looking down). Whereas the 3rd dimension indeed is necessary to bring down the Kruskal stress index to reasonable levels (i.e. 0.27), the first two dimensions (*Figure 40*) does seem to allow for some interesting interpretations. First, corroborating findings from the two case studies in the article, the production structures of these five Western economies are relatively similar and stable over time. Their structural trajectories are overall unidirectional, more linear, and seemingly ending up closer to each other in 2011 compared to 1995. In contrast, most of the 'Eastern' production structures experience dramatic structural transformations. The structural trajectories of Bulgaria, Latvia, Hungary and Poland are particularly notable, traversing large distances in this 'structural space'. Lithuania, and perhaps also Hungary, seem to experience retrograde structural trajectories, where Lithuania, together with Romania, do not move very far away from their starting position. This is in line with the sequence index plot of the 12-type classification (see Figure 15 in manuscript): of the seven 'Eastern' countries starting off as 'Agriculture & Food'-type economies in 1995, only Lithuania and Romania remain as this type throughout the 1995-2011 period.

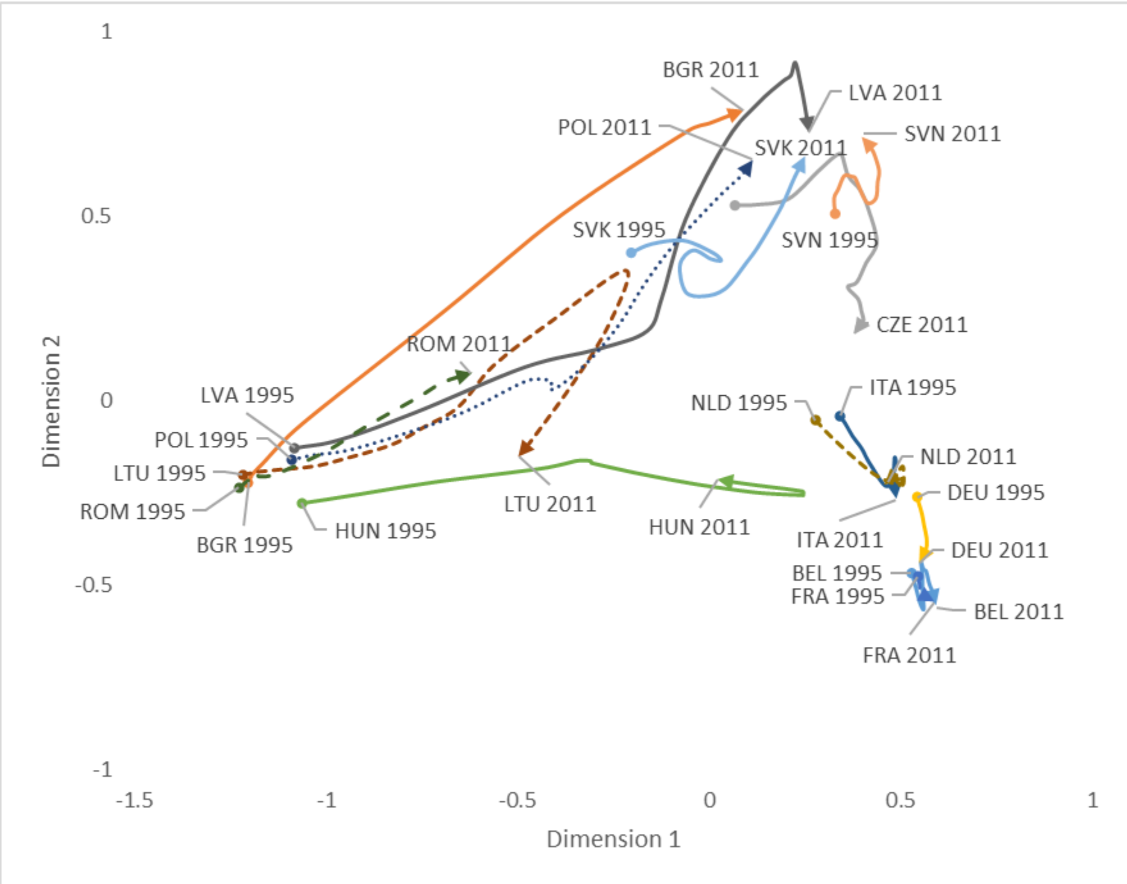

Figure 40: Classical multidimensional scaling (dimension 1 and 2) of structural trajectories in the European Union, 1995-2011

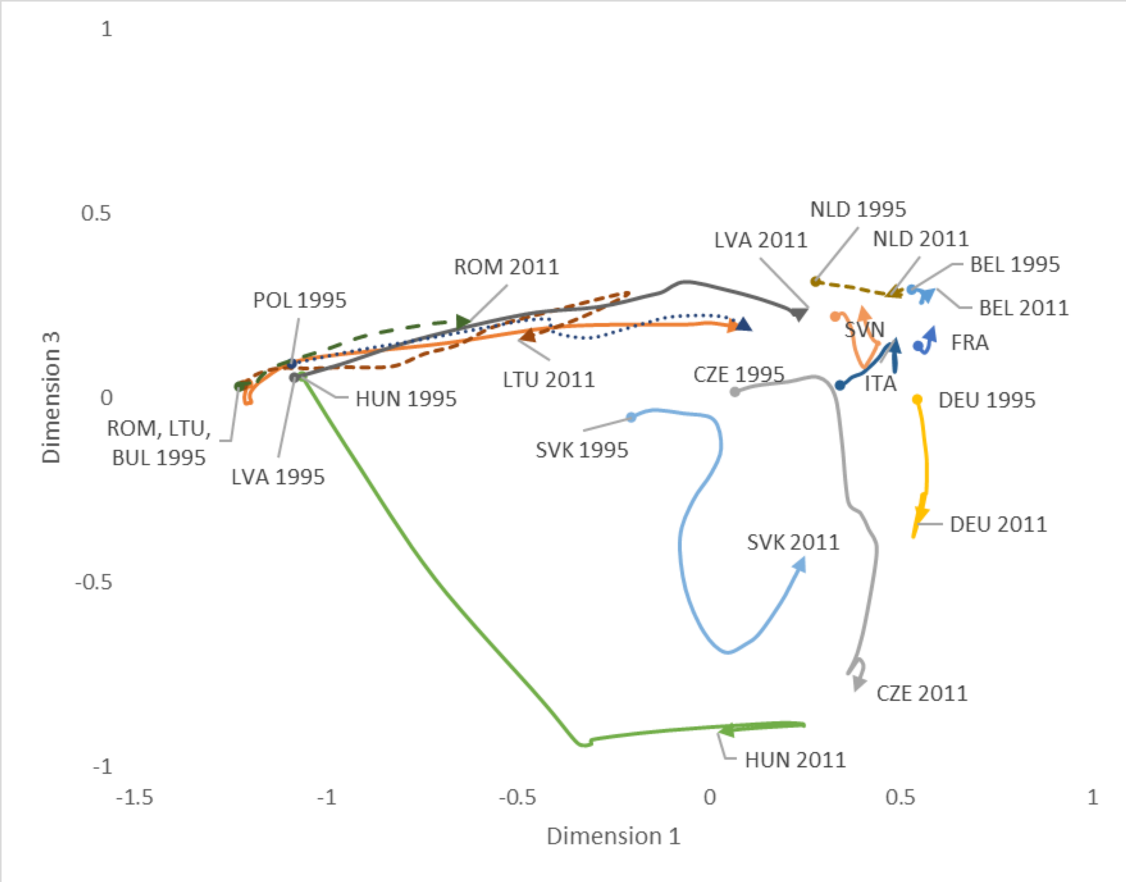

Figure 41: Classical multidimensional scaling (dimension 1 and 3) of structural trajectories in the European Union, 1995-2011

Although both Hungary and Czech Republic exhibit movement towards the 'Western' cluster, a notable aspect of *Figure 40* is the lack of East-West structural convergence. As concluded from the longitudinal plots in the paper (see Figures 21 and 22 in the manuscript), the transformations of the 'Eastern' production structures did not markedly affect the average structural dissimilarity between the two regions. This finding is well reflected by the first two dimensions of the MDS solution above: despite a significant transformation of several of the Eastern production structures during this period, they overall remain equidistant to their 'Western' counterparts. Additionally, albeit relatively short, the trajectories of the 'Western' structures seem to move them further away from their Eastern neighbors.

Multidimensional scaling could potentially be a useful supplement to the existing tools for fingerprint analysis proposed in this article. However, similar to all such techniques, it is of course imperative that relevant goodness-of-fit measures, such as the Kruskal stress index here, remain within acceptable boundaries. In the context of fingerprinting, tentative explorations of the WIOD13-based fingerprints seem to indicate that three dimensions are needed to arrive at such acceptable levels. Thus, the visualization and interpretation of such rescaled data should then preferably instead be done through interactive and/or virtually augmented/VR tools.