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Yet another space: Why the Industry Space adds value to the understanding of structural change and economic development

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ABSTRACT

We introduce the Industry Space based on value-added exports as a complementary visualisation of economic development and structural cross-country differences to the established Product Space, which relies on gross exports. Since value-added exports disentangle global and national value chains, we argue they enable a more accurate and holistic depiction of an economy's capabilities. Specifically, the Industry Space links 51 industries to each other based on the similarity in required capabilities. We emphasize the need for value-added exports by providing evidence that using gross exports significantly changes the similarities between industries. Applying the concept to comparative country case studies, we show that the Industry Space is a useful tool to investigate the economic structure between countries and over time.

1. Introduction

More than a decade ago, (Hidalgo et al., 2007) introduced the Product Space, which brought forward an understanding of economic development as a structural process on top of a network of products. Specifically, it maps products to each other based on the similarity in required capabilities. As capabilities are not observed, the underlying theoretical model assumes that export specialisations accurately reflect a country's capabilities. If export specialisations of two specific products are frequently observed jointly, it follows that the capabilities required to produce this good efficiently and competitively are similar.

However, the Product Space is based on gross exports, which may not be as informative due to an increased fragmentation of international trade. The last decades of economic integration can be characterised by a deepening of global value chains, which has led to a decrease in domestic value-added embodied in gross exports (Johnson and Noguera, 2017). Goods produced in global value chains cross borders frequently. At each border crossing, the overall value of the good is reflected in gross export statistics, although the value-added of each individual country and industry is only a small share of the overall value. This also entails the issue of double-counted exports. Moreover, domestic services are embodied in the trade of goods as well. Various services contribute to the production of a final or intermediate good within an economy, e.g. wholesale trade or R&D. In gross trade data, the value-added embodied in these services used as intermediates is assigned to the product that is ultimately exported.

To tackle the issues associated with gross exports, value-added exports, which can be retrieved from Inter-Country Input-Output Tables prove to be useful. They are defined as the value-added a specific industry contributes to goods and services that are eventually consumed abroad (Johnson and Noguera, 2012; Koopman et al., 2014).

Indeed, it can be shown that conclusions based on export specialisations may differ depending on the applied data. Using value-added and gross export data from the World Input-Output Database (WIOD; Timmer et al., 2015), we calculate the difference between the Revealed Comparative Advantage (*RCA*, Balassa, 1965) based on value-added exports and based on gross exports. Out of 2290 country-industry combinations, the specialisation index dif-

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fers in 372 cases (16.24%) using $RCA \geqslant 1$ as cut-off, with a mean absolute difference in the index of 0.576.[1]

This implies that value-added exports may also be crucial in understanding economic development or economic structures overall. Since value-added exports can only be retrieved on an industry-level, simply depicting value-added export specialisations on top of the Product Space is not possible. Hence, we introduce the concept of the Industry Space based on value-added exports in this article as a complementary visualisation of economic development and structural cross-country differences. Similar to the Product Space, the Industry Space relates 51 industries to each other based on the similarity in required capabilities. We show in this paper that the Industry Space enables a more accurate and holistic depiction of an economy's structure, since it takes foreign value-added as well as the role of services in trade into account.

Our article is related to two strands of the literature that are itself closely related. First, it builds upon literature on the Product Space. Since its introduction, the Product Space proved to be an useful tool to visualise and understand the economic development of nations. For example, a number of studies show that economic development is subject to path-dependencies. That is, economies grow by diversifying their product portfolio based on their current capabilities or by specialising in less ubiquitous and more complex products, which are close to current specialisations in the Product Space (Coniglio et al., 2018; Content and Frenken, 2016; van Dam and Frenken, 2020; Hausmann and Hidalgo, 2011; Hidalgo and Hausmann, 2009; Reinstaller and Reschenhofer, 2019; Saviotti and Frenken, 2008). The idea of relatedness has also been applied to other data sources. For example, (Catalán et al., 2020) build a science and technology cross-space using data on scientific publications and patents.

Second, this article is strongly connected to the literature on economic complexity. The understanding of economic development on top of a network led to the emergence of iterative metrics, which have their roots in machine learning algorithms, exploiting its network structure and quantifying the amount of productive knowledge embedded in a country. They are now known as Economic Complexity (Hidalgo and Hausmann, 2009) or Economic Fitness (Tacchella et al., 2012).[2] Specifically, they use gross export specialisations and define complexity with respect to two dimensions. First, a country's complexity is positively linked to the diversification of its export specialisations. Second, a country's complexity is negatively linked to the ubiquity of the products it is specialised in.

A large number of studies, subsequently, finds that economic complexity is positively associated with economic growth at the national level (Felipe et al., 2012; Ferrarini and Scaramozzino, 2016; Hidalgo and Hausmann, 2009; Kali et al., 2013), as well as at the regional level (Balland et al., 2020; Chávez et al., 2017; Gao and Zhou, 2018; Pugliese and Tübke, 2019). In addition to that, including economic complexity in GDP forecasting models is found to improve the accuracy considerably (Tacchella et al., 2018). While gross exports are the most common data basis for approximating economic complexity, the methodological approach is not limited to gross exports. Rather, it has been, among others, applied to data on patents (Balland and Rigby, 2016) or industry labor force flows (Neffke and Henning, 2013). A comprehensive state-of-the-art assessment of the literature on economic complexity as well as its relationship to traditional economic models is given in (Hidalgo, 2021).

In a recent contribution, (Koch, 2021) argues that value-added exports are able to more accurately approximate a country's economic complexity and an economy's structure. Specifically, complexity in terms of value-added exports yields substantially different country rankings in comparison to established indices, and can explain GDP per capita growth in a cross-country growth model considerably better.[3] This paper can be understood as complementary to (Koch, 2021), enabling a visualisation of complexity in terms of value-added exports, in analogy to the Product Space.

This article is structured as follows. In Section 2, we introduce the concept of the Industry Space and discuss its structure as well as the development of similarities over time. We also provide evidence for the need of value-added exports. Section 3 aims to show the concept's usefulness in discussing the economic structure of China and the USA on top of the Industry Space as a case study. Moreover, we investigate the differences between a gross and a value-added export approach discussing characteristics of the Japanese and the Indian Industry Space. Using gross exports would alter the Industry Space overall significantly and lead to potentially misleading conclusions in analysing the structure of countries.

2. The Industry Space

Based on the approach outlined in (Koch, 2021), we propose the Industry Space as a novel visualization of an economy's structure. In contrast to the Product Space, the Industry Space also includes services, and can thus be interpreted as a visualisation of the whole economy. However, while the Product Space links more than 1200 products to each other based on the similarity of required capabilities (Hidalgo et al., 2007), the investigation of value-added exports only allows for the depiction of 51 industries.[4]

The required data are obtained from the WIOD (Timmer et al., 2015). Based on the method by (Koopman et al., 2014) and (Johnson and Noguera, 2012), we retrieve value-added exports for all industries in all covered countries. Specifically, the WIOD covers 43 lower-middle- to high-income-countries and more than 50 industries each according to the ISIC Revision 4. An extensive list of covered industries and their respective abbreviation is provided in Appendix A.[5]

Methodologically, the Industry Space is similar to the Product Space as outlined in (Hidalgo et al., 2007). It is assumed that export specialisations, i.e. the Revealed Comparative Advantage (*RCA*, (Balassa, 1965), are an accurate latent measurement of an economy's capabilities. In the context of this study, we investigate export specialisations in terms of value-added exports (*VAX*). Specifically, the *RCA* is defined as

$$RCA_{c,s} = \frac{VAX_{c,s}/\sum_s VAX_{c,s}}{\sum_c VAX_{c,s}/\sum_{c,s} VAX_{c,s}} = \frac{VAX_{c,s}/\sum_c VAX_{c,s}}{\sum_s VAX_{c,s}/\sum_{c,s} VAX_{c,s}} \tag{1}$$

[1] Fig. A.1 in Appendix A displays the distribution of deviations.

[2] Both metrics aim to capture economic complexity, but with slightly different methodological approaches. While (Hidalgo and Hausmann, 2009) use a linear algorithm, (Tacchella et al., 2012) argue that non-linearities need to be taken into account. In a recent contribution, (Sciarra et al., 2020) propose a further metric aiming to reconcile both approaches. For a thorough methodological discussion we recommend the recent paper by (Hidalgo, 2021).

[3] See Table A.1 in Appendix A for a comparison between complexity based on value-added exports and gross exports, and Table A.2 for a ranking of the most complex industries.

[4] In a similar context, although using inter-industry labor flows and, thus, a different data basis, an Industry Space has also been introduced in (Neffke and Henning, 2013) and (Neffke et al., 2017). Just as the Product Space, the Industry Space as proposed by us depicts the relationship of industries based on trade data, which is available for a large number of countries, whereas the data availability of inter-industry labor flows is more limited.

[5] In the following, we will focus on 51 industries out of the 56 industries, which are covered in the WIOD in total. Specifically, we exclude industries, which are either not relevant in evaluating an economy's structure in terms of export specialisations, or the respective data only cover a small share of countries. The excluded industries are: activities of households, human health and social work services, activities of extraterritorial organisations, education, and public administration and defence.

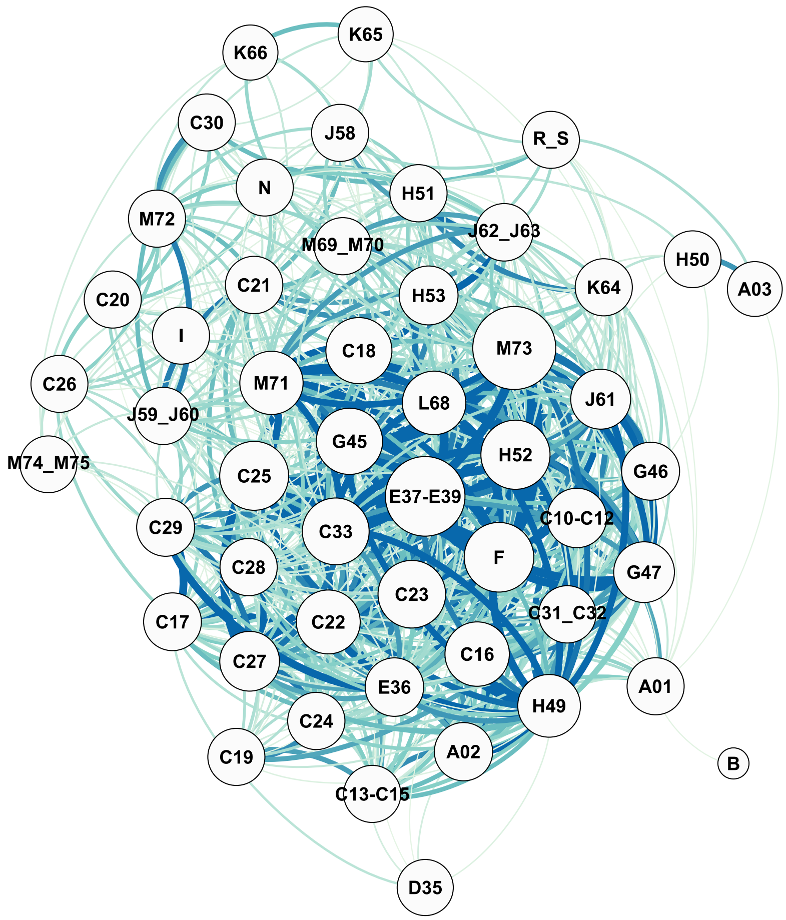


Fig. 1. The Industry Space in 2007.

Country c is specialised in industry s if $RCA_{c,s} \geqslant 1$. That is, if the share of industry s on the overall value-added exports of country c is larger than the share of industry s on the worldwide value-added exports. This is equivalent to saying that the value-added export market share of country c in industry s exceeds the value-added export market share of country c over all industries.

In a second step, the similarity between industry i and j in year t, denoted by $\phi_{ij,t}$, is expressed as the conditional probability that a country is specialised in industry i, i.e. $RCA_{c,i,t} \geqslant 1$, given that it is specialised in industry j. In order to take the non-linearity in the adjacency matrix into account, the minimum of these pairwise conditional probabilities is applied, i.e.

$$\phi_{ij,t} = min\{P(RCA_{c,i,t} \geqslant 1 | RCA_{c,j,t} \geqslant 1), P(RCA_{c,j,t} \geqslant 1 | RCA_{c,i,t} \geqslant 1)\} \tag{2}$$

Fig. 1 depicts the Industry Space for 2007, relating industries to each other based on their similarity in required capabilities, or empirically, based on the co-occurence of value-added export specialisations (see Table A.3 for a comprehensive list of industry abbreviations).[6]

As Fig. 1 shows, a dense cluster of industries forms in the middle of the Industry Space around a number of various service industries. Manufacturing industries, denoted by the letter C in front, are located on the left part of the Industry Space.[7] For example, the manufacturing industries for fabricated metal products (C25), electrical equipment (C27), special purpose machinery (C28), and motor vehicles (C29) are strongly connected. This implies that the capabilities required to excel in producing these manufacturing products are similar. Other industries such as mining and quarrying (B) or fishing (A03) are less well embedded in the Industry Space.

The nodes' size in Fig. 1 is proportional to the eigenvector centrality of the respective industry within the overall network of industries. Eigenvector centrality measures the importance of a specific node in the network by not only taking the weights of its own links into account but also the link weights of its neighbors. For a formal assessment, let M be an adjacency matrix of dimension $S \times S$ consisting of the link weights ϕ_{ij} (Eq. 2), where S denotes the number of industries. Then, we can write the average centrality of industry i, weighted with the connections to its neighbours and normalized by some constant λ, as

$$x_i = \frac{1}{\lambda} \sum_{j=1}^{S} M_{ij} x_j = \frac{1}{\lambda} \sum_{j=1}^{S} \phi_{ij} x_j \tag{3}$$

This can be rewritten in matrix notation as

$$\lambda \mathbf{x} = \mathbf{M}\mathbf{x}, \tag{4}$$

which shows the equivalence of determining the average centrality of industry i as described in Eq. (3) to finding eigenvalue λ corresponding to eigenvector $\mathbf{x}$. In accordance to the Perron-Frobenius theorem, the eigenvector corresponding to the largest eigenvalue is non-negative and referred to as eigenvector centrality (Newman, 2003). Hence, we refer to x_i as the eigenvector centrality of industry i.

[6] The network visualization is created in Gephi using the algorithm ForceAtlas 2 (Jacomy et al., 2014). Only links with $\phi_{ij} > 0.3$ are shown.

[7] We stress that whether industries are located on the left, right, top or bottom part of the Industry Space is arbitrary. However, the relation to other industries, i.e. the formation of clusters, is not arbitrary.

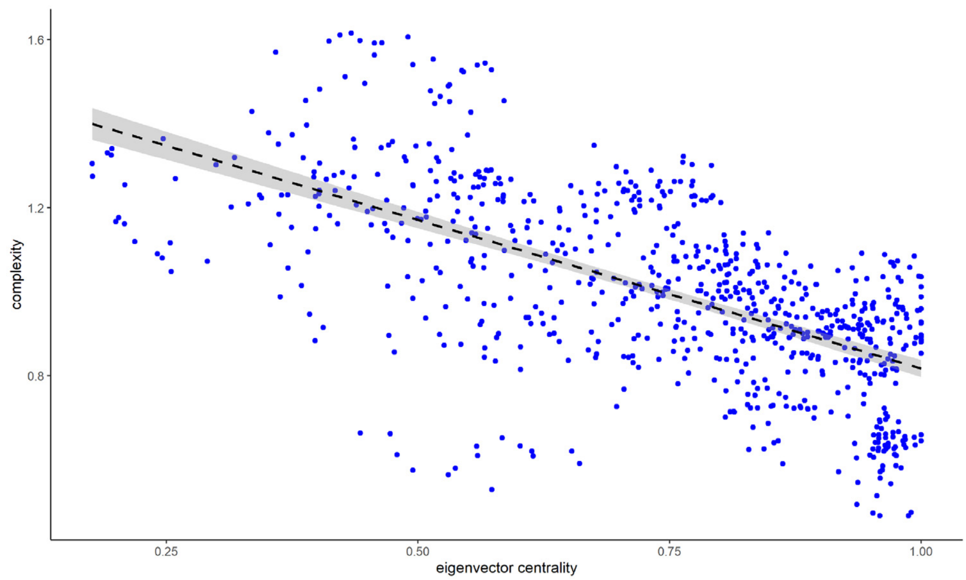


Fig. 2. Pooled scatter plot between an industry's eigenvector centrality and complexity.

Based on the eigenvector centralities of the Industry Space, the service industry advertising and market research (M73) is the most central industry in 2014, followed by other industries in the core of the Industry Space, while the nodes in the periphery are less central.

The interpretation of a node's eigenvector centrality is not straightforward. A high centrality stems from a frequent co-occurrence of value-added export specialisations in the respective industry with other industries. This, in turn, indicates that the capabilities required to excel in this industry are required in many other industries, too, and cannot be described as unique. Hence, it follows that, most probably, many countries have these capabilities at their disposal, making the industry less ubiquitous and, thus, less complex. This line of thought is supported empirically: Plotting the nodes' eigenvector centralities and their respective complexities, as retrieved by (Koch, 2021), reveals a significantly negative relationship. Fig. 2 depicts the relationship between an industry's eigenvector centrality and it's complexity level, pooled for the whole sample, i.e. 2000 to 2014. A ranking of industries with respect to complexity is provided in Table A.2 in Appendix A.

2.1. Value-added vs. gross exports in the Industry Space

In this section, we shed further light on the need for value-added exports in the analysis of economic development on top of networks such as the Industry or the Product Space. As outlined in the introduction, the deepening of global value chains leads to potentially different conclusions in export specialisations, depending on whether gross or value-added export data are used. Value-added exports do not only take into account that imported intermediates, and thus foreign value-added, are incorporated in gross exports, but the concept of value-added exports also allows for disentangling national value chains. Specifically, the value-added that services contribute to manufacturing exports are embodied in gross exports of the respective manufacturing industry. Value-added exports enable to trace back the value-added and attribute it to the respective service industry.

To further emphasize the differences between value-added exports and gross exports, we calculate the similarities between industries $\phi_{ij,t}$ (see Eq. 2), which are the basis of the Industry Space, using gross exports in the calculation of *RCA* (see Eq. 1). This is equivalent to the similarities in the Product Space, despite a higher level of aggregation and the inclusion of services. We then compare $\phi_{ij,t}$ based on gross exports to $\phi_{ij,t}$ based on value-added exports.

To reveal differences, we regress $\phi_{ij,t}$ for both export concepts on two types of dummies, aiming to capture variation in link weights between and within industry categories. For example, a link between A (=agriculture) and B (=mining) is assigned a 1 for the dummy A, a 1 for dummy B and zero otherwise. Additionally, if a link connects two subcategories within a broader industry, e.g. fishing and forestry within A, we assign a 1 to dummy $within_A$ in addition to dummy A and zero otherwise. That is, if both types of dummy variables are included in the regression, A captures the average link weight *between* any subsector of A and other industries outside A, while dummy $within_A$ captures the average link weight *within* all subsectors of A. That is, within-coefficients refer to connections from one 2-digit industry to another within the same 1-digit industry category. We do this for the broad industry categories A (agriculture), $C-F$ (manufacturing industries, energy supply and construction) and $G-R$ (service industries). Moreover, we control for time fixed-effects. Eventually, we can compare the magnitude of the conditional probabilities between the Industry Space based on value-added and gross exports. Results are displayed in Table 1.

Note that the constant in the regression represents the coefficient for industry, energy supply and construction ($C-F$), for which the highest conditional probabilities can be observed. These serve as a benchmark. In the first two columns of Table 1 we find that on average the conditional probabilities related to agriculture (A) tend to be lower than for our benchmark ($C-F$). This is true for both cases, value-added and gross exports. The same observation can be made for B, where the difference is even more pronounced.

For our benchmark sector ($C-F$) we find higher conditional probabilities in the second column of the table, which describes value-added exports. Furthermore, linkages between service industries and the rest of the economy are significantly stronger in case of the value-added exports compared to gross exports.[8] This indi-

[8] To see this clearly, we subtract the coefficient for $G-R$ from the benchmark coefficient. This gives $0.305-0.013=0.292$ for gross exports and $0.376-0.047=0.329$ for value-added exports. The difference is clearly significant if taking the standard errors into account.

Table 1
Linkages between broad industry categories by gross exports and value added exports.

	Dependent variable: ϕ_{ij}			
	gross exports (1)	value-added exports (2)	gross exports (3)	value-added exports (4)
A, agriculture	−0.069***	−0.080***	−0.027***	−0.069***
	(0.003)	(0.004)	(0.005)	(0.005)
$within_A$			0.053**	0.030
			(0.023)	(0.023)
B, mining and quarrying	−0.217***	−0.260***	−0.175***	−0.249***
	(0.006)	(0.006)	(0.006)	(0.006)
$C-F$, manufacturing *(constant)*	0.380***	0.393***	0.305***	0.376***
	(0.005)	(0.005)	(0.007)	(0.007)
$within_{C-F}$			0.088***	0.018***
			(0.006)	(0.006)
$G-R$, services	−0.079***	−0.057***	−0.013**	−0.047***
	(0.002)	(0.003)	(0.006)	(0.006)
$within_{G-R}$			0.019***	0.018***
			(0.003)	(0.003)
Time fixed effects	yes	yes	yes	yes
Observations	19,125	19,125	19,125	19,125
R^2	0.115	0.125	0.125	0.127
Adjusted R^2	0.115	0.125	0.124	0.127

Note: All regressions account for unobserved heterogeneity over time (time fixed effects). In the interpretation of the displayed results, it is important to note that the industry category $C-F$ (all manufacturing industries, energy supply and construction) reflects the intercept coefficient. The coefficients of all other regressors must be interpreted as deviations from the intercept. A denotes agriculture, B denotes mining and quarrying, $G-R$ summarizes service industries. $within_A$, $within_{C-F}$ and $within_{G-R}$ capture links observable only within the respective industry categories, that is from one 2-digit industry to another within the same 1-digit industry category. A complete list of industry codes is provided in Table A.3. Sample: 2000–2014. $^*p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

cates that the Industry Space based on value-added exports takes the indirect role of services industries more appropriately into account.

Columns (3) and (4) differentiate between links *within* ($within_A$, $within_{C-F}$ and $within_{G-F}$) and *between* (A, B, $C-F$, $G-R$) broad industry categories. Still, links based on value-added export specialisations tend to be higher than based on gross export specialisations. This holds for all broad industry categories except B. Furthermore, we find that conditional probabilities *within* industries are on average higher than *between* industries. This finding supports the underlying theoretical model, which states that ϕ_{ij} reflects the similarity in required capabilities, since it can be reasonably assumed that capabilities within a broad industry category are more similar than between industry categories. This result is also confirmed for more narrowly defined industry categories (see Table A.4 in Appendix A).

The results presented in this section show that the distinction between gross and value-added exports in calculating the similarity of required capabilities in industries is indeed highly relevant, as $\phi_{ij,t}$ significantly differs in the two cases. The interpretation of these results is twofold. First, it shows that for industries whose products are depicted in the Product Space, i.e. industries A, B, and $C-F$, the links to other industries significantly differ using value-added exports instead of gross exports. Second, the distinction between gross and value-added exports is particularly important for service industries. In total, the results emphasize the relevance of value-added exports not only to accurately depict the relationship of manufacturing industries or their products to each other, but also to take the important role of (domestic) services in trade into account.

2.2. Evolution of the Industry Space over time

For the Product Space, (Hidalgo, 2009) finds that its structure remains fairly constant over time. This section investigates the developments of the Industry Space over time, specifically between 2000 and 2014, to see whether the same implication holds for the Industry Space.

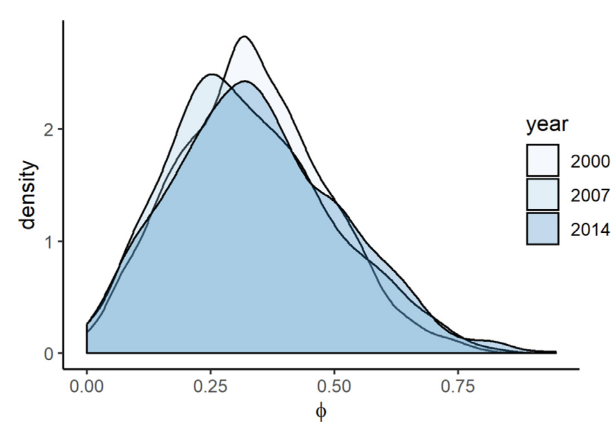


Fig. 3. Density of ϕ_{ij} for 2000, 2007, and 2014.

As depicted in Fig. 3, plotting the density distributions of ϕ_{ij} for 2000, 2007, and 2014, the overall structure of link weights of the Industry Space did not change strongly over time. That is, there is no pronounced shift towards higher or lower average link weights. However, It can be seen that there is some variation between the years, as the distribution is for example flatter in 2007 and 2014 than in 2000, which also yields significant two-sample Kolmogorov-Smirnov-tests between each of the years.

Furthermore, the significance of specific industries may have changed. A visual inspection of the Industry Spaces for 2000 and 2014 (see Fig. A.2 in Appendix A) reveals some developments. For example, fishery (A03) has been more strongly connected to other industries in 2000 compared to 2014. Changes are also observ-

Table 2
Relevance of broad industry categories in the Industry Space over time.

	Dependent variable: ϕ_{ij}			
	2000–2007 (1)	2008–2014 (2)	2000–2009 (3)	2010–2014 (4)
A, agriculture	-0.061^{***}	-0.102^{***}	-0.068^{***}	-0.104^{***}
	(0.005)	(0.005)	(0.004)	(0.006)
B, mining & quarrying	-0.245^{***}	-0.276^{***}	-0.252^{***}	-0.276^{***}
	(0.008)	(0.009)	(0.007)	(0.010)
$C-F$, manufacturing (*constant*)	0.394^{***}	0.413^{***}	0.393^{***}	0.402^{***}
	(0.005)	(0.005)	(0.005)	(0.006)
$G-R$, services	-0.062^{***}	-0.050^{***}	-0.060^{***}	-0.051^{***}
	(0.003)	(0.004)	(0.003)	(0.005)
Time fixed effects	yes	yes	yes	yes
Observations	10,200	8925	12,750	6375
R^2	0.117	0.134	0.121	0.134
Adjusted R^2	0.116	0.133	0.120	0.133

Note: All regressions account for unobserved heterogeneity over time (time fixed effects). In the interpretation of the displayed results, it is important to note that the industry category $C-F$ (manufacturing, energy supply and construction) reflects the intercept coefficient. The coefficients of all other regressors must be interpreted as deviations from the intercept. *A* denotes agricultural industries, *B* mining and quarrying. $G-R$ summarizes service industries. A complete list of industry codes is provided in Table A.3. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

able in the nodes' size, expressed in terms of the eigenvector centrality of the respective industry. Two examples are financial services (K64) and administrative and support services (N), which are both more central in 2014 compared to 2000, and, thus, also are illustrated by larger nodes. However, changes in centrality measures simply stem from changes in the link weights ϕ_{ij} (see Eq. 3). To further investigate the evolution of link weights in the Industry Space depending on the broad industry category, we regress the link weights on dummy variables indicating whether a specific broad industry category is part of a link, as discussed in the previous section. We also account for unobserved heterogeneity over time using time fixed-effects. The regression coefficients, thus, indicate the relative interconnectedness of industry categories. This approach is analogous to the one employed in the previous section. Table 2 displays the regression results for four subsamples with respect to the included time period, using the middle of our sample, i.e. 2007, and the financial crisis, i.e. 2009, as cut-off points.

It can be seen that service industries ($G-R$) have become more strongly interconnected in the Industry Space over time, which reflects the increase in trade in services. This observation holds both for 2007 and 2009 as cut-off point. Also, manufacturing industries ($C-F$) became more relevant over time, while the interconnections of mining and quarrying (*B*) and agricultural industries (*A*) decreased. Interpreting these results with the theoretical model of the similarity in required capabilities in mind gives rise to the conclusion that the capabilities required to excel in service and manufacturing industries have become more similar to other industries over time.

A closer look at more specific industry categories reveals different patterns across service industries. Specifically, administrative and support service activities (*N*) have become more integrated in the Industry Space. This category includes a wide range of services, ranging from call centers or other business support activities to packaging services, employment activities, and travel agencies. Also, the services transportation and storage (*H*), real estate activities (*L*) as well as professional, scientific and technical activities (*M*) have become more relevant over the years (see Table A.5 in Appendix A). In contrast, the link weights from and to agriculture industries (*A*) decrease.[9]

3. Case studies

The Industry Space can be used to visualize the structure of economies. To enable an easy interpretation of the visualisations we fix the Industry Space in 2007 (as depicted in Fig. 1), i.e. the middle of our sample, and depict the structure of economies and their process over time on top of it.[10] For visualizing economies, we rely on the *RCA* indicator (see Eq. 1). Specifically, the saturation of each node in the following illustrations is proportional to the respective *RCA*.[11]

The Industry Space can be applied to visualize cross-country structural differences as well as to depict processes of structural change within an economy. In the following, we compare the Industry Spaces for China and the United States of America, as well as for Japan and India.

China vs. USA. Fig. 4 depicts the Industry Space for China[12] and the United States in 2000 and 2014. Comparing the Industry Spaces for 2014 (Fig. 4b and d), structural differences between the two economies become apparent. China is focussed on the bottom of the Industry Space, with the largest specialisation in terms of value-added exports in the manufacturing of textiles (C13-C15). Furthermore, China is specialised in other manufacturing industries such as wood product manufacturing (C16), manufacturing of non-metallic mineral products (C23), and manufacturing of computer, electronic and optical products (C26) as well as electrical equipment (C27). The United States, however, show pronounced specialisations in the top area of the Industry Space, in particular in publishing activities and multimedia production activities (J58, J59_J60). Further relevant specialisations of the United States are manufacture of transport equipment (C30), and scientific R&D (M72), advertising and market research (M73) as well as activities auxiliary to financial services (K66).

9 Additionally, Table A.6 in Appendix A reveals the ten most pronounced changes in the link strength between two specific industries. This supports the findings described above as administrative and support service activities (*N*) are involved in the largest increases, while the opposite holds for agriculture industries (*A*).

10 The year we fix is arbitrary, but the middle of the sample is a reasonable approach and also pursued in the literature on the Product Space. Moreover, as shown in the previous chapter, the Industry Space does not change massively.

11 To simplify the comparability of the visualisation between different countries and for being able to visually compare diversification of economies, we express the *RCA* in relation to the maximal *RCA* in the respective country and year.

12 Note that in the WIOD China is defined as the Republic of China including the special administrative regions Hong Kong and Macau.

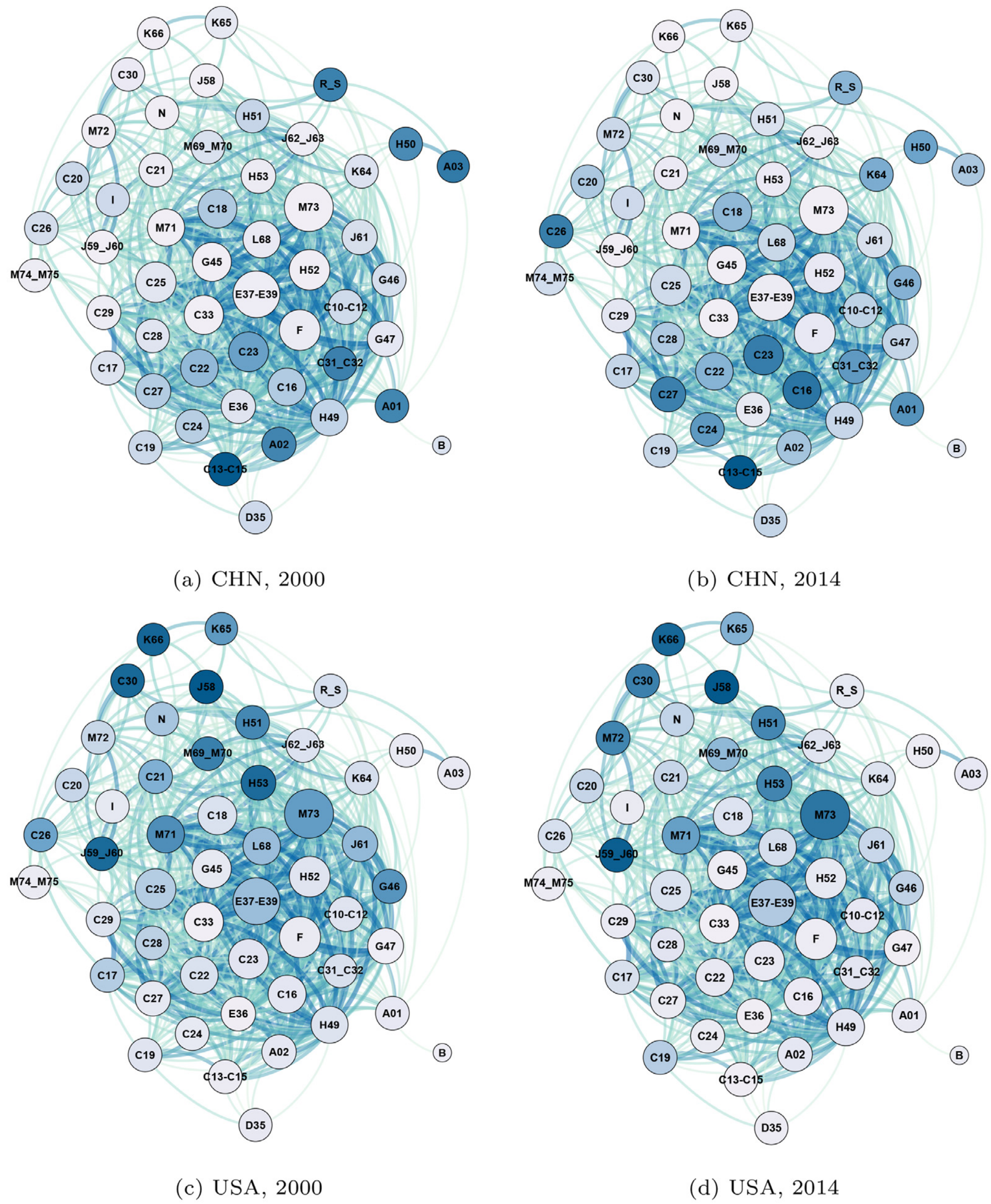


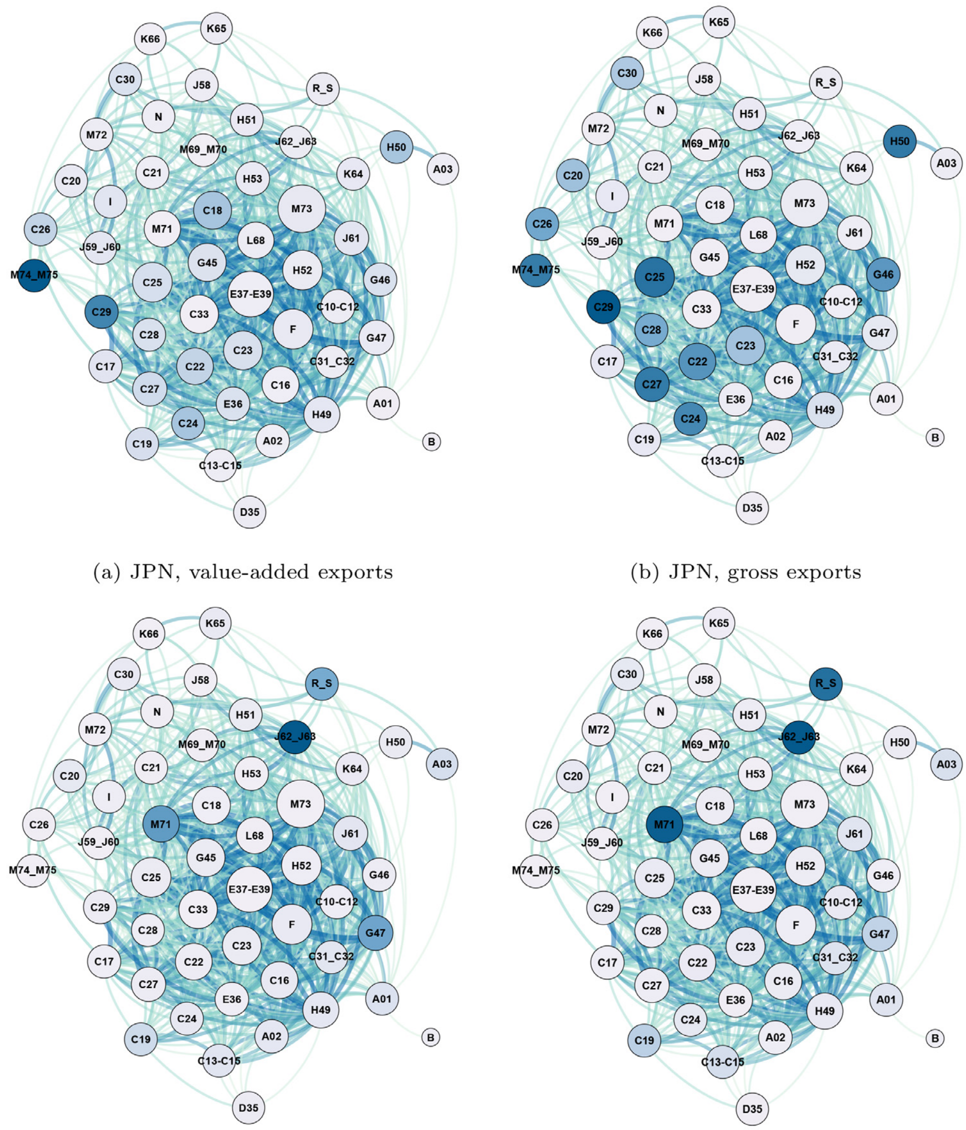
Fig. 4. Industry Spaces for China and the USA, 2000 and 2014.

Moreover, the visualisation allows for an interpretation of development over time. For China, it can be seen that there has been a transition from specialisations at the right end of the Industry Space (industries R_S, A03) in 2000 to more pronounced specialisations in manufacturing industries in 2014 on the middle and left part of the Industry Space. Also, China could slightly increase its value-added export specialisation in scientific R&D (M72). Meanwhile, the United States progressed to specialise more deeply in services and less in manufacturing. That is, specialisations in scientific R&D (M72) and advertising (M73) have increased from 2000 to 2014, while specialisations in manufacturing industries, e.g. manufacturing of computer or electronic products (C26), paper and paper products (C17) or fabricated metal products (C25), decreased. This structural change is also mirrored in a less pronounced specialisation in wholesale trade (G46), which is a service adjacent to manufacturing industries.

The comparison between the Industry Space of China and the USA is insightful for two reasons. First, the visualisation indicates that China is oriented towards manufacturing industries, while the United States are mainly focussed on service industries. This is a finding, which cannot be concluded from the Product Space, as it does not include services. Second, comparisons over time reveal structural processes in the two economies. Specifically, the manufacturing industries, which the USA have forfeited specialisations in, are those in which China excelled between 2000 and 2014. This finding is in line with the literature on the decline in manufacturing in the United States (e.g. Autor et al., 2013; Pierce and Schott, 2016; Timmer and Pahl, 2021).

Further Industry Spaces for a selection of countries (Germany, United Kingdom, Indonesia, India, Japan, and South Korea) and short descriptions are provided in Appendix B.

Japan and India. Illustrations of the Industry Space can also be applied to convey the importance of value-added exports in the



(a) JPN, value-added exports

(b) JPN, gross exports

(c) IND, value-added exports

(d) IND, gross exports

Fig. 5. Industry Spaces for Japan and India in 2014, value-added and gross exports.

discussion of economic development. Specifically, we will go into detail for two countries, i.e. Japan and India.

The case of Japan is in particular interesting, because it stresses the need for value-added exports once more. The upper panel of Fig. 5 compares the specialisation patterns of Japan in 2014 with gross and value-added exports. It can be seen that the use of gross exports would lead to considerably different conclusions than value-added exports convey. Specifically, based on gross exports, one may be tempted to state that Japan's economic strengths are in particular in manufacturing industries such as manufacturing of motor vehicles (C29), electrical equipment (C27), or fabricated metal products (C25). However, investigating value-added exports yields that Japan is in particular specialised in professional services (M74_M75). The difference in gross and value-added export specialisations reflects the fact that the products of professional services are used in national value chains as intermediates to produce manufacturing goods, e.g. cars. While gross exports attribute all export revenues in manufacturing goods to the respective manufacturing industry, value-added exports enable tracing the domestic value-added contributions of goods or services, which are processed as intermediates in national value chains.

The lower panel of Fig. 5 compares India's specialisation patterns in 2014 with respect to gross and value-added exports. In terms of value-added exports, information service activities (J62_J63) account for the largest *RCA* in India. However, if gross exports had been applied, the Revealed Comparative Advantage in architectural and engineering activities (M71) would be almost as high in 2014.[13] This indicates that India is active in architectural and engineering activities, but in terms of value-added information service activities are more central.

4. Conclusion

In this article, we introduce the Industry Space based on value-added exports, which can be retrieved from Inter-Country Input-Output Tables, as a complementary visualisation of economic de-

[13] Specifically, the ratio of the *RCA* in industries J62_J63 and M71 is 0.54 if using value-added exports, but 0.93 if using gross exports.

velopment and structural cross-country differences to the established Product Space based on gross exports.

The motivation for the Industry Space stems from the increasing importance of global value chain trade since the beginning of the century. Frequent trade of intermediate products results in gross exports being potentially misleading if evaluating a country's strengths and weaknesses on this basis. Specifically, this is the case for two reasons. First, gross exports incorporate the value of imported intermediate products. As border crossings are frequent in global value chain trade, the value-added that each individual country contributes may be small, eventually. This also entails the issue of double-counted exports. Second, the role of services in trade is not accurately reflected in gross export statistics. The production of goods does not only depend on foreign intermediate products but also on domestic intermediate inputs, e.g. wholesale trade or transport services. The direct trade in services, as reflected in service gross exports, is only a small share of the services traded as embodied in goods. Both aspects have the consequence that export specialisations in terms of gross exports might be misleading.

Hence, we propose the Industry Space, which links 51 industries to each other based on the similarity in required capabilities. These are approximated by the probability of co-occurence of value-added export specialisations, where value-added exports are defined as the value-added a specific industry contributes to goods and services that are eventually consumed abroad. Indeed, we show that the similarities between industries based on value-added exports significantly differ from the ones based on gross exports, which supports the need for value-added exports in this context. We also show that the overall structure of the Industry Space remains fairly stable between 2000 and 2014, although some service industries became more and agricultural industries became less integrated.

In analogy to the Product Space, the Industry Space can be used to depict an economy's structure on top of it, measured in terms of value-added export specialisations. In case studies, we show that the Industry Space is indeed a useful tool to investigate the economic structure between countries and over time. Specifically, we discuss the locations of USA and China on top of the Industry Space and their development between 2000 and 2014. The illustrations support the economic literature on the decline in manufacturing in the USA, while China gains ground. Furthermore, illustrations of the economic structures of Japan and India, both in terms of gross and value-added export specialisations, emphasizes the need for value-added exports in viewing economic development once more, as the conclusions based on the two approaches differ considerably.

Nonetheless, the Industry Space has its advantages and disadvantages compared to the established Product Space. On the one hand, the Industry Space provides a more holistic picture of an economy's structure, since services are included, while the Product Space focusses on goods. Also, applying value-added exports instead of gross exports allows for taking foreign value-added in imported intermediate products as well as domestic value-added in other industries into account. On the other hand, however, we see two drawbacks to this approach. First, data availability in terms of value-added exports is still limited, since Inter-Country Input-Output Tables are required. Hence, the Industry Space presented in this article is based on data of 43 lower-middle- to high-income countries and 51 industries, although it would enlightening to have a larger sample, especially with respect to developing countries. Second, policy recommendations based on the Industry Space are more abstract, as industries represent a more aggregate level of economic activities compared to products. While the level of aggregation with respect to products may be too narrow, the level of aggregation with respect to industries may be too broad, especially if focusing on particular value chains of interest to policy makers. These might be promising avenues for future research, as soon as more detailed data sources become available.

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CRediT authorship contribution statement

Philipp Koch: Conceptualization, Methodology, Formal analysis, Visualization, Writing – original draft, Writing – review & editing. **Wolfgang Schwarzbauer:** Methodology, Formal analysis, Writing – original draft, Writing – review & editing.

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Appendix A

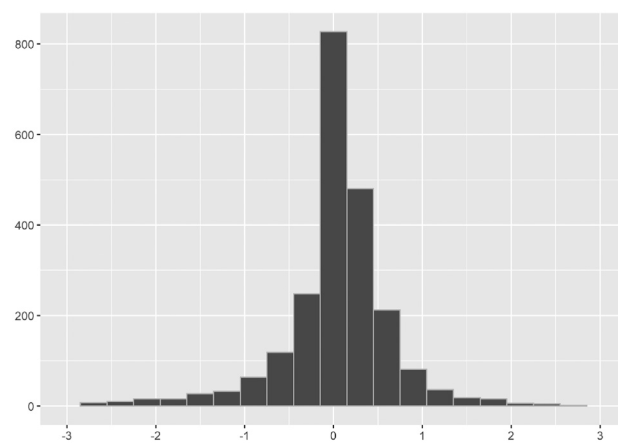


Fig. A.1. Distribution of differences between the Revealed Comparative Advantage in value-added and gross exports.

Table A.1
Top 15 most complex countries using value-added and gross exports, 2014.

Rank	value-added exports	gross exports (ECI)	gross exports (EF)
1	USA	JPN	CHN
2	CHN	CHE	DEU
3	DEU	DEU	JPN
4	GBR	TWN	ITA
5	JPN	KOR	USA
6	FRA	SWE	FRA
7	KOR	CZE	ESP
8	ITA	USA	IND
9	CAN	AUT	BEL
10	NLD	FIN	GBR
11	ESP	SGP	NDL
12	IND	GBR	AUT
13	RUS	SVN	KOR
14	CHE	HUN	CZE
15	BEL	FRA	CHE

Note: The complexity ranking with respect to value-added exports refers to the results of (Koch, 2021). The ranking of countries in terms of economic complexity using gross exports (ECI, 6-digit data, Hidalgo and Hausmann, 2009) is acquired from the Observatory of Economic Complexity (oec.world). The economic fitness (EF) ranking using gross exports following the methodology by (Tacchella et al., 2012) is taken from the World Bank Data Catalog.

Table A.2
Top 15 most complex industries using value-added exports, 2014.

Rank	Industry (ISIC Rev. 4)	
1	C30	Transport equipment excl. motor vehicles
2	C26	Computer, electronic and optical products
3	B	Mining and quarrying
4	M72	Scientific R&D
5	I	Accommodation and food service
6	A03	Fishing and aquaculture
7	C20	Chemicals
8	M74_M75	Professional, scientific and technical activities n.e.c.
9	J59_J60	Media production and broadcasting
10	C28	Machinery and equipment n.e.c.
11	K65	Insurance, reinsurance and pension funding
12	C13-C15	Textiles, wearing apparel and leather
13	C24	Basic metals
14	J58	Publishing activities
15	H51	Air transport

Note: The ranking of industries in terms of economic complexity using value-added exports is based on the methodology outlined by (Koch, 2021). For a complexity ranking of 4- or 6-digit products in terms of gross exports according to (Hidalgo and Hausmann, 2009), see the Observatory of Economic Complexity (oec.world).

Table A.3
Industries according to ISIC Rev. 4.

Code	Description
A01	Crop and animal production, hunting and related service activities
A02	Forestry and logging
A03	Fishing and aquaculture
B	Mining and quarrying
C10-C12	Manufacture of food products, beverages and tobacco products
C13-C15	Manufacture of textiles, wearing apparel and leather products
C16	Manufacture of wood and of products of wood and cork, except furniture
C17	Manufacture of paper and paper products
C18	Printing and reproduction of recorded media
C19	Manufacture of coke and refined petroleum products
C20	Manufacture of chemicals and chemical products
C21	Manufacture of basic pharmaceutical products and preparations
C22	Manufacture of rubber and plastic products
C23	Manufacture of other non-metallic mineral products
C24	Manufacture of basic metals
C25	Manufacture of fabricated metal products, except machinery and equipment
C26	Manufacture of computer, electronic and optical products
C27	Manufacture of electrical equipment
C28	Manufacture of machinery and equipment n.e.c.
C29	Manufacture of motor vehicles, trailers and semi-trailers
C30	Manufacture of other transport equipment
C31_C32	Manufacture of furniture; other manufacturing
C33	Repair and installation of machinery and equipment
D35	Electricity, gas, steam and air conditioning supply
E36	Water collection, treatment and supply
E37-E39	Sewerage; waste collection, treatment and disposal activities
F	Construction
G45	Wholesale and retail trade & repair of motor vehicles and motorcycles
G46	Wholesale trade, except of motor vehicles and motorcycles
G47	Retail trade, except of motor vehicles and motorcycles
H49	Land transport and transport via pipelines
H50	Water transport
H51	Air transport
H52	Warehousing and support activities for transportation
H53	Postal and courier activities
I	Accommodation and food service activities
J58	Publishing activities
J59_J60	Motion picture, video, music and television programme production
J61	Telecommunications
J62_J63	Information service activities, e.g. computer programming
K64	Financial service activities, except insurance and pension funding
K65	Insurance, reinsurance and pension funding, except compulsory social security
K66	Activities auxiliary to financial services and insurance activities
L68	Real estate activities
M69_M70	Legal and accounting activities; activities of head offices; management consultancy
M71	Architectural and engineering activities; technical testing and analysis
M72	Scientific research and development
M73	Advertising and market research
M74_M75	Other professional, scientific and technical activities; veterinary activities
N	Administrative and support service activities
R_S	Other service activities

Table A.4
Linkages between industry categories by gross exports and value added exports.

	Dependent variable: ϕ_{ij}			
	gross exports	value added exports	gross exports	value added exports
A, agriculture	−0.059***	−0.074***	−0.026***	−0.051***
	(0.003)	(0.003)	(0.004)	(0.004)
B, mining and quarrying	−0.207***	−0.253***	−0.173***	−0.230***
	(0.005)	(0.005)	(0.006)	(0.006)
C, manufacturing *(constant)*	0.343***	0.368***	0.288***	0.329***
	(0.004)	(0.004)	(0.005)	(0.005)
D, energy	0.043***	−0.066***	0.077***	−0.043***
	(0.005)	(0.005)	(0.006)	(0.006)
E, sewerage	0.049***	0.048***	0.081***	0.072***
	(0.004)	(0.004)	(0.004)	(0.004)
F, construction	0.062***	0.074***	0.096***	0.098***
	(0.005)	(0.005)	(0.006)	(0.006)
G, trade	−0.003	0.025***	0.031***	0.048***
	(0.003)	(0.003)	(0.004)	(0.004)
H, transport	0.011***	0.005*	0.045***	0.029***
	(0.003)	(0.003)	(0.003)	(0.003)
I, accommodation and food	−0.106***	−0.088***	−0.072***	−0.065***
	(0.005)	(0.005)	(0.006)	(0.006)
J, information & communication	−0.047***	−0.010***	−0.012***	0.014***
	(0.003)	(0.003)	(0.003)	(0.003)
K, financial services	−0.144***	−0.122***	−0.116***	−0.102***
	(0.003)	(0.003)	(0.004)	(0.004)
L, real estate	0.012**	0.066***	0.045***	0.090***
	(0.005)	(0.005)	(0.006)	(0.006)
M, professional / scientific services	0.009***	−0.011***	0.045***	0.014***
	(0.003)	(0.003)	(0.003)	(0.003)
N, administrative / support services	−0.068***	−0.074***	−0.034***	−0.050***
	(0.005)	(0.005)	(0.006)	(0.006)
R, arts and entertainment	−0.067***	−0.087***	−0.034***	−0.064***
	(0.005)	(0.005)	(0.006)	(0.006)
$within_A$			0.068***	0.059***
			(0.021)	(0.022)
$within_C$			0.089***	0.062***
			(0.004)	(0.004)
$within_E$			0.184***	0.018
			(0.036)	(0.037)
$within_G$			0.036*	0.060***
			(0.021)	(0.022)
$within_H$			0.025**	0.019
			(0.012)	(0.012)
$within_J$			0.029*	0.042***
			(0.015)	(0.015)
$within_K$			0.309***	0.173***
			(0.021)	(0.022)
Time fixed effects	yes	yes	yes	yes
Observations	19,125	19,125	19,125	19,125
R^2	0.204	0.216	0.230	0.226
Adjusted R^2	0.204	0.215	0.229	0.226

Note: All regressions account for unobserved heterogeneity over time (time fixed effects). In the interpretation of the displayed results, it is important to note that the industry category *C* (manufacturing) reflects the intercept coefficient. The coefficients of all other regressors must be interpreted as deviations from the intercept. The *within* coefficients capture links observable only within the respective industry categories, that is from one 2-digit industry to another within the same 1-digit industry category. A complete list of industry codes is provided in Table A.3. Sample: 2000–2014. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

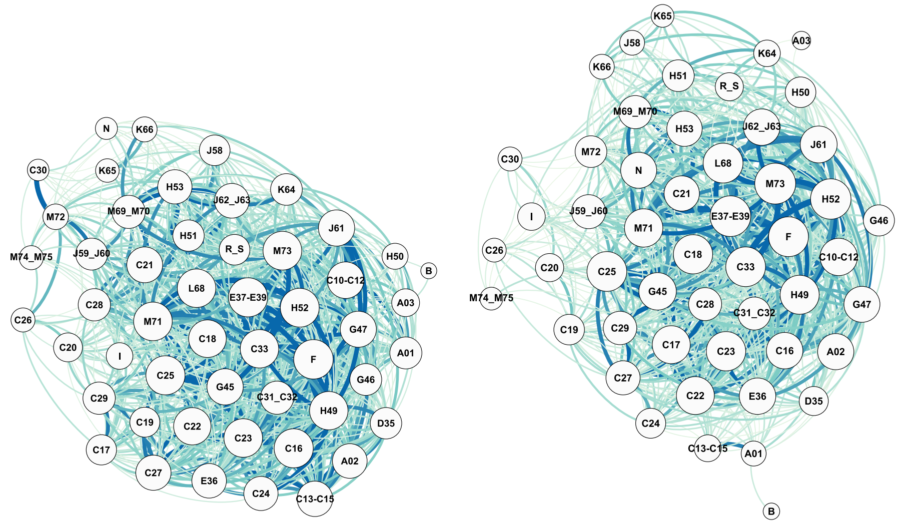
Table A.5
Link strength in dependence of broad industry categories.

	Dependent variable: ϕ_{ij}			
	2000–2007 (1)	2008–2014 (2)	2000–2009 (3)	2010–2014 (4)
A, agriculture	−0.057***	−0.093***	−0.064***	−0.094***
	(0.004)	(0.005)	(0.004)	(0.006)
B, mining and quarrying	−0.242***	−0.267***	−0.247***	−0.266***
	(0.007)	(0.008)	(0.006)	(0.010)
C, manufacturing *(constant)*	0.373***	0.383***	0.371***	0.371***
	(0.005)	(0.005)	(0.005)	(0.005)
D, energy	−0.078***	−0.053***	−0.071***	−0.058***
	(0.007)	(0.008)	(0.006)	(0.010)
E, sewerage	0.037***	0.062***	0.041***	0.063***
	(0.005)	(0.006)	(0.005)	(0.007)
F, construction	0.068***	0.080***	0.071***	0.080***
	(0.007)	(0.008)	(0.006)	(0.010)
G, trade	0.028***	0.021***	0.029***	0.016***
	(0.004)	(0.005)	(0.004)	(0.006)
H, transport	−0.001	0.012***	0.0001	0.014***
	(0.004)	(0.004)	(0.003)	(0.005)
I, accommodation and food	−0.088***	−0.089***	−0.086***	−0.094***
	(0.007)	(0.008)	(0.006)	(0.010)
J, information & communication	−0.008**	−0.011**	−0.006*	−0.016***
	(0.004)	(0.005)	(0.004)	(0.005)
K, financial services	−0.122***	−0.123***	−0.120***	−0.126***
	(0.004)	(0.005)	(0.004)	(0.006)
L, real estate	0.053***	0.081***	0.058***	0.083***
	(0.007)	(0.008)	(0.006)	(0.010)
M, professional / scientific services	−0.023***	0.004	−0.020***	0.007
	(0.004)	(0.004)	(0.003)	(0.005)
N, administrative / support services	−0.140***	0.001	−0.122***	0.023**
	(0.007)	(0.008)	(0.006)	(0.010)
R, arts and entertainment	−0.091***	−0.084***	−0.088***	−0.086***
	(0.007)	(0.008)	(0.006)	(0.010)
Time fixed effects	yes	yes	yes	yes
Observations	10,200	8925	12,750	6375
R^2	0.227	0.229	0.224	0.235
Adjusted R^2	0.225	0.227	0.223	0.233

Note: All regressions account for unobserved heterogeneity over time (time fixed effects). In the interpretation of the displayed results, it is important to note that the industry category C (manufacturing) reflects the intercept coefficient. The coefficients of all other regressors must be interpreted as deviations from the intercept. A complete list of industry codes is provided in Table A.3. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

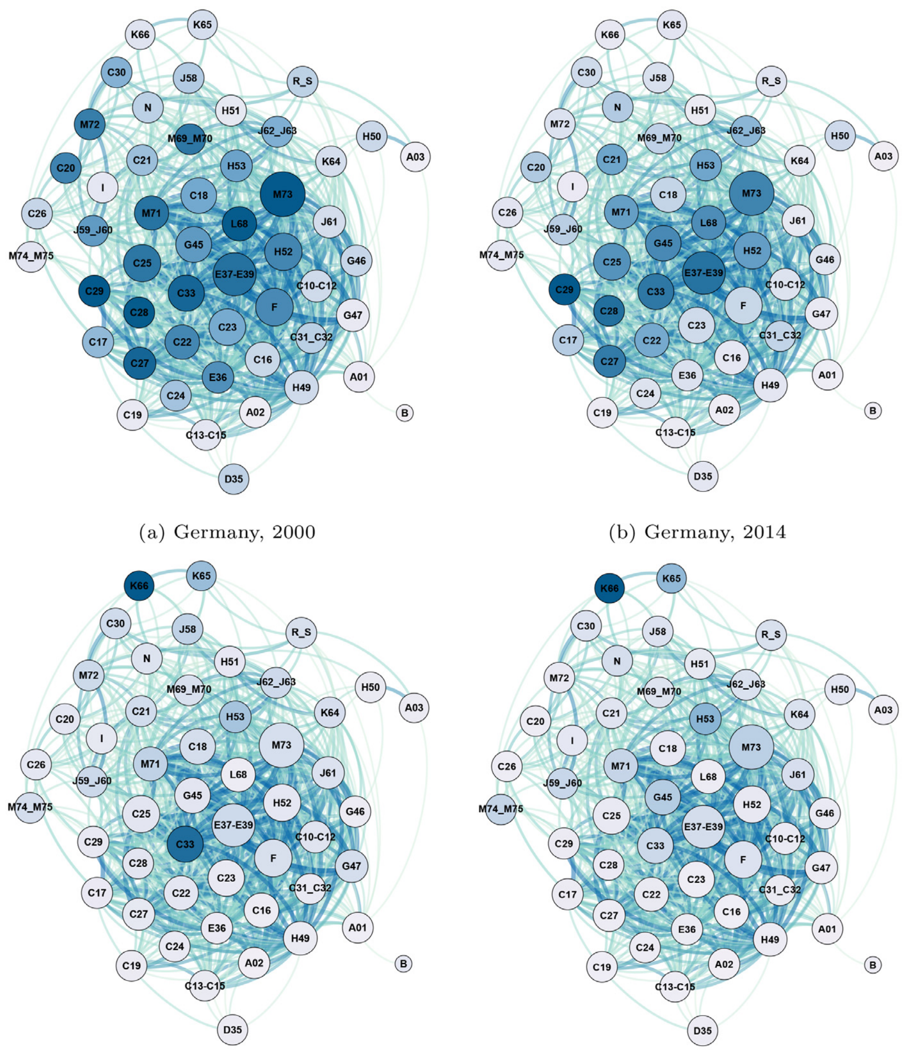
Table A.6
Most pronounced change of link weights between industries over time.

2000–2007		2007–2014		2000–2014	
C30 - R_S	0.29	H50 - H53	0.35	C17 - N	0.5
C18 - J61	0.27	M71 - N	0.33	M71 - N	0.46
G45 - J61	0.25	K66 - R_S	0.33	L68 - N	0.40
C17 - N	0.24	M69_M70 - N	0.32	H50 - H53	0.38
C16 - G45	0.24	K64 - K66	0.32	C17 - C22	0.36
...		...		...	
C28 - K66	−0.30	C29 - K64	−0.38	C30 - M72	−0.4
A03 - C10-C12	−0.30	C30 - M72	−0.28	J59_J60 - R_S	−0.38
A03 - C24	−0.28	C28 - K64	−0.25	A01 - J58	−0.37
D35 - H53	−0.27	A03 - H50	−0.24	A01 - J61	−0.36
C31_C32 - K65	−0.26	C18 - J58	−0.24	A03 - C10-C12	−0.36



(a) 2000 (b) 2014

Fig. A.2. The Industry Space in 2000, and 2014.



(a) Germany, 2000 (b) Germany, 2014

(c) United Kingdom, 2000 (d) United Kingdom, 2014

Fig. B.1. Industry Space for Germany and the United Kingdom, 2000 and 2014.

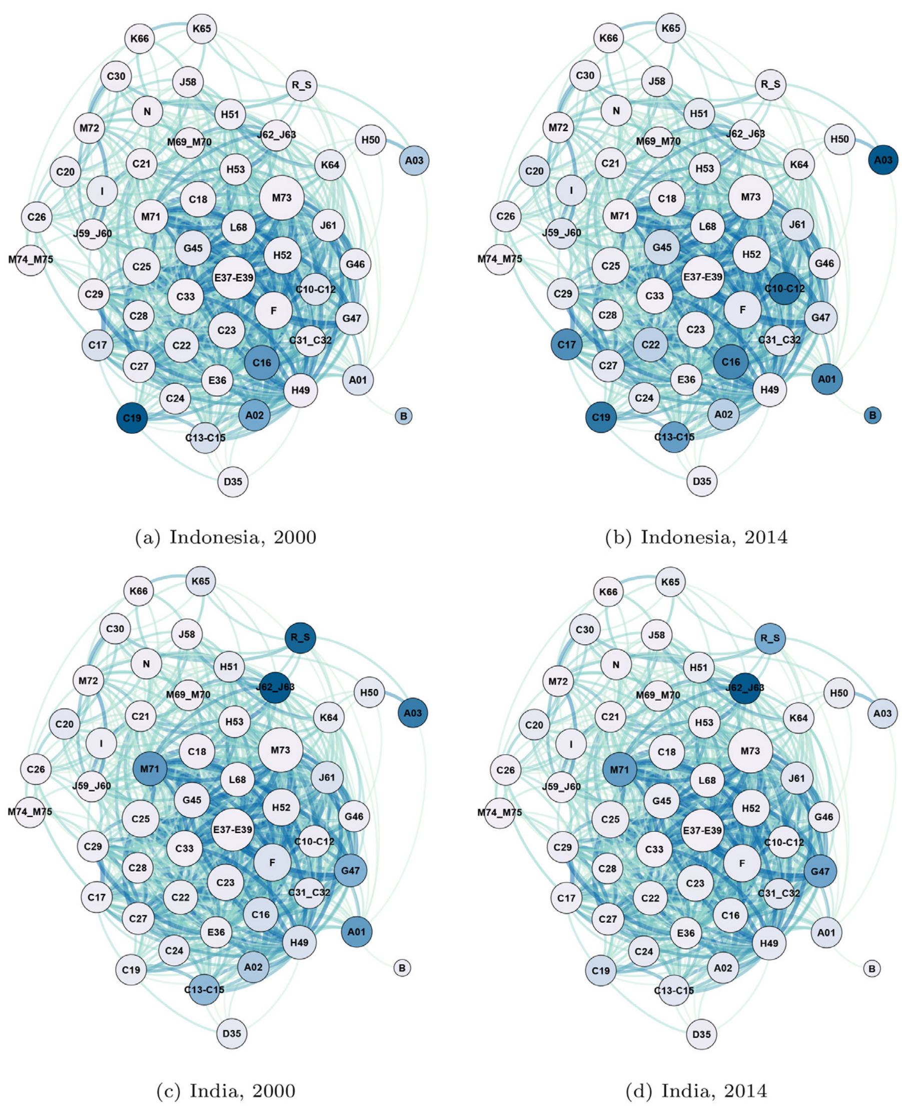
Appendix B

This Appendix describes a selection of Industry Spaces of further countries. Specifically, the Industry Spaces for Germany and the United Kingdom (Fig. B.1), Indonesia and India (Fig. B.2), as well as Japan and South Korea (Fig. B.3) are shown for 2000 and 2014, respectively.

A number of interesting observations emerge from the provided illustrations. Germany, for example, became even more concentrated on manufacturing of motor vehicles (C29) between 2000 and 2014, despite being very diversified in the center of the Industry Space in general. It can be observed that between 2000 and 2014 Germany has lost in terms of value-added export specialisation in the manufacturing of chemicals (C20) and scientific R&D (M72). In contrast, the United Kingdom is predominantly focused on activities auxiliary to financial and insurance services (K66), which can be described as services to enable the functioning of financial marketplaces.

The Industry Spaces for Indonesia and India (Fig. B.2) also reveal interesting patterns. Indonesia, for example, went from being concentrated on value-added exports in the manufacture of coke and refined petroleum products (C19) to a more diversified structure with fishery (A03) being the most pronounced value-added export specialisation, although this reflects a jump from one end of the Industry Space to the other. India, however, has its highest specialisation in information service activities (J62_J63).

Japan and South Korea are situated similarly in the Industry Space (Fig. B.3). Both countries tend to have higher specialisations in the left area of the Industry Space, although South Korea's economic structure is more diversified. Japan, however, shows a high concentration on the service industry 'other professional, scientific and technical activities' (M74_M75). This industry can be seen as the sum of professional, scientific and technical activities, which cannot be classified as legal counselling, engineering, R&D, or advertising. One example is designing activities.



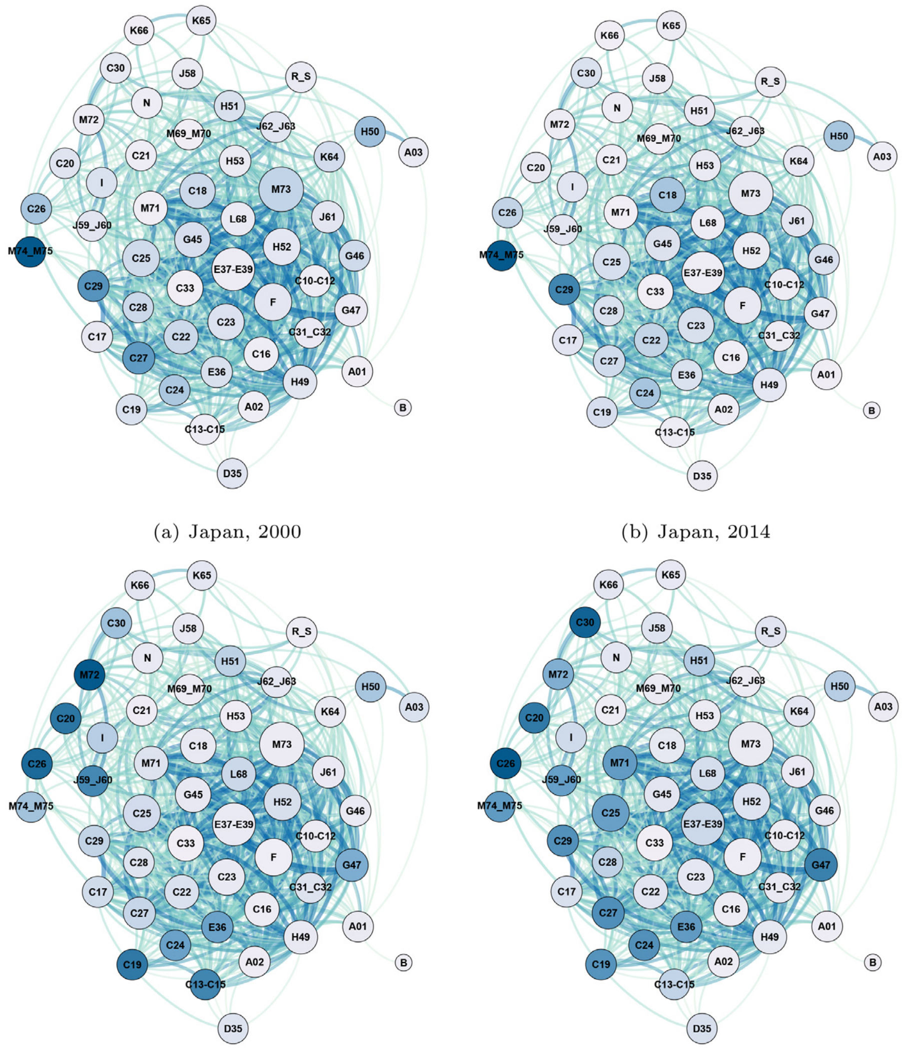
(a) Indonesia, 2000

(b) Indonesia, 2014

(c) India, 2000

(d) India, 2014

Fig. B.2. Industry Space for Indonesia and India, 2000 and 2014.



(a) Japan, 2000 (b) Japan, 2014

(c) South Korea, 2000 (d) South Korea, 2014

Fig. B.3. Industry Space for Japan and South Korea, 2000 and 2014.

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