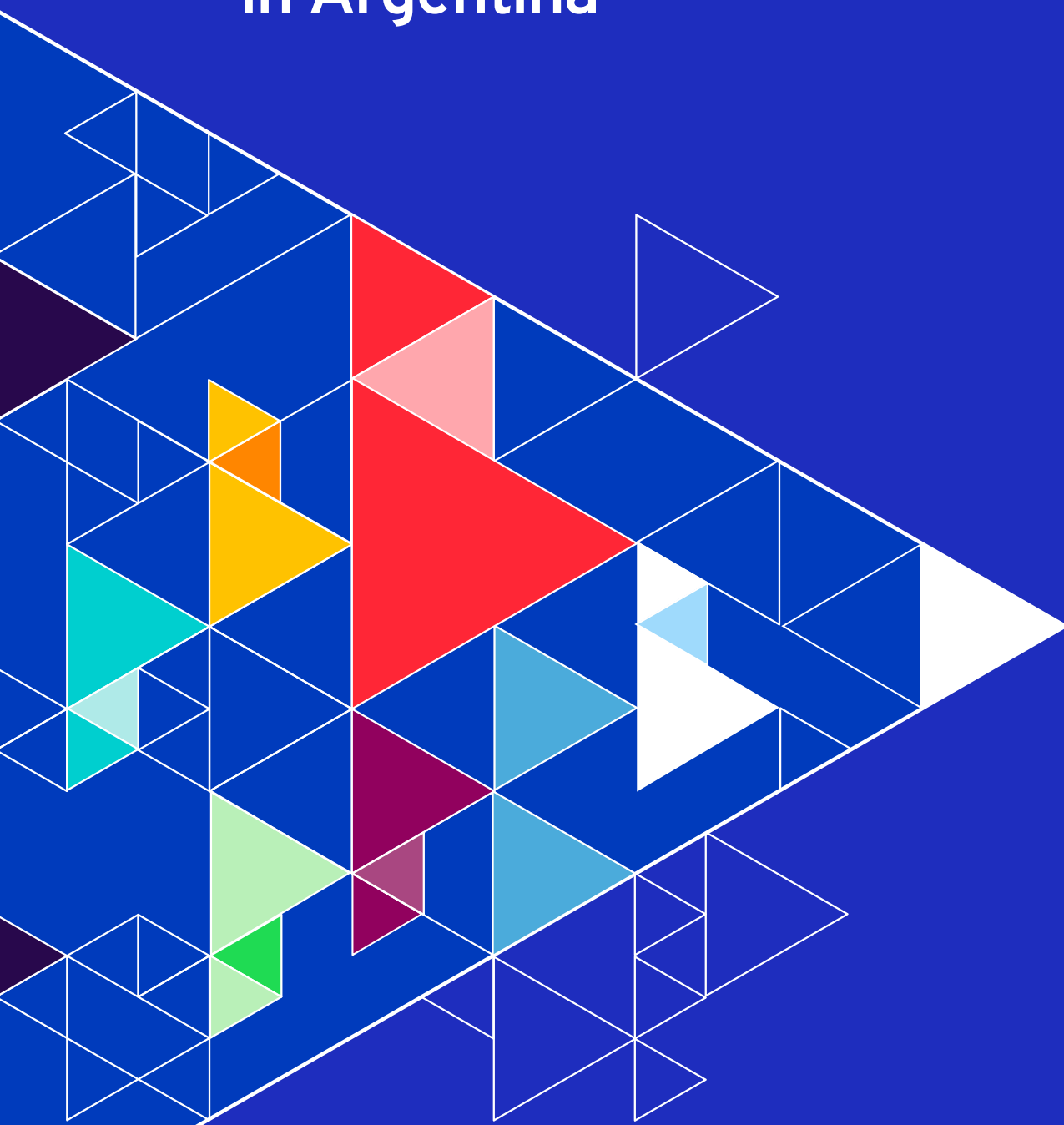
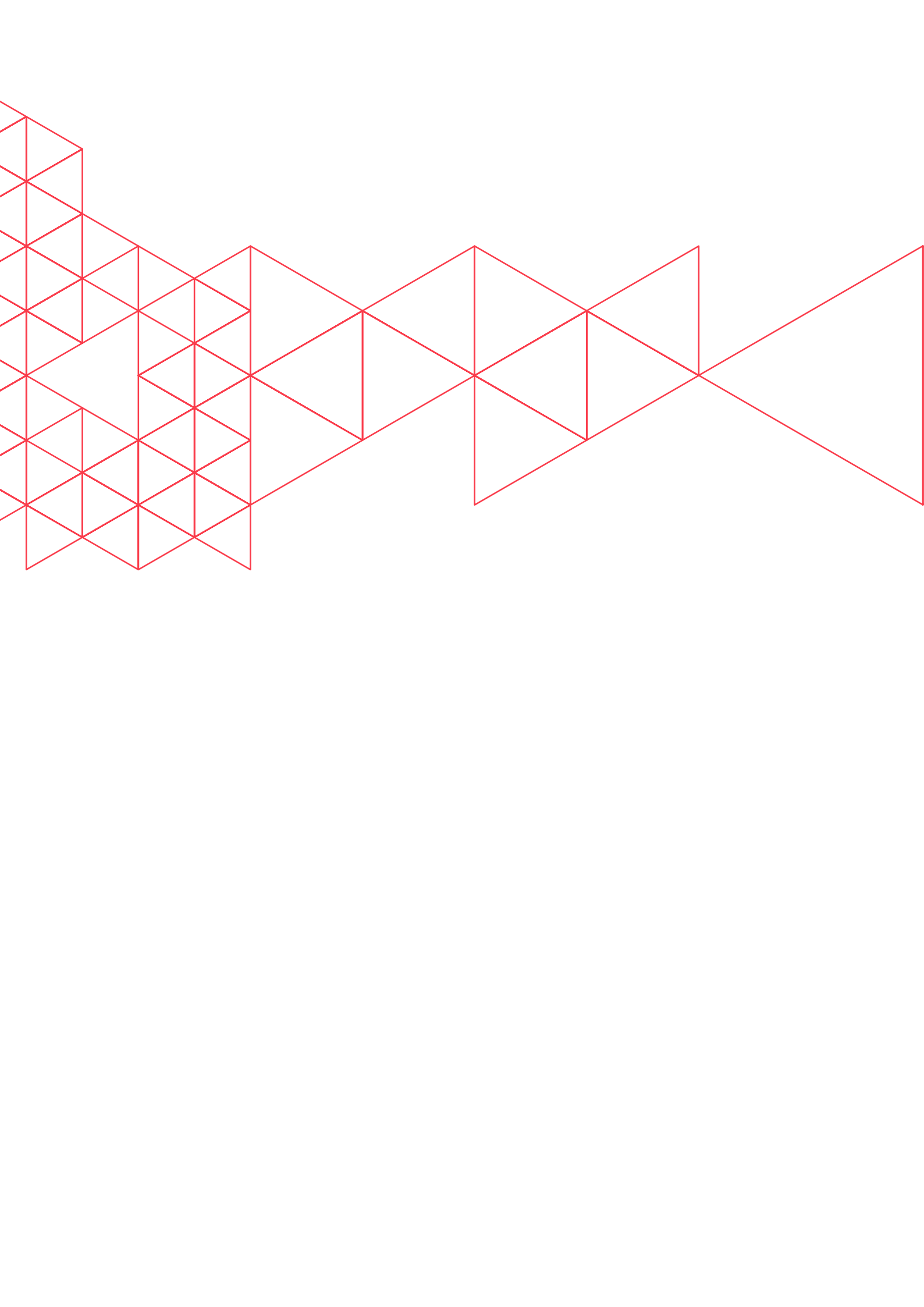




International
Labour
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► Identifying potentials for productive diversification using skill-relatedness networks in Argentina





- ▶ **Identifying potentials
for productive diversification
using skill-relatedness networks
in Argentina**

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► Foreword

This report was prepared by the Investment, Sectoral Strategies and Transitions Team of the Employment in Investments (EMPINVEST) Branch of the ILO. It contributes to the work on sustainable and inclusive sector-specific strategies and supports the promotion of full, productive and freely chosen employment. It is a translation of the report originally published in the ILO Office in Buenos Aires in 2025, which was peer-reviewed, validated and presented to ILO constituents in Argentina in cooperation with the Unión Industrial de Argentina (UIA). The report formed part of technical support to identify emerging sub-sectors or groups of products with a high export potential.

This report examines job transitions to identify workers' skills valued by employers and provides support for interaction among productive activities. Skill-relatedness networks (SRNs) are used to capture the latent capabilities of workers in engaging in activities that require higher skill-relatedness levels with a focus on export potential. Five clusters were observed: a dynamic industrial core, an agricultural core, a services and production core that were complementary to the industrial core, a support core with financial intermediation and IT, and a functional periphery. These groupings helped articulate the network of productive activities and provide analytical value to the exercise undertaken in this paper. The groupings have a high export potential corresponding to existing professional competences of the national workforce and have a high employment generation potential.

This report aligns with the work of ILO's EMPINVEST Branch focusing on employment promotion by identifying where jobs can be created through investments, trade, sectors or technology choices.

Mito Tsukamoto

Chief, Employment in Investments Branch (EMPINVEST)
Employment Policy, Job Creation and Livelihoods Department

► Table of contents

Foreword	5
Table of contents	6
Abstract	8
Acknowledgements	9
Executive summary	10
1. Introduction	12
2. The skill-relatedness method	14
3. Data collection and analysis	15
4. Methodology	16
5. Results	18
6. Product space	36
References	42
Annex	44

► Table of figures

Figure 1. Employment transitions between and within sectors, 4-digit ISIC Rev. 4 level, 2014–2023,	18
Figure 2. D-measure distances among SRNs	19
Figure 3. Persistence of sectors in hierarchical clustering: matrix heat map, $M_{k \times n}$, of co-occurrences, 2014 and 2023	20
Figure 4. Sectoral co-occurrence based cluster summary	22
Figure 5. Demographic characteristics by cluster: employment statistics (A); sectoral growth and share of exporting 2021-2022 (B); and sectoral wage gap 2022 (C)	24
Figure 6. Average values of employment flows between clustered sectors, 2021-2022	26
Figure 7. Average number of links between clustered sectors, 2021-2022	26

Figure 8. Stratum of the 135 most significant links, $SR > 0.9$	27
Figure 9. Ego network of direct connections and interconnections for sector A.113	29
Figure 10. Ego network of direct connections and interconnections for sector C.2930	30
Figure 11. Ego network of direct connections and interconnections for sector K.6419	31
Figure 12. Distribution by regular strata and selected strata: Distribution of links by regular strata (A); Subgraphs and selected strata of significance (B); Subgraphs and selected strata for specific ego networks (C)	32
Figure 13 Proportion of exporting firms by sector:V	35
Figure 14. Distribution of activities and products with median PCI greater than 0.5, 2022	38

► Table of tables

Table 1. Sectoral clusters: Sectoral count and employment share, 2021-2022	23
Table 2. ISIC activities by selected PCI and group membership	39

► Abstract

Data regarding the job transitions of workers delivers insights into worker skills valued by new employers and provide support for interactions among productive activities. Skill-relatedness networks (SRNs) facilitate an understanding of the most significant information from those exchanges. Thus, SRNs can capture the latent capabilities of individuals in engaging in activities that require higher skill-relatedness levels. This paper explores SRN interactions in Argentina over the past decade and identifies the most significant relationships and their potentials for productive diversification with focus on export potential.

► Acknowledgements

The present paper was produced under the guidance of the International Labour Organization (ILO) and edited by Elizabeth Fagan. The author would like to thank Viktoriya Semeshenko for insightful conversations regarding analytical and applied aspects of the paper. Further acknowledgment is given to Christoph Ernst at ILO for his time and consideration of the paper, to Victoria Castillo and the *Observatorio de Empleo y Dinámica Empresarial* (OEDE) for preparation and interpretation of the data, to Pablo Dragún, Daniela Rozenbaum and Ignacio Corral of *Unión Industrial Argentina* (UIA) for their willingness to discuss the methodologies and results of the ongoing analysis that forms the basis of this paper. This is a work in progress.

Executive summary

Employment transitions deliver insight regarding both the skills of workers who are in an employment transition, and the firms that demand those skills of their employees. Firms' respective economic activities can be used to aggregate and interpret these interactions from a broader view, as a national production network. The skill-relatedness (SR) methodology proposes a relatedness indicator for industries or productive sectors that represents the network of interactions and allows for the extraction of an "industrial space". That methodology is like the product-space method, which is based on international trade data and on the hypothesis of the existence of latent skills in observed employment flows.

This paper explores the structure and grouping of the skill-relatedness network in Argentina during the pre-COVID-19 period from 2009 to 2014 from the perspective of SR with a focus on the development potential of a set of activities that is considered innovative. The paper aims to use SR analysis to include the full spectrum of productive activities and leverages the systemic approach adopted in other recent studies on this subject.

For the preparation of this paper, inter-annual SR networks in Argentina between 2014 and 2023 were built and analysed with the objective of identifying the connectivity structure in the light of Argentina's employment mobility and observations on the steps taken by exporting firms. Particular attention was given to the diversification of export activities. Based on the use of high granularity SRNs with 4-digit ISIC Rev. 4, the analysis explored the persistence of intersectoral connectivity structures. Relevant meso-structures of sectoral clusters were identified, since they contained useful information on the functionality of the system generated by employment exchanges. An analysis of the composition of inter-cluster exchanges revealed their functional characteristics and informative exchange structures about employment and SR flows.

Five clusters were identified: a highly dynamic industrial core; an agricultural core; a core with services and production complementary to the industrial core; a support core with financial intermediation and information technology activities; and a functional periphery. An analysis of those clusters was useful in that it highlighted the network of productive activities and provided analytical value. Furthermore, by calculating the distances between the inter-annual structures of interactions among sectors, connectivity regimes with differences and similarities were identified, which confirmed similarities in the transitions in 2021 and 2022 (referred to as regime R2). Using those structures, the corresponding SRNs were significantly correlated in terms of SR among different activities that are identified by hierarchical clustering (HC) groups and by the proportion of exporting firms in each sector. Links showing higher SR imply that connected sectors present a large degree of similarity in terms of their unobserved skills, or "human capital" requirements. Thus, when determining which sectors to prioritize consideration should be given to those that are not current exporters (engaging in new activities with a view to breaking into external markets); and/or, those that already export but wish to increase their export-related activities (new firms in sectors that currently export, although to a lesser extent than desired). This paper provides a methodology for making those decisions by leveraging interpretative tools such as the aforementioned clustering.

Finally, when referencing the information obtained from the SR-based analysis with that obtained from the product-space analysis, it was possible to identify correlations in activities arising from the selection of exported products using a high product complexity index (PCI). The analysis found that for high values of SR and PCI indicators, recommendations for the selection of activities were similar. However, SR-based recommendations are more comprehensive since they take into consideration the whole spectrum

of productive activities, unlike PCI, which is based only on exportable products.

Two important points regarding the analysis should be noted. Firstly, the recommendation of activities that correspond to high PCI products does not have a weight or intensity as the SR indicator does. By using a criterion that reflects SR levels, a calculation can be made based on the skills required in the labour input of the production function of linked activities. Although those skills are unobserved, they can be calculated from employment flows that exceed a random threshold. In this sense, the SR indicator is a more accurate indicator of local productive processes (and capabilities) than a product-based productive diversification recommendation calculated based on international trade data. Secondly, recommendations based on SR will be more comprehensive since, unlike PCI which is based on exportable products, they allow the entire spectrum of productive activities to be considered.

This paper adopts an integral and systematic approach with a view to analysing employment transition data at a high level of disaggregation, with a specific application of SR indicator data, which is based on a network science approach. In contrast to traditional approaches to employment analysis, which tend to be focused at the economic sector level, the approach used in this paper covers disaggregated sectors and their interactions, a dataset that is very complex to study. In conclusion, the present paper should be considered an initial step towards the interpretation and understanding of data on a different scale, an exercise that presents challenges but also unique opportunities.



1. Introduction

Employment transitions deliver insight regarding both the skills of workers who are in an employment transition, and the firms that demand those skills of their employees. The workers who transition to a firm engaged in a different economic activity from their previous work carry with them unobservable information or skills that are valued by the new employer. Those job changes are not infrequent but rather occur year after year and can be interpreted as interactions among various economic sectors. Practically speaking, that naturally occurring interaction establishes a productive network mediated by employment changes.

Similar to the product space methodology, stated by Hidalgo et al. in their seminal work “The product space conditions the development of nations”, which draws on international trade data, and assuming the existence of latent skills of workers in observed employment flows, the SR method utilizes a relatedness indicator among industries or productive sectors that reflects the network of interactions among productive sectors and allows for the extraction of an “industrial space”. In their works, “Skill Relatedness and Firm Diversification” and “Inter-Industry Labor flows”, the authors Neffke and Henning, and Neffke et al. analysed, respectively, the industrial spaces of Sweden and Germany. They found that when they summarized the productive organization in a meaningful way, the indicator was useful for predicting the diversification of activities among firms.

In analysing Argentina, De Raco and Semeshenko explored the industrial space in Argentina and compared the structure of industrial spaces in Argentina and Germany. The authors identified important differences in connectivity and productive organization between the two countries, with a higher level of connectivity, a more developed core-periphery structure and a more dynamic industrial core in Germany, while the core structure had less depth and less specific characteristics in Argentina. De Raco, Tumini and Ernst explored the structure and clustering of a SRN by calculating an average number of

transitions between 2009 and 2014, focusing on the development potential of innovative activities. In that analysis, aspects of the productive structure in the period prior to the COVID-19 pandemic were examined from the perspective of SR. Clusters were extracted and a summary of the distribution of SR linkages associated with the study group was presented. Interactions among clusters of innovative activities and significant skill-relatedness linkages for activities within each cluster as well as among the activities across clusters were identified. However, the analysis only considered part of the system, namely innovative activities, meaning that future work will be needed to study the totality of productive activities. Using a systematic approach to the analysis of private registered employment transitions among industries at a high level of disaggregation, such as those examined here, subsequent works have examined the structure of the networks of employment flows and the associated industrial space for Argentina.

The authors showed that both the flow networks and the SR networks established complex interaction modalities involving all the activity sectors defined at the 4-digit ISIC level. Those networks also presented a functional structure of “core and periphery”, which characterized the core as a group or groups of sectors with very high rates of interaction, including employment exchanges and/or skill-relatedness, and high interaction rates with other groups. On the other hand, the periphery would be defined as a group of sectors with low interactions among themselves and high rates of interaction with sectors belonging to the core. In more recent analysis, the evolution and functional characteristics of employment flow networks were investigated. The networks of inter-annual employment flows were analysed and a strong correlation was found between changes in their structures and the evolution of real economic activity. From that research, a methodology for the comparison of connectivity structures was developed.

The present paper builds on previous research analysing the Argentine labour market prior

to the COVID-19 pandemic and it expands coverage of SRNs to include the full spectrum of productive activities through the adoption of a systemic approach, as developed in previous research. This paper analyses inter-annual SRN in Argentina between 2014 and 2023 with the objective of exploring the evolution of the connectivity structure in the light of recently observed Argentine employment mobility and trade in goods during the COVID-19 pandemic and the diversification potential of exporting activities that are of special interest in terms of productive diversification.

This paper is organized into six sections. In the first section, the concept of skill-relatedness is introduced. The second section presents the empirical information on which the estimates are

based. The third section details the methodology used, including the development of the relevant indicator and the grouping methods employed. In the fourth section, the results outline group characteristics across all activity sectors to identify emerging high-potential export opportunities, particularly in view of existing competences in the country, and interrelations with other sectors along with their diversification potential. In the fifth section, those results are compared with the outcomes of related research based on the product complexity indicator. Finally, the sixth section discusses key takeaways of the analysis and sets out several recommendations.

2. The skill-relatedness method

The SR method draws on the principle of relatedness, which states: “two activities, such as products, industries or research areas are related when they require similar knowledge or inputs” (Hidalgo et al., The Principle of Relatedness, 2018). The SR method assumes that an empirical analysis of cross-industry employment exchanges takes into account unobservable information on skills acquired in the industry in which a worker is employed prior to their job transition, and that the industry they have transitioned to finds a highly desirable skill set in their new employee. Thus, if employment flows from one industry to another are observed to be larger than expected, given a randomness criterion, it will be inferred that the flows are not random. In other words, connections among industries give rise to a systematic structure of demand in the skills that workers have acquired in their previous employment. An exchange indicator between each pair of industries can be used to chart the interconnections or networks among all productive sectors known as an industry space. In the industry space it is possible to identify certain industries so as to explore and analyse the overall structure of connectivity.

It should be noted that the SR method is closely related to product space analysis and the economic complexity approach, which is an application of the principle of relatedness and

the analysis of the co-occurrence of exported products in countries that share a basis of knowledge, such as technological know-how or capabilities, for example. However, the SR method uses input-based measures, such as labour (*L* for example), as an input to the production function of a firm, while the product space calculation is the result of an outcome-based measure. Although the product space analysis is performed on product categories, including those classified by the Harmonized System 2007 (HS07), and the industry space analysis is performed on industrial activity categories, such as those classified by the International Standard Industrial Classification of All Economic Activities (ISIC Rev 4)¹, a partial correspondence can be identified between the conclusions obtained in the HS07 classification at the product level and those obtained in the ISIC Rev 4 at the industry level.

This paper adopts that approach to identify potential areas for diversification in productive activity through and analysis of SR due to labour mobility. Areas identified from the product space analysis are also mapped to industries through a set of correspondence tables.

¹ This feature allows for integration with various complex network methodologies, such as the one used in product-space analysis. For further information, see Concordances in Classifications, available at: <https://unstats.un.org/unsd/classifications/Econ>.

3. Data collection and analysis

To construct the SR indicator, administrative employment data was used. In Argentina, those data are collected by *Sistema Integrado Previsional Argentino* (SIPA), namely the national pension system, and are handled by the *Observatorio de Empleo y Dinámica Empresarial* (OEDE), which collects employment and business information and is part of the Ministry of Human Capital. To compare the diversification recommendations for the product space analysis with foreign trade, data from the Product Complexity Index (PCI) produced by the Observatory of Economic Complexity (OEC) were used.

3.1. Statistical classifiers

The employment transition data used for this paper correspond to the 4-digit sectoral disaggregation of the ISIC Rev 4 economic activity classifier. Based on the classification of productive activities used for SR analysis and comparison with the product complexity index (PCI), classifier conversions were made according to the United Nations Statistics Division concordances of economic statistics.² The Harmonised System HS07 classification of foreign trade products was used, which is compatible with the Central Product Classification (CPC 2) of products for conversion into ISIC Rev 4 economic activities.

3.2. Employment and firms

To calculate the SR indicator, data on employment flows or inter-annual transitions among industries as defined at the 4d ISIC Rev 4 level were collected and classifications were built using panels of individuals with registered private sector employment. For the purposes of this paper

the terms “activities”, “productive sectors” and “industries” will be used interchangeably. They will be used in a broad sense, referring to the different classifications included in the chosen system, ISIC Rev. 4 at the 4 digits level. In addition, other relevant data such as sectoral employment endowment, characteristics of the wage distribution and disaggregation by proportions of women and young people (under 25 years of age) were used. Fortunately, sectoral information on the proportion of exporting companies was available, namely, the data provided by OEDE correspond to the years from 2014 to 2023, making it possible to extract nine ($T=9$) transition periods, including 2014–15, 2015–16, 2016–17, 2017–18, 2018–19, 2019–20, 2020–21, 2021–22, and 2022–23. Those transition periods are referred to in the paper by their “base” year (2014 for the 2014–15 transition, for example).

3.3. Product complexity

The aforementioned PCI was used in the analysis and required data were extracted from export data according to HS07 to 4d classification, as provided by the OEC, for selected years during the reference period.³

2 For further information see: <https://unstats.un.org/unsd/classifications/Econ>.

3 For further information see: <https://oec.world/es/rankings/pci/hs4/hs07>

4. Methodology

The methodology used comprised three stages: (a) calculation of the SR indicator and construction of the associated SRNs; (b) calculation of the structural distances among SRNs; and, (c) extraction of sectoral groupings. Firstly, inter-annual networks of available inter-sectoral employment flows were constructed, the SR indicator was computed for each of the networks and SRNs were developed. Secondly, distances between each pair of the obtained networks were calculated to compare their connectivity structures over time. Thirdly, hierarchical clustering was used to identify groups of sectors and a table reflecting the co-occurrence of sectors and groups was constructed for all available periods. The steps taken to construct the methodology are described in the following subsections.

4.1. Skill-relatedness

The concept of SR draws on a comparison of observed employment changes and the output of a “null model” that is used to define a basis for comparison generated by a random benchmark criterion. Reference material on the topic states that this criterion is similar to the ratio of observed values to expected values in a similarity ratio and is constructed using the following procedure.

4.1.1 Null model

Using a generally asymmetrical square table or matrix of observed employment flows (F_{ij}) a matrix of expected flows (F_{ij}^e) is calculated and used as a random threshold. It is constructed based on the edges or margins, which may include totals for rows, $F_{i\cdot}$, columns, $F_{\cdot j}$ and table, $F_{\cdot\cdot}$ of the observed flow matrix such that:

$$F_{ij}^e = \frac{F_{i\cdot} \cdot F_{\cdot j}}{F_{\cdot\cdot}} = \frac{\text{total outflows}_i * \text{total inflows}_j}{\text{total flows}}$$

The matrix reflects random flows in that sectoral exchanges are proportional to outflows and

inflows between sectors with respect to total flows. For each cell an associated matrix is calculated (SR_{ij}) with the ratio of the observed value and the expected value such that:

$$SR_{ij} = \frac{F_{ij}}{F_{ij}^e} = \frac{\text{observed flows}_{ij}}{\text{expected flows}_{ij}}, \text{ with } SR_{ij} \in [0, +\infty)$$

Thus, values of the indicator lower than unity, $SR_{ij} \in [0, 1)$ do not significantly differ from a random distribution, while values greater than unity, $SR_{ij} \in [1, +\infty)$, show deviations from the random distribution proposed as a reference. The matrix, like the original flow matrix, represents employment exchange relationships among participating sectors and is considered the fundamental matrix, such as an adjacency matrix for example, of the interaction network. Since SR is not bounded to the right, the indicator is normalized and symmetrized with respect to 0 using the following transformation:

$$\widehat{SR}_{ij} = \frac{SR_{ij} - 1}{SR_{ij} + 1}, \text{ with } SR_{ij} \in [1, 1).$$

Thus, positive values reflect related skills, and negative values reflect unrelated skills with respect to the defined null model, and their magnitude indicates the intensity of the relationship. Conversely, in the adjusted SR matrix obtained by averaging the indicators across sectors, and are symmetrized with respect to the main diagonal such that:

$$\widehat{SR}_{ij}^{sym} = \frac{\widehat{SR}_{ij} + \widehat{SR}_{ji}}{2}, \text{ with } \widehat{SR}_{ij}^{sym} \in [-1, 1),$$

That formula is equivalent to averaging the sum of the matrix with its transpose. The matrix summarizes symmetric intersectoral flows, which are used as a basis for network analysis, and it represents the undirected network of interactions

in terms of the $\widehat{SR}$ indicator.⁴ To avoid notation cluttering, in the following SR it will be used to refer to the adjusted and symmetrized SR indicator ($\widehat{SR}_{ij}^{sym}$).

In conclusion, the paper considers only positive values of the indicator ($SR > 0$), which are referred to as SRNs, and which summarize only the significantly non-random links or interactions according to the null model. They are interpreted as a network of proximities among productive activities.

4.2 Distances

The structural features inscribed in the topology of the networks, such as the organization of interconnections, affect the flow of information within those networks, both for the case of employment flows and of SR intensities. To compare the connectivity structures of SRNs, the D-measure (distance) is used (Schieber et al., 2017). That measure facilitates a comparison of networks of the same size, such as the same set of nodes or sectors for example, and here it is used to compare $\left(\frac{T}{2}\right) = 36$ fundamental matrices of the available SRNs.

4.3 Hierarchical clustering

Given that the number of industries selected at the 4-digit ISIC Rev. 4 level used in this paper exceeded 400 sectors, it was necessary to find methods that grouped them in a meaningful way to identify their similarities and differences. In clustering analysis, the objects or economic sectors in this case, were grouped together based on information extracted from the data that allowed for describing the objects and the relationships among them. A graph-based agglomerative hierarchical clustering method (HC) was used to analyse natural groupings in SRNs for Argentina. That is an incremental method that treats each observation as an individual cluster to hierarchically agglomerate the total dataset into a single group. Agglomeration is commonly illustrated using dendrograms, which summarize the process and the hierarchical relationships

between observations in the dataset. The linkage criterion among objects determines the distance between sets of observations based on the calculated distances between pairs of observations. The farthest neighbour criterion, also known as the maximum or complete linkage, is used. That criterion calculates the distance between the farthest objects of two different clusters, which in this case were sectors. In certain applications of the HC method, either the number of clusters K to be obtained or the height h for cutting the dendrogram, is determined. In this paper, we chose to categorize $K = 6$ clusters as groups of sectors according to the similarity of structural connections in the inter-annual networks. After analysing the co-occurrences of each sector and their groupings the persistence of the assignments was evaluated and HC was used again to extract $K = 5$ groups of sectors, and certain functionalities in the most recent networks were identified. Details of that analysis are provided in the following section.

⁴ The direction of inflows/outflows between any pair of sectors does not focus on any connections between the two, but their relative relevance for comparison with other connections may be reflected in the weighting of the sum of the flows.

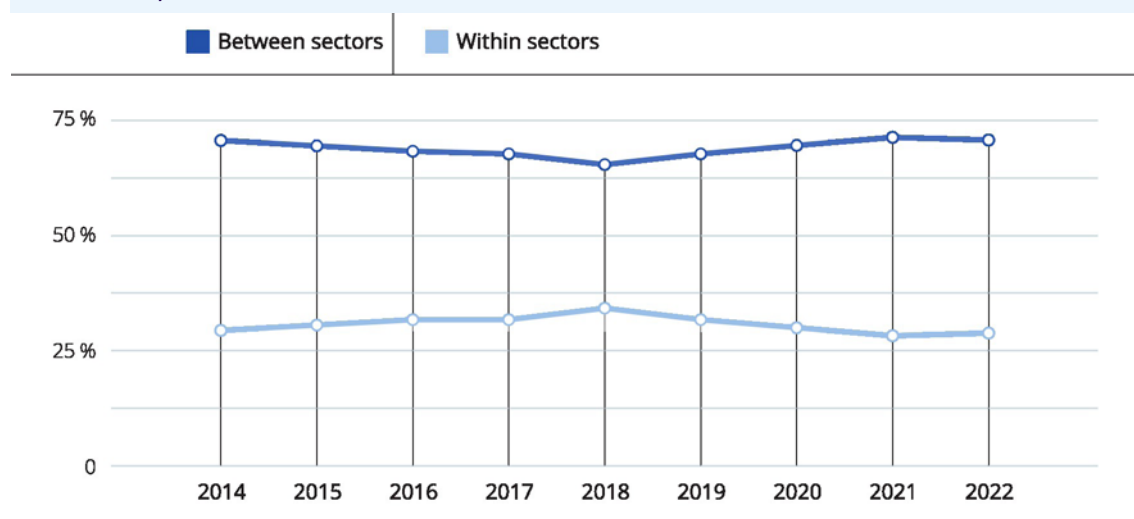
5. Results

Employment transitions between ISIC Rev. 4 to 4-digit activities during the analysis period served as the basis for calculating the SR indicator (SR) and are illustrated in Figure 1. Job transitions between industries are observed and account for approximately three quarters of total transitions, while those occurring within the same sectoral definition account for the remaining quarter. On the other hand, Figure 1 illustrates that both types of transitions are positively correlated with real gross domestic product (GDP). The intersectoral

employment transitions result in higher volatility with respect to the cycle, while those occurring within the same sector are more procyclical.

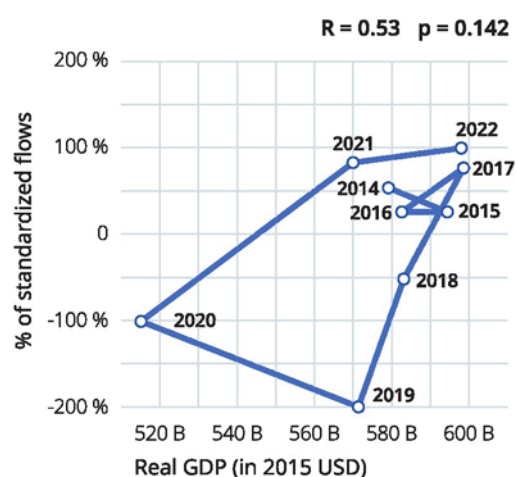
After constructing the SRNs in the analysis, stability of the connectivity structure was evaluated. In other words, the presence or absence of links in each constructed network were evaluated. The SRNs focused not only on the links that reflected higher observed employment flows, but on some of them having small flows but deemed statistically significant in terms of

► **Figure 1. Employment transitions between and within sectors, 4-digit ISIC Rev. 4 level, 2014–2023,**

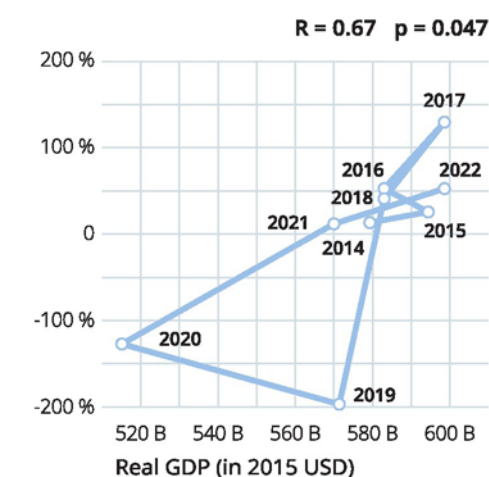


► Correlation with real GDP

► Between sectors



► Within sectors



Source: Author elaboration in base of SIPA data, 2024.

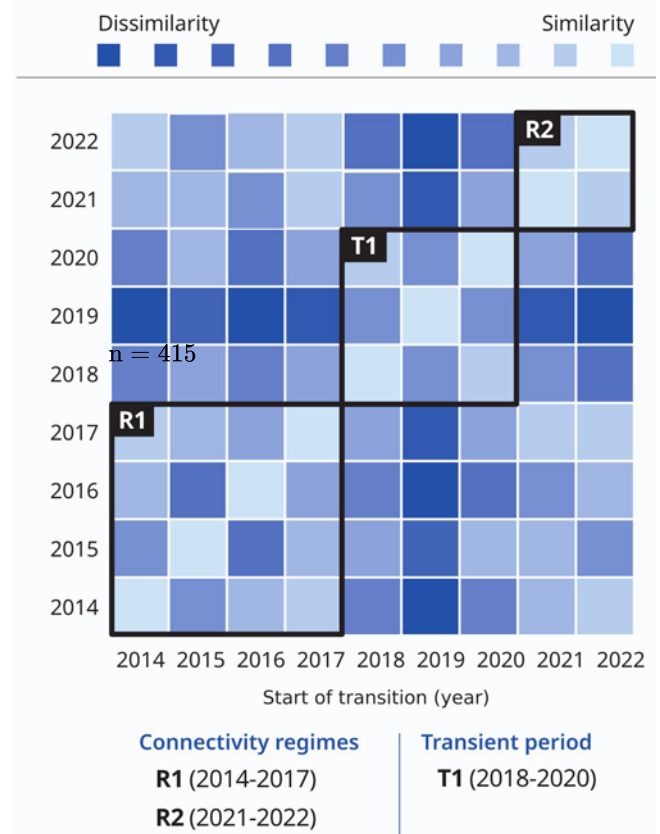
the null model used. To this end, the binarization of the SR indicator in the SRNs was calculated for each of the periods of inter-annual transitions between 2014 and 2023. It was observed that they presented changes in the connectivity structure extracted from the binary adjacency matrix associated with each SRN, computed as 1 for $SR > 0$ links and 0 for the remaining ones.

Next, we used the D-measure to compute the pairwise distance between the binary networks. Results showed a connectivity regime (R1) between 2014 and 2017, another connectivity regime (R2) between 2021 and 2022, and a transitional period (T1) between 2018 and 2020. The transitional period differed from the two regimes, but this result was expected due to the effects of the disruption of employment transitions caused by the COVID-19 pandemic. However, in the data the change began in 2018 possibly associated with the conjunctural situation of the labour market and a slow down in local economic activity.

Figure 2 presents the D-measure matrix and heatmap of pairwise distances among the binary connectivity structures of the SRNs during nine transitions observed between 2014 and 2023⁵. Those measures are focused on similar sub-periods within an analysed period, and provide a similarity criterion. The results are from the perspective of the SR indicator, which was obtained from administrative data of employment flows and both preserved the temporal dimension and avoided the averaging of periods, which could have included substantively different connectivity data.

In the most recent connectivity regime, R2 (2021-2022), the intersectoral connectivity structures were similar during the years included and also shared certain traits with the years included in R1 (2014-2017). Thus, the selection of the last two transition years for the subsequent analysis was considered valid. Therefore, in the foregoing results, the networks of those years were averaged and recalculated the SR indicator from aggregated flows to evaluate the most significant

► Figure 2. D-measure distances among SRNs



Source: Author's elaboration based on SIPA data, 2024.

SRN interactions. The averaged network is referred to as R2.

Inter-annual, SRN and binary, networks were also used to extract information on the meso-structure of the intersectoral connectivity. For this paper, particular interest was placed on the persistence over time of links among productive sectors, $n = 415$ the stability of the productive network and its potential evolution. For that reason, the persistence of the membership of each of the ($K = 6$) sectors in extracted from each of the networks was analysed⁶. Figure 3 shows the persistence of sectors in hierarchical clustering, as explained below.

5 For clarity, year to year transitions are referred to by their year of origin.

6 The choice of $k=6$ groups to be extracted in each period was conveniently made in order to establish a limited dataset for assessing the co-occurrence of sectors and identify the persistence of their proximity in terms of hierarchical groupings. This parameter could be determined by different criteria as, for example, the silhouette coefficient or the elbow method, but here we preferred a simplified criterion to focus on the persistence analysis.

► **Figure 3. Persistence of sectors in hierarchical clustering: matrix heat map, $M_{k \times n}$, of co-occurrences, 2014 and 2023**

Heatmap of matrix $M_{k \times n}$ of co-occurrences in the assignment of the $n=415$ sectors to the groups selected in each of the nine transitions observed between 2014 and 2023.

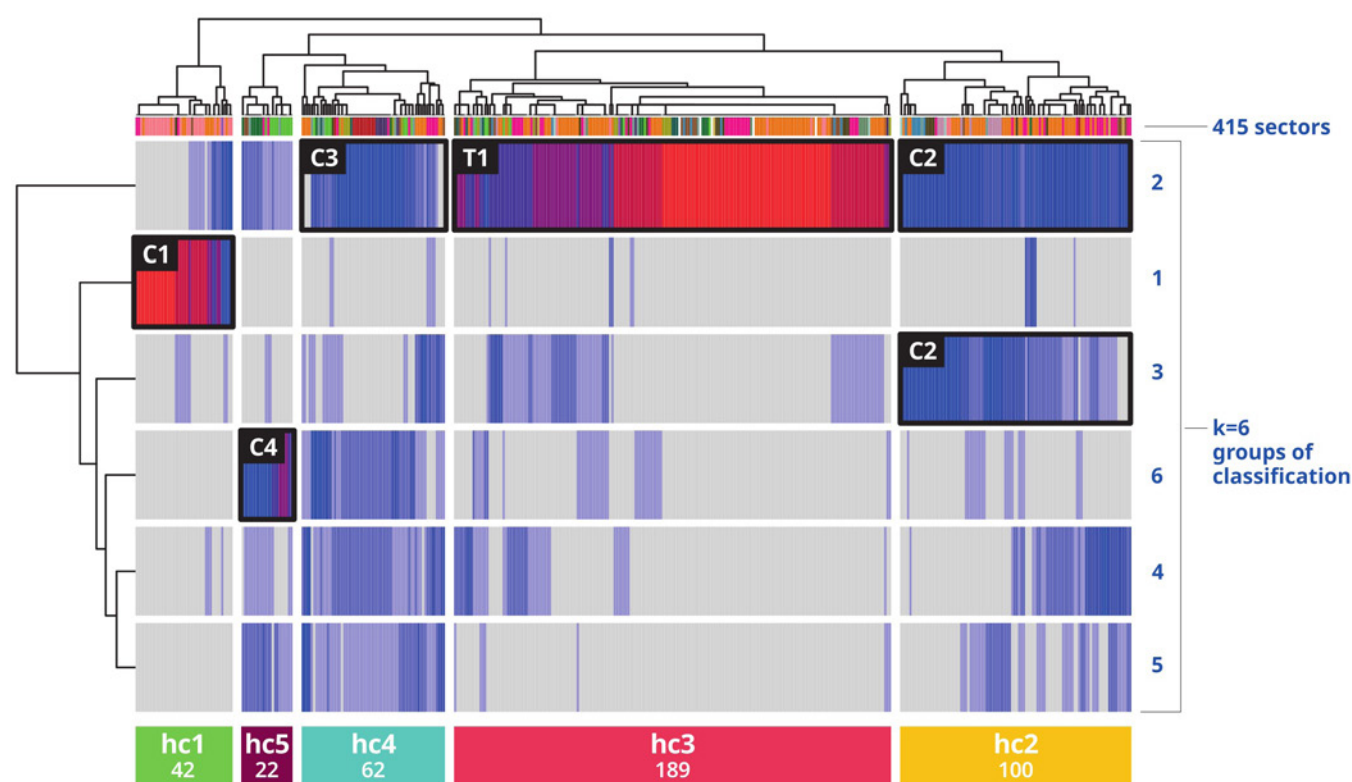
Sectoral division, ISIC Rev 4 activity classifier



Sectoral co-occurrence intensity in each of the $k=6$ groups



Greater persistence means sectors sharing groups most of the analysed periods.



Source: Author elaboration based on SIPA data, 2024.

Figure 3 is a graphic representation of a table of co-occurrences for the $K = 6$ clustering of sectors on each of the $T = 9$ binary connectivity structures of the SRNs using hierarchical clustering. The table is ordered into rows and columns with a new application of hierarchical groupings to identify the persistence of the occurrence of each sector within the six groups.

In the table, the horizontal dendrogram shows the selected $K = 6$ groups in each SRN over time, with a gray to red colour scale, while the vertical dendrogram presents the hierarchical clustering of the co-occurrence of assigned sectors per group. We chose to separate the $HC = 5$ groups into five columns, which were then used for further analysis due to the informative

nature of the observed co-occurrence structure.⁷ The colour scheme utilizing the A-U scale, as defined in the top of the figure, identified the ISIC Rev. 4 sectoral division classification, while the 0-9 scale of grey to red identified the intensity of sectoral co-occurrence in each of the groups. Regions with higher persistence, or colours closer to red, indicated the persistence of sectors in the same $k = 6$ group as the time periods count of co-occurrence. Descriptive information on the top 30 sectors for each group, in decreasing order of employment for the period of 2021-2022, is included in the Annex.

A general observation that can be made on the basis of available data, as reflected in the heat map matrix provided in Figure 3 and Table 1, is that almost all groupings included sectors belonging to several letters or large divisions (in other words, the most aggregated classification). Group *hc3*, which had the largest number of sectors, also presented the greatest heterogeneity in terms of aggregate classification. Conversely, groups *hc1* and *hc5* reflected more specialization and demonstrated a high sectoral concentration in terms of their respective letter classification. Regions with greater persistence, shown as colours closer to red, were highlighted. This indicates the sectors that shared the same group in most periods. Specifically, it should be noted that: (a) the vertical cluster *hc1* grouped almost all of letter A (agriculture, livestock, forestry and fishing, and associated services) and was consistently located in the *k1* horizontal group; (b) the *hc3* cluster included sectors that mostly fell into the *k2* horizontal group and, in turn, shared practically half of the time with the *hc2* and *hc4* clusters; (c) the vertical cluster *hc5*, covering financial intermediation, insurance, and computer and accounting services, persistently appeared in the *k6* horizontal group.

Firstly, the vertical *hc1* cluster grouped almost all sectors into the A letter and was consistently located in the horizontal *k1* cluster. Secondly, the *hc3* cluster included sectors that mostly shared the *k2* horizontal cluster and, in turn, shared half of the time with sectors of *hc2* and *hc4*. Lastly, the vertical *hc5* cluster, which included specialized financial intermediation, insurance, and computer and accounting services, appeared with some

persistence in the horizontal *k6* cluster. Figure 4, below, provides an overview of the five sectoral clusters for 2022, with each cluster colour coded at the top. Those clusters are identified based on temporal co-occurrence analysed before.

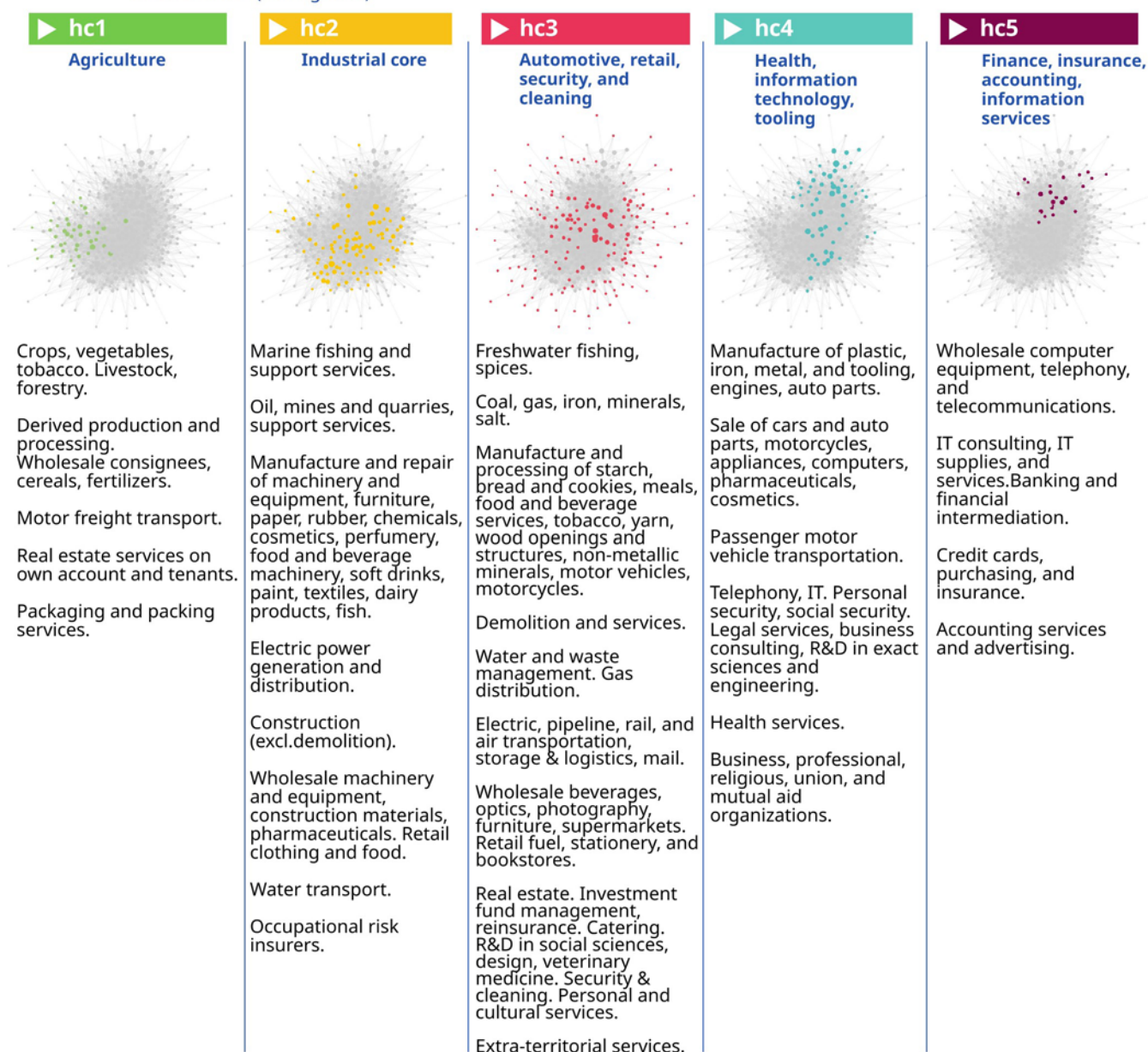
The *hc2* cluster was composed of 100 sectors and captured almost 30 per cent of private employment in the reference period and constituted the industrial core. The cluster included marine fishing and support services; petroleum, mining and quarrying and their support services. It also included the manufacture and repair of machinery and equipment, furniture, paper, rubber, chemical, cosmetics and perfumery, food and beverage machinery, soft drinks, paint, textiles, dairy and fish. Additionally, electric power generation and distribution, and almost all construction (excluding demolition services) were also part of the cluster. Lastly, it included wholesale sales of machinery and equipment, construction materials, pharmaceuticals and retail sales of apparel and food, water transportation and occupational risk insurance services.

As shown in Table 1, the *hc3* cluster was the most heterogeneous and included 189 sectors, or 45.5 per cent of the total analysed across the entire spectrum of productive activities, which together accounted for 19.4 per cent of private sector employment in Argentina. The cluster included freshwater fishing; production of coal, gas, iron, minerals and salt; the manufacture and processing of starch, bakery products, cookies and meals; food and beverage services; malt and beer production; tobacco, yarns, openings and wooden structures for construction, non-metallic minerals; production of automobiles and motorcycles as well as demolition, water supply and waste management services. The cluster also included the distribution of gas and the transportation of electricity, by pipelines, railroads, air and complementary services; storage and logistics; and mail services. Activities related to wholesale sales included beverages; optics and photography; furniture; supermarkets and kiosks; as well as retail sales of fuels; stationery; and bookstores. Real estate; investment fund management; reinsurance; camping and catering services; social science R&D

⁷ Note that the strict sectoral composition of the groups depends on the stability of the dataset analysed.

► **Figure 4. Sectoral co-occurrence based cluster summary**

Abbreviated summary and position in the 2022 SRN of the groups {hc1, ... , hc5} identified based on temporal co-occurrence (see Figure 3)



Source: Author elaboration based on SIPA data, 2024.

► Table 1. Sectoral clusters: Sectoral count and employment share, 2021-2022

Sectorial distribution by HC=5 and ISC Rev4 letter

HC	A	B	C	D	E	F	G	H	I	J	K	L	M	N	P	Q	R	S	U	Total	%
1	26		10				3	1				1		1						42	10,1
2	2	6	43	2		11	20	6	2		1		2	4		1				100	24,1
3	6	10	70	3	6	2	29	11	2	9	6	1	4	11	2		6	10	1	189	45,5
4			12				8	1		7	2		5	2	6	11	2	6		62	14,9
5							2			10	6		2	2						22	5,3
Total	34	16	135	5	6	13	62	19	4	26	15	2	13	20	8	12	8	16	1	415	100,0

Employment by HC=5 and ISIC Rev4 letter - share and sectoral total (in thousand)

HC	A	B	C	D	E	F	G	H	I	J	K	L	M	N	P	Q	R	S	U	%	2022
1	5,22		3,47				1,21	2,31				0,49		0,05						12,8	822
2	0,18	1,42	7,13	0,74		6,35	8,30	0,49	3,44		0,44		0,64	0,37		0,03				29,5	1.984
3	0,02	0,08	4,14	0,14	0,87	0,04	4,81	2,30	0,52	0,10	0,03	0,35	0,07	4,47	0,03		0,61	0,78	0,03	19,4	1.269
4			4,08				3,24	2,03		0,97	0,76		1,21	2,35	7,62	5,15	0,65	4,09		32,2	2.095
5							0,14			2,70	1,64		0,80	0,89						6,2	405
Total	5,42	1,50	18,82	0,88	0,87	6,39	17,70	7,13	3,96	3,77	2,87	0,84	2,72	8,13	7,65	5,18	1,26	4,87	0,03	100,0	6.575

services; photography and design; and veterinary services were also part of the cluster. Importantly, the cluster included security and cleaning services, which are often associated in such SR networks. Finally, encompassed car rental services; personal, library, cultural, recreational, and leisure services; and offshore services. In this paper, the cluster is hereafter referred to as the automotive production and retail, security and cleaning services cluster. It will be examined further on since it serves as a highly synergistic functional periphery to the industrial core.

The *hc4* cluster consisted of 62 sectors that account for 32.2 per cent of total private employment in Argentina. The cluster included the economic activities of: plastic; iron; metal and tool and die making; engines and auto parts; auto and auto parts sales; motorcycles; home appliances; computers; pharmaceuticals and cosmetics; automotive passenger transportation; telephone and information technology services; personal insurance and social security; legal services; business consulting; R&D in exact sciences and engineering; health services; and services for business, professional, religious,

trade union and mutual organizations. The cluster is hereafter referred to as the health, information technology and tooling cluster. It will also be examined in more detail later in this paper as a complementary core, given that it is highly synergistic with the industrial core.

The *hc5* cluster consisted of 22 sectors that account for 6.2 per cent of total private employment. This group did not include industrial activities, as noted by the letter C, in the ISIC Rev. 4 system, but rather included: wholesale of computer, telephone and telecommunications equipment; computer consulting and provision of computer services; banking and financial intermediation; credit/purchase cards and insurance; accounting services and advertising. The *hc5* cluster is hereafter referred to as the finance, insurance, accounting and information technology group, and reflects relatively high-wage activities. It will be examined further as a support core that has greater synergy with the *hc3* and *hc4* clusters than with the industrial core.

Figure 5 provides an overview of the key sectoral demographic characteristics of each of the *hc =5* clusters identified. In Figure 5a, the

► **Figure 5. Demographic characteristics by cluster: employment statistics (A); sectoral growth and share of exporting 2021-2022 (B); and sectoral wage gap 2022 (C)**



Source: Author elaboration based on SIPA data, 2024.

group *hc3* was characterized as periphery with 189 sectors and showed a high concentration of sectors with low employment participation (5a second graph) but indicated high dynamism in terms of employment growth in 2021-2022 (5a first graph). In terms of the proportion of women (5a third graph) the sectors in that group reflected average participation in the

economy as a whole of approximately 30 per cent, but the group also included sectors with high participation levels among women of up to 75 per cent. The distribution of youth participation (5a fourth graph) appeared to be similar to that of the industrial core. On the other hand, the complementary core *hc4* showed a more concentrated total employment distribution

of its sectors of higher proportions than in the other groups, while the distribution of female participation of its sectors were the highest. However, the distribution of youth participation in *hc4* appeared to be lower than in the rest of the groups. At the other extreme, the agricultural core was characterized by high concentrations of male and youth employment.

When examining the sectoral wage gap with respect to the average wage as of 2022, as shown in Figure 5c, the *hc1* group was characterized by the presence of a negative gap in almost all the included sectors. That was in contrast to the sectors of group *hc5*, the complementary core of finance, insurance, accounting and information technology, which had the highest values of positive wage gap concentration.

Figure 5b illustrates the distribution of sectoral growth (left) as indicated by the number of firms and in the share of exporting firms as a portion of the total number of firms (right), by membership group. It can be seen that the group presented the greatest heterogeneity in terms of sectoral classifications, as illustrated in Table 1, and showed the highest rates of employment variability, as seen in Figure 5a. Regarding the proportion of exporting firms, which accounted for only 1.4 per cent of the more than 560,000 firms in existence in the country, it was observed that the proportional distribution was “long tailed”, a phenomenon that was similarly observed in the agricultural (albeit with a slightly higher median) and industrial cores and the functional periphery (*hc1*, *hc2* and *hc3*). In contrast, groups *hc4* and *hc5* had substantially lower proportions of exporting firms.

Interesting observations on employment flows can be made when the characterization of the HC=5 meso-structure identified in the SRNs is applied (see Figure 6 for the flows that originated the R2 network as an average from 2021-2022). In general terms, the shares of employment illustrated in Table 1 and cumulative flows shown in Figure 6 had a correlation higher than 0.9 and were similar in the five groups identified. However, certain differences provide insights regarding the functional aspects of interactions among sectors. The interactions within each group, as shown on the main diagonal of the employment exchange matrix, demonstrated exchanges among the sectors within each group, while those occurring outside the diagonal represent interactions

between any sector in the group and another sector belonging to the remaining groups. In network science terminology, the core periphery structure characterizes the function of a cluster of nodes as core when they demonstrate high interaction rates among cluster members, and to a lesser extent, interaction with members of other clusters. The function is defined as periphery when they have clusters with low interaction rates among members and higher interaction rates with other clusters.

Many of the clusters had hub characteristics. A simple core periphery indicator could be calculated as the ratio CP_{out} or CP_{in} between flows within the group and flows whose destination or origin were from other groups. Values close to and greater than 1 for a group implied core-type behaviour, while values close to zero implied periphery-type behaviour. In the subsequent analysis, four cores with different relative importance and diverse characteristics, as well as one periphery, were identified. As shown in Figure 6, the cluster *hc2* appeared as a core with high interaction among cluster participants and high interaction between the sectors in other clusters and these sectors. It included 24.1 per cent of total employment and covered 100 sectors. The cluster *hc3* presented periphery characteristics and featured low interaction both within the cluster and between it and the other clusters and included 45.5 per cent of total employment and covered 189 sectors. The other clusters functioned as cores with lower relative participation.

The *hc2* group captured 18 per cent of the total flows in exchanges among its members, while at the same time it was the group that concentrated the greatest number of flows as a whole, with 34 per cent of the total. The overall $CP > 1$ value of this group indicates also that it functioned as a core, with more interactions among its members than with other groups. In particular, there was a synergy of exchanges with sectors of the complementary core *hc4* and periphery *hc3* groups, although the group also maintained interactions with the *hc1* agricultural core cluster. In addition, the group *hc4* captured 12.8 per cent of the total flow among its members and also maintained high interaction levels with the industrial core *hc2* and the periphery *hc3*. The *hc1* group also captured 6.6 per cent of the total

► **Figure 6. Average values of employment flows between clustered sectors, 2021-2022**

Labor flows between sectoral clusters
(average values 2021-2022)

R2	hc1	hc2	hc3	hc4	hc5	Total	CP. out	CP. in
hc1	6,6	3,3	1,6	1,7	0,3	113,4	0,9	1,0
hc2	3,2	18,0	5,0	6,9	1,6	34,8	1,1	1,1
hc3	1,5	5,1	3,1	3,9	0,9	14,5	0,3	0,3
hc4	2,2	6,5	4,1	12,8	2,8	28,4	0,8	0,8
hc5	0,3	1,3	0,9	2,6	4,0	9,0	0,7	0,8
Total	13,6	34,2	14,6	28,0	9,6	100,0		

Source: Author elaboration based on SIPA data, 2024.

flows among its members and maintained high relative interaction, or approximately one quarter of its interactions with the industrial core *hc2*. Lastly, the cluster *hc5* captured 4 per cent of the total flows among its members and maintained high relative interaction with the complementary core *hc4* and the industrial core *hc2*.

As in Figure 6, the relative shares of the clusters observed in terms of high-significance SR links shown in Figure 7 were maintained. In terms of finding the most significant *SR links*, there were two primary ways to filter them out for analysis purposes: (a) by selecting SR links with certain criteria and observing the activities, or nodes, and observing relevant connections; (b) by selecting a *particular sector*, or node, of interest to observe its direct connections or ties by level of importance

Regarding the first criterion and the significance of the links, Figure 8 shows the subgraphs, or connected portions of the SRN, that emerge when selecting the links that cross the threshold of

► **Figure 7. Average number of links between clustered sectors, 2021-2022**

Links with $1 \geq SR > 0.75$ between clusters
(average counts 2021-2022)

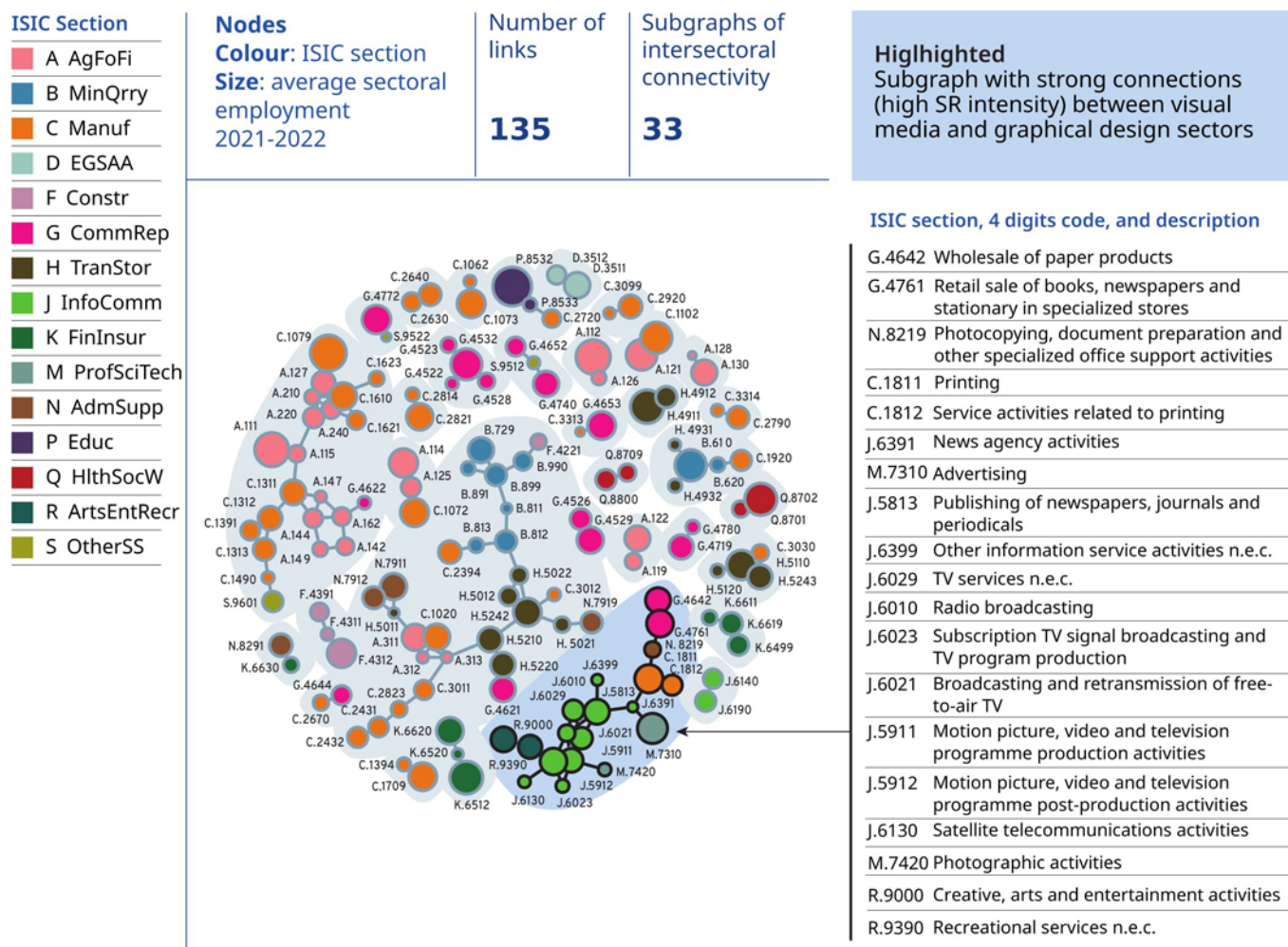
R2	hc1	hc2	hc3	hc4	hc5	Total
hc1	128	12	22	2	0	163
hc2	12	158	96	28	3	296
hc3	22	96	63	58	21	259
hc4	2	28	58	97	23	208
hc5	0	3	21	23	39	85
Total	163	296	259	208	85	1010

Source: Author elaboration based on SIPA data, 2024.

$SR > 0.95$ and represent the highest SR levels. By emphasizing the links first, the entire network was analysed and filtered according to a parameter or criterion of significance.⁸ In that case, the 135 links that responded to this criterion partially unite 143 sectors and compose 33 small subgraphs, which were subsets of nodes connected and separated from the rest into “islands” of the same colour. The colours of the nodes represent the ISIC Rev. 4 letter classification, and the size represents average employment in the sector. In the selected subgraph it is possible to observe different letter sectors that are connected to one other, which upon identification, suggest that they are sectors that make up part of the visual and graphic media value chain. Thus, activities in the manufacturing industry, retail and wholesale services, information services and others related to this chain are connected through links of greater significance or proximity. That type of exploratory analysis is useful for understanding

8 In the literature on complex networks, that practice is referred to as reduction, filtering or pruning of a weighted network.

► Figure 8. Stratum of the 135 most significant links, SR>0.9



Source: Author elaboration based on SIPA data, 2024.

and interpreting the effect of the indicator as a weighting factor for the kinship of skills.

The maximum SR weighting possibly highlights the value of the (latent) skills associated with work experience in companies of related activities within the relevant value chain. It is possible to verify that for successively lower values of the SR indicator, the links represent more distant connections to the value chain for a particular activity. However, the more detailed the sectoral definition, the greater the complexity in exploring and interpreting those relationships. Previous work in this area has identified that a higher granularity of data allows for greater heterogeneity at the cost of greater complexity.

When using lower granularity of data, for example, traditionally done at the letter or two-digit ISIC level for employment transitions, the graphs were practically complete with all possible connections, and were more stable since they do not vary structurally in their connections, but only in their intensities.

In terms of the second criterion considered here, namely, analysis of specific sectors, three sectors of different letter classification were used: one primary sector activity (A.113-Growing of vegetables and melons, roots and tubers), one manufacturing sector activity (C.2930-Manufacture of parts and accessories for motor vehicles), and one services sector

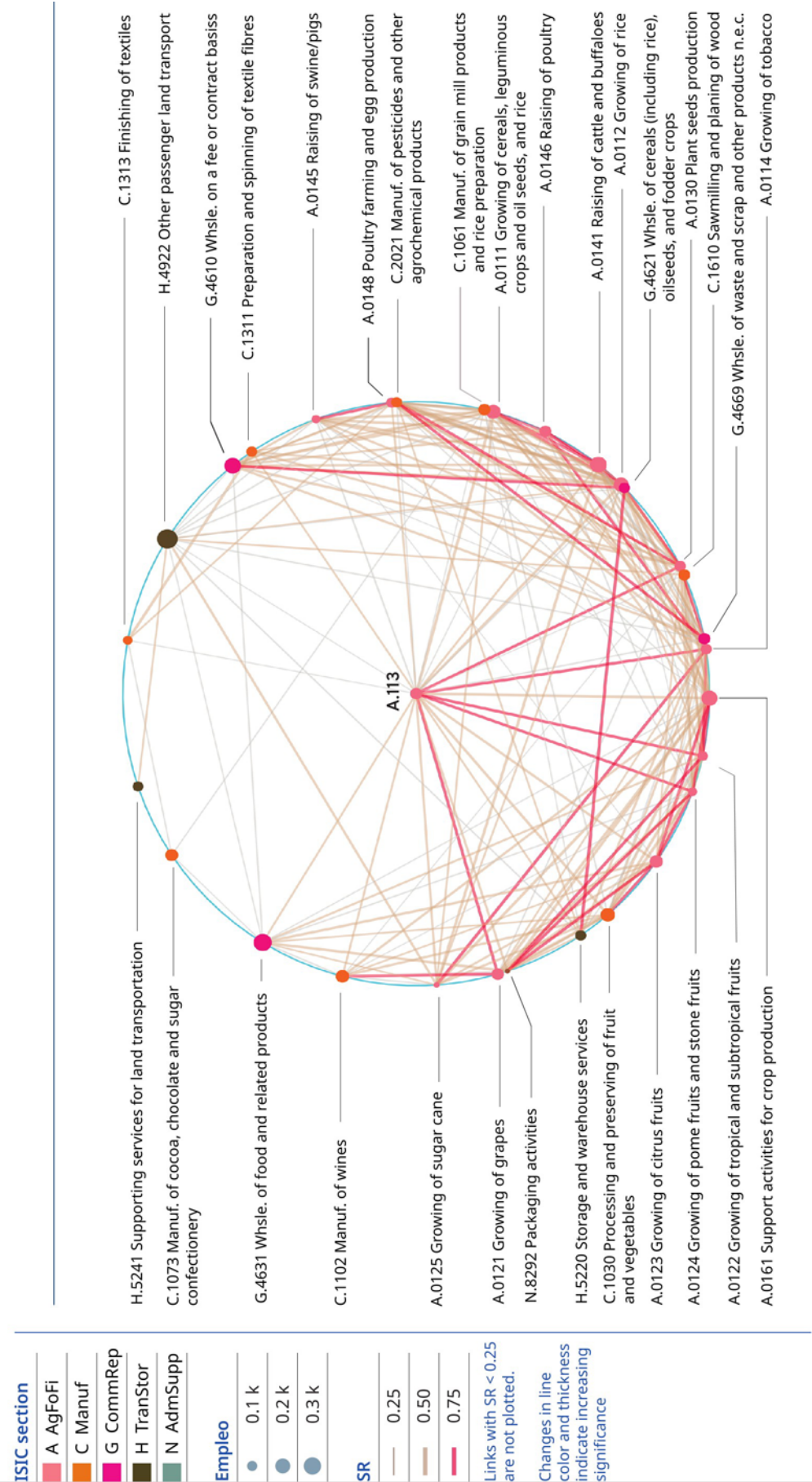
activity (K.6419-Financial service activities, except insurance and pension funding, other monetary intermediation). Figures 9, 10 and 11 show the networks of direct connections centred on each of the three sectors selected, otherwise known as ego-nets. The selected sectors were placed in the core and surrounded by sectors with direct or indirect connections. The thickness and colour of the links for $SR < 0.25$ were not plotted, thus indicating increasing significance in SR and the colour of the nodes, and were referred to by the ISIC Rev. 4 letter of each sector.

For example, in the case of sector A.113, Figure 9 demonstrates that the most significant links were between sectors of the same large sector, or letter A, a phenomenon already seen in the previous stage of clustering. Most of the sectors represented by letter A belonged to the agricultural core group, with high rates of specificity and persistence. Highly significant links were also observed between some of the sectors, and shown as thick, red links that do not pass through the centre. A reasonable conclusion could be that these links reflect sets of skills valued by employers in different agricultural sectors, comprising both specialized and general

knowledge, including that acquired through work experience in other sectors linked to agriculture. In the case of the selected industrial sector, C.2930, Figure 10 shows many links. The sector has established a large number and wide variety of direct connections of medium (tan lines) and high (red lines) SR intensity with diverse manufacturing industrial sectors. Lastly, in the case of K.6419, as shown in Figure 11, a large number of medium and highly significant links, albeit with a greater variety of sectors across several ISIC Rev. 4 letters were present. That pattern makes sense in terms of the skills demanded by the financial intermediation sector, given that it requires more heterogeneous experience in terms of background knowledge in financing needs and instruments.

In order to deepen the level of analysis and interpretation possible from SRNs, it is important to understand what type of information those sectoral interconnection structures provide, as well as to identify the industrial space that facilitates an understanding of sector proximity in terms of SR. Figure 12.A illustrates the distribution of the SR indicator links that support the SRN.

► Figure 9. Ego network of direct connections and interconnections for sector A.113

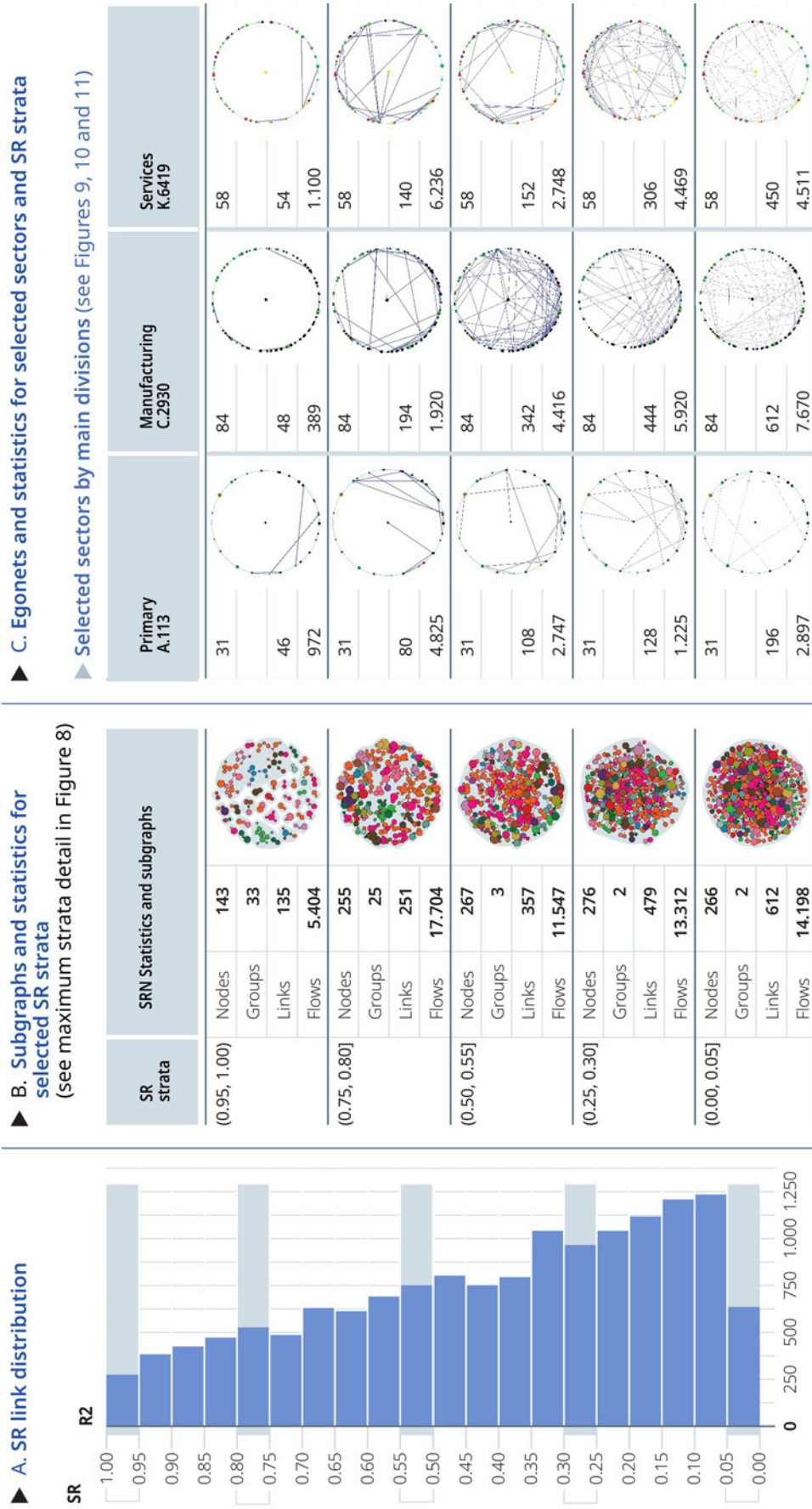


Source: Author elaboration based on SIPA data, 2024.

K.6419: Retail banking, wholesale banking, and financial intermediation services provided by financial companies, savings companies, and credit unions



► **Figure 12. Distribution by regular strata and selected strata: Distribution of links by regular strata (A); Subgraphs and selected strata of significance (B); Subgraphs and selected strata for specific ego networks (C)**



Source: Author elaboration based on SIPA data, 2024.

There is a linear decrease in links as the value of the indicator increases. To demonstrate the linkage structures and the information that can be extracted for the evaluation of productive diversification recommen-

dations, subgraphs and statistics are noted in Figure 12 as contour lines, and the sections or strata of the SR values from least significant (0.00, 0.05] to most significant (0.95, 1.00) are plotted. In Figure 12.B, for each selected SR value all sectors and connections in that stratum are shown.⁹

Thus, the analysis of SR strata highlighted the aspects of the SRN and a specific range of SR values that are significant. However, from the point of view of productive diversification, it was interesting in the analysis to identify certain sectors from which proximity according to kinship of skills could be identified. That process facilitated an understanding of diversification potential. Figure 12.C shows the immediate connectivity neighbourhood, also known as the ego network or egonet, of three productive activities, which were mapped in order to analyse the connections of each stratum within the direct environment of connections of a particular activity in the SRN.

Figure 12.B highlights the fact that when low SR levels (0, 0.5] were evident, connectivity was higher. Thus, it was possible to build an almost completely connected network, although connections only existed among slightly more than half of the sectors, or 266 of the 415 that made up the SRN. The 612 links that were identified captured a portion of the original employment flows that included 14,198 people, or approximately 5 per cent of the flows within the SRN. That result was similar in the other two strata, although with fewer links, which showed that higher employment flows were associated with increased SR. It was noteworthy that connectivity strongly decreased towards the higher SR strata and the subgraphs showed splitting into several groups or components, which presented atomistic-type structures. It was therefore interesting to note what type of connections could be expected in the strata of connections with greater SR kinship. The higher SR strata were then used in developing recommendations.

Once a sector of interest was identified, direct connections were investigated to understand the proximity to each activity with which it was connected. In figures 12.B and 12.C the same SR significance layers

are evaluated on the basis of the egonets shown in figures 9, 10 and 11. The results of the analysis showed that, in most cases, the sectors presented few direct links in each SR significance stratum, shown here radially from the centre. It was only in the case of the industrial sector of C.2930 that several direct links appeared among the different strata, and particularly in the stratum of $SR \in (0.50, 0.55)$.

Regarding the distribution of the most significant SR links $SR \in (0.75, 1.00)$, Figure 7 shows the highest concentration of links between the industrial core (*hc2*) sector and the sectors of the agricultural core (*hc1*). That is followed in importance by links within the health services, automotive and industrial production support groups (*hc4*), and between the industrial core (*hc2*) and the periphery (*hc3*). In general terms, relative shares of the groups observed were maintained in terms of employment flows. A list of 30 SR linkages by cluster, and in decreasing order in terms of indicator value, is given in the annex to the present report.

Given the results shown in the figures, analysing the characteristics of a SRN by strata provided a graphic illustration and facilitated an understanding of the networks with significant interactions. However, primary points of interest were the results of analysing the strata that accumulated the highest SR intensity, while the lower values were defined by the objectives of the analysis or public policy needs.

A further point of interest in the analysis of this paper was an investigation of current exporting sectors. To that end, the proportion ϵ_i , $i \in \{1, \dots, N\}$, of exporting firms by sector was explored. Figure 13. A illustrates the sectoral distribution of that proportion. Given the large number of sectors with a low or zero proportion of exporting firms (two-thirds of the n sectors included in the analysis), that information was used as a starting point for further analysis and formulating directions for policy recommendations. Figure 13.B showed the density of ϵ in each HC group and ϵ -strata. When looking at the marginal distribution of the defined ranges of ϵ as shown in the totals column of Figure 13.B, it can be seen that 21.9 per cent did not export, 44.1 per cent included up to 5 per cent of exporting firms out of the total number firms in each sector, 11.3 per cent had between 5 and 10 per cent of exporting firms, and the remaining 22.7 per cent, or 94 sectors, had between 10 and 68 per cent of exporting firms. On the other hand,

⁹ It should be noted that a stratum does not necessarily contain all interconnected sectors. This is because it is possible that some of the links connecting the SRN may be of lower or higher valence than the stratum chosen for analysis.

the distribution of ϵ in identified HC groups showed that the highest concentration of sectors in the highest ranges of ϵ_i exporting firms was found in the *hc3* periphery and the *hc2* industrial core. Figure 13.C showed the distribution by origin and destination of the links $SR > 0.75$ that were illustrated in Figure 7. The highest proportion of links, at 28.2 per cent, was observed between sectors with a low proportion of exporting firms. That included up to 5 per cent of the total number of firms in the origin as well as destination sectors, which together accounted for 50.2 per cent of the total of those $SR > 0.75$ links. The second highest number of links, at 10.3 per cent, were links between sectors that included more than 10 per cent of exporting firms. That was a category that represented 21.7 per cent of the total number of links. The third highest number of links, at 9.8 per cent, were between sectors with up to 5 per cent of firms and those that did not export at all. A lower number of links, 6.7 per cent, were observed between sectors with more than 10 per cent of exporting firms and sectors with up to 5 per cent of exporting firms.

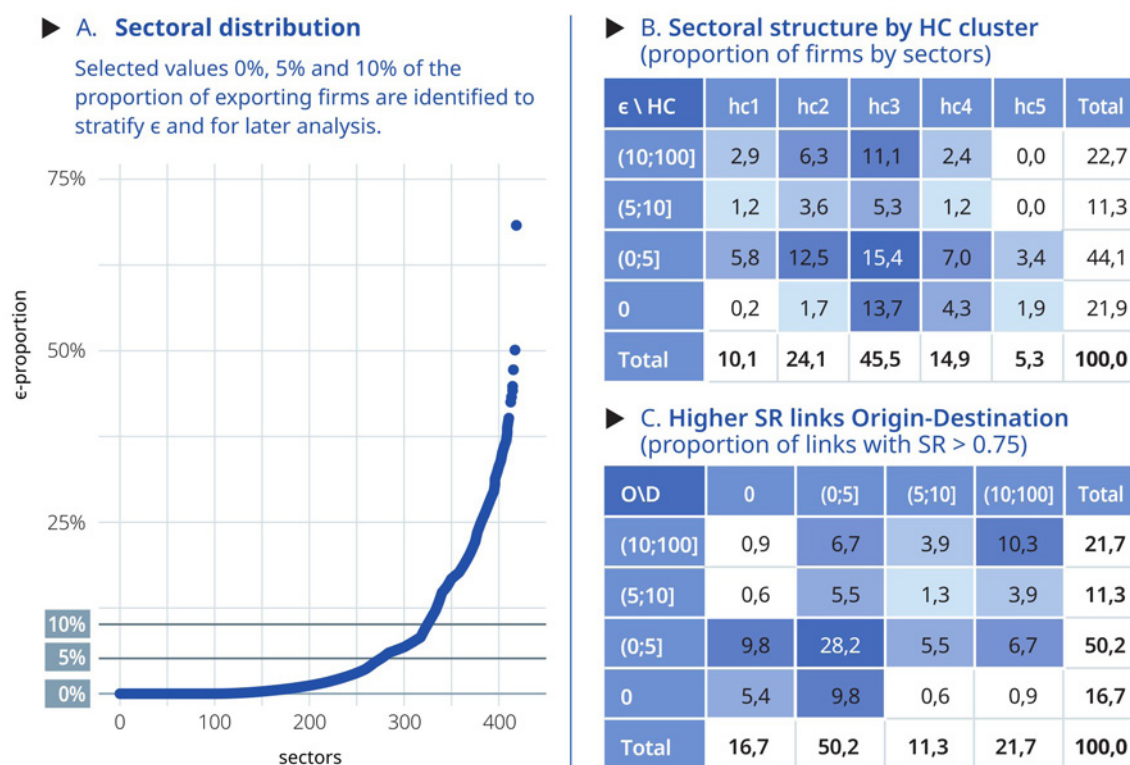
Up to this point, the analysis based on the SRNs highlighted useful elements and approaches for the prioritization of productive sectors aimed at export diversification. Given that links with higher SR implied that the connected sectors presented greater degrees of similarity among human capital requirements, the choice of sectors to be prioritized should consider those that: (a) are not currently exporters (extensive margin); (b) are current exporters but would like to increase their activities (intensive margin). This paper provides a methodology to facilitate export-diversification decisions and includes assistive interpretation tools such as clustering.

The SR relationships observed between the activities belonging to the clusters shown in Figure 8 could be used to identify significant meso-scale connections that could be strengthened through sectoral prioritization, for example, activities in the industrial core (*hc2*) being connected to activities in the complementary core (*hc4*). Alternatively, the information on the proportion of exporting firms of sectors connected by links with higher SR could be used to identify and prioritize non-exporting sectors, or those with a low proportion of exporting firms, that are connected to sectors with a higher proportion of exporting firms.

A final noteworthy observation of the analysis is that the methodological contribution stands out. It proposes an integral and systematic approach to the analysis of employment transition data at a high level of disaggregation, with a specific application of SR indicator data through the adoption of a network science approach. In contrast to a traditional approach to employment analysis that is usually performed at the aggregated economic sector level of either letter or two-digit sectors, the approach of this paper included disaggregated sectors and their interactions, which are usually very complex to study in terms of the volume and heterogeneity of the information they contain.¹⁰ Particularly, this paper avoided the problem of the criteria for selecting specific sectors to diversify, since that would have introduced complexities regarding the evaluation of alternatives inherent to industrial or production policy objectives, but paved the way to further analysis in that direction.

10 The increase in data volume introduced by explicitly incorporating certain interactions into the analysis was measured in several orders of magnitude with respect to traditional data, such as, for example, 18 1-digit ISIC Rev. 4 sectors with a potential of $18 \times 17 = 306$ interactions, versus 415 4-digit ISIC Rev. 4 sectors with a potential of $415 \times 414 = 171,810$ interactions.

► Figure 13. Proportion of exporting firms by sector:



Source: Author elaboration based on SIPA data, 2024.

6. Product space

The Product Space (PS) is a representation of the projection of products traded in the international trade network and allows for the visualization and understanding of the complexity underlying the relationships between countries and products in terms of the diversity and ubiquity of those exchanges.¹¹ From that analysis it is possible to extract indicators regarding country and product complexity. That makes it possible to quantify the complexity of each entity and identify the diversification possibilities for countries and products with respect to observed export structures. One conclusion reached by researchers is that countries with a more diversified export structure are associated with higher economic complexity indices and higher GDP per capita. Products with higher PCI values demonstrate greater sophistication in terms of the capabilities required for their production. The resulting high level of value-added means that they are more likely to be found among the exports of countries with high GDP per capita.

In the light of the results and general recommendations for productive diversification stemmed from the SR-based analysis in this paper, it was possible to conduct a comparison between those outcomes and the results calculated using the PCI to identify possibilities for the diversification of exportable products with higher levels of complexity. Here it should be noted that, unlike in the previous analysis, which included both goods and services production activities, in the PCI analysis it was only possible to draw conclusions about the production of exported goods.

The forgoing exercise used PCI data obtained from the Observatory of Economic Complexity (OEC). Using the PCI data of products coded with the HS07 classifier, tables that corresponded with CPC 2 and ISIC Rev. 4 were created. Thus, we obtained a set of productive activities along with a variety of products and their PCI scores. Since PCI scores change over time according to observed

trade flows, the closing years of 2017 and 2022 in the identified SRN connectivity regimes were chosen to explore the variability of the PCI indicator, with 5,858 products in 39 activities and 5620 products in 40 activities for 2017 and 2022 respectively. The distribution of PCI scores by corresponding productive activity code were calculated and the 42 activities for which the median PCI was greater than 0.5 were selected and are shown by HC grouping assignment in Table 2. Figure 14 shows the list of those activities with the number (n) to the right of each annual graph and the distribution of the associated PCI (107 products) for both years in decreasing order of their respective PCI median values. It was therefore possible to verify that the vast majority of the 40 activities belonged to the manufacturing industry, identified as division C, ISIC Rev. 4.

Table 2 presented the list of identified activities along with their respective HC group assignment. The activities were mostly concentrated in the first three groups. As previously observed in the description of the demographic characteristics of the firms, those groups were characterized by a sectoral distribution of exporting firms shifting towards higher median values than those of the other groups. In fact, when cross-referencing this list of activities with the information on exporting firms available in Argentina, 26 were identified and only one of them (M.7420-Photography services) had no exporting firms, 5 had a proportion of less than 5 per cent of exporting firms, 4 had a proportion of up to 10 per cent of exporting firms and the remaining 16 activities had proportions of exporting firms between 11 per cent and 48 per cent. All those results are shown as outliers on the right side of Figure 14.

When that data was compared with the information obtained in the previous SR analysis, it was possible to identify correlations among the activities that corresponded to the selected PCI scores. Those activities were mostly in the manufacturing industry and 37 of the 42 sectors

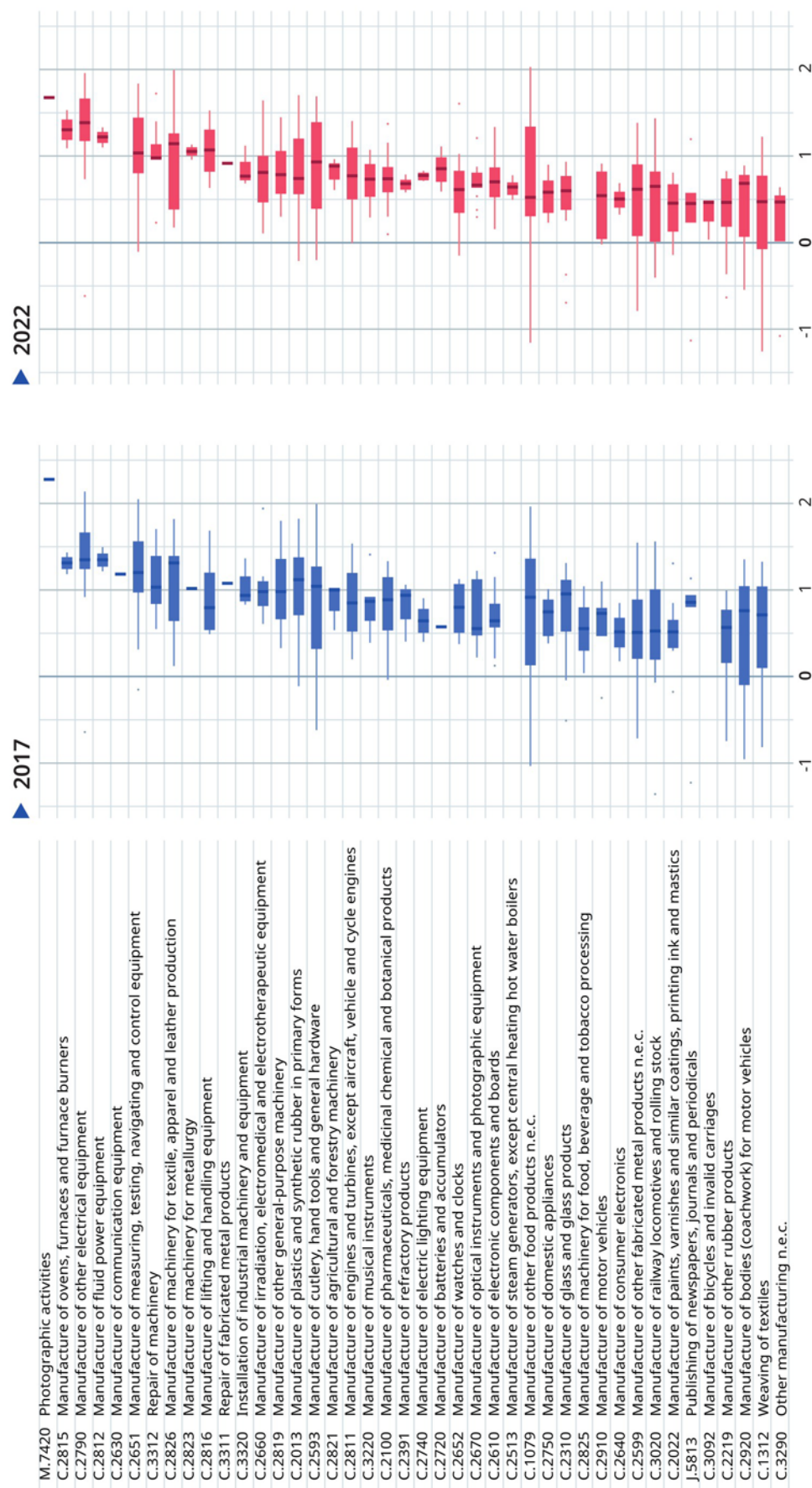
11 The product space restricts analysis to including only exported products and excludes the export of services, which imposes a natural limitation on the relationship with the production of services that comprised the SR analysis.

with high PCI scores appeared in 118 of the highest SR links that totalled 1,010. That finding indicated that, when high values for both SR and PCI criteria were considered, similar conclusions could be drawn and thus the recommendations were substantiated by diverse data and theoretical evidence. In other words, SR and PCI are complementary methods for recommending productive diversification.

It is important to note two points here. The first point is of greater relevance, namely, the recommendation that corresponds to high PCI was not quantified with a valence or intensity in the way that the SR indicator was. The use of SR level-based criteria revealed the skills that

were required based on labour inputs in the production function of the linked activities. Although those skills are not observed, they exist behind registered employment flows that exceed a random threshold based on margins. Therefore, the SR indicator was observed to be closer to the local production process than the productive diversification recommendations that were chosen based on products whose ranking was calculated based on international trade data. The second point to be noted is that recommendations based on SR were more comprehensive because, unlike PCI which was based on exportable products, the SR view allowed for the entire spectrum of productive activities to be considered.

► Figure 14. Distribution of activities and products with median PCI greater than 0.5, 2022



Source: Author elaboration based on data from the Observatory of Economic Complexity (OEC).

► Table 2. ISIC activities by selected PCI and group membership

hc2	hc3	hc4	hc5
C.1079 Manufacture of other food products n.e.c.	M.7420 Photography activities	C.2910 Manufacture of motor vehicles	J.5813 Publishing of newspapers, magazines and other periodicals
C.1312 Weaving of textile products	C.2391 Manufacture of refractory products	C.2670 Manufacture of optical instruments and photographic equipment	
C.2100 Manufacture of pharmaceutical products, medicinal chemicals and botanical products for pharmaceutical use	C.2013 Manufacture of plastics and synthetic rubber in primary forms	C.2652 Manufacture of clocks and watches	
C.2022 Manufacture of paints, varnishes and similar coating products, printing inks and mastics	C.2310 Manufacture of glass and glass products	C.3220 Manufacture of musical instruments	
C.2219 Manufacture of other rubber products	C.2593 Manufacture of cutlery, hand tools and hardware	C.2513 Manufacture of steam generators, except hot water boilers for central heating	
C.3311 Repair of fabricated metal products	C.2811 Manufacture of engines and turbines, except engines for aircraft, motor vehicles and motorcycles		
C.2819 Manufacture of other types of general-purpose machinery	C.2815 Manufacture of furnaces, hearths and burners		
C.3312 Repair of machinery	C.2826 Manufacture of machinery for the production of textiles, apparel and leather goods		
C.3320 Installation of industrial machinery and equipment	C.2823 Manufacture of metallurgical machinery		
C.2816 Manufacture of lifting and handling equipment	C.2610 Manufacture of electronic components and circuit boards		
C.2825 Manufacture of machinery for the production of food, beverages and tobacco	C.2720 Manufacture of batteries and accumulators		
C.2812 Manufacture of fluid propulsion equipment	C.2740 Manufacture of electrical lighting equipment		
C.2651 Manufacture of measuring, testing, navigation and control equipment	C.2630 Manufacture of communications equipment		
C.2920 Manufacture of bodies for motor vehicles; Manufacture of trailers and semi-trailers	C.3020 Manufacture of locomotives and rolling stock		
C.2640 Manufacture of consumer electronics	C.2910 Manufacturing of motor vehicles		

Source: Author's elaboration based on SIPA data, 2024.

Comments and recommendations

This paper presented an analysis of employment transitions based on private registered employment flows in Argentina between 2014 and 2023 using the SR indicator, which represents the proximity of skill requirements between productive sectors. The indicator facilitated the formulation of recommendations for productive diversification with an export orientation. Using the SR indicator, a methodology based on complex network methods was presented and SRNs were constructed to analyse significant interactions among more than 400 sectors as classified at the ISIC Rev. 4-level. A methodology that facilitated the analysis of the stability of the intersectoral connectivity structures generated by the indicator was developed, and the interpretation of that disaggregated data created relevant groupings that persisted over the observed period. Then, general recommendations on the diversification of productive activities were formulated after identifying activities that shared skill requirements according to the SR indicator criteria. Finally, a simple comparison was done based on the diversification recommendations that resulted from the PCI and based on the product space analysis performed using international trade data. In conclusion, the recommendations based on the SR indicator provided valuable information regarding skills shared among activities and their relation to the value chains in which they were inserted. On the other hand, a comparison of recommendations for diversification of activities with those based on the PCI indicator revealed correlations and complementarity, although the PCI indicator did not include services and other non-manufacturing activities.

Based on the construction of high granularity inter-annual SRNs using ISIC Rev. 4, this paper first explored the persistence of intersectoral connectivity structures. Relevant meso-structures of sectoral clusters ($HC_i, i \in \{1, \dots, 5\}$) were identified because they contained useful information regarding the system generated by employment exchanges. By analysing the composition of inter-cluster exchanges, functional characteristics and informative exchange structures in terms of employment and SR flows were identified. Five clusters were observed.

These included a highly dynamic industrial core, an agricultural core, a core with services and production that were complementary to the industrial core, a support core with financial intermediation and information technology activities, and a functional periphery. Those groupings were instrumental in articulating the network of productive activities and providing analytical value to the exercise undertaken in this paper.

By calculating the distances between the inter-annual structures of interactions between sectors, connectivity regimes with differences and similarities were thus identified and similarities in the years 2021 and 2022 (referred to as regime R2) were confirmed. Using that period as a basis for analysis, the corresponding SRNs presented links of high significance in terms of SR ($1 \geq SR > 0.75$) among the different activities identified by each HC group and by the proportion of exporting firms in each sector.

The links with higher SR implied that the connected sectors showed a high degree of similarity in terms of unobserved human capital requirements. Therefore, when choosing the sectors to prioritize, policy makers should consider those that: a) are not currently exporters (thus encouraging the generation of new activities for the external market, or extensive margin); b) currently export but wish to increase their export development (new firms in sectors that currently export but less than desired, or intensive margin). This paper provided a methodology with elements that facilitate decisions by leveraging interpretation tools, including the groupings developed herein.

Finally, by cross-referencing the information obtained in the SR-based analysis with information from the product space analysis, it was possible to identify correlations in the $SR > 0.75$ links and activities that were evident when exported products with high PCI were selected. Based on the analysis, we concluded that, when high values for both SR and PCI were considered, recommendations for the selection of activities were in a similar direction. However, recommendations based on SR were more comprehensive, because unlike PCI which is based on exportable products, SR evaluations consider the whole spectrum of productive activities.

That fact means that some of the recommendations formulated based on an analysis of the PCI of particular products associated with the ISIC Rev. 4 activities could be broadened in scope to include the extensive margin by identifying products with high PCI currently not exported by the country. In the area of product space, this would imply improving the Economic Complexity Index (ECI) index of the country's economic complexity and evaluating the capabilities that existing firms require for their production. The associated activities resulting from the search for exportable products with high PCI could be the focus of further analysis and for recommendations made based on the most significant SR linkages, which reflect overlapping capabilities among the linked sectors. Another possible recommendation could be to widen the intensive margin by increasing the number of firms that export an already exported product and for which the analysis of more significant SR linkages appears to be promising.

Two comments can be made on the recommendations done. The first point is of greater relevance, namely, the recommendation that corresponds to high PCI does not have a weight or intensity in the way that the SR indicator was. Although those skills are unobserved, they can be quantified from registered employment

flows exceeding a random threshold based on marginal counts. Therefore, the SR indicator was observed to be closer to the local production process than the product-based productive diversification recommendations formulated with regard to products whose ranking was calculated based on international trade data. The second point to be noted is that, as previously mentioned, recommendations based on SR were more comprehensive because, unlike PCI, which was based on exportable products, the SR view allowed for the entire spectrum of productive activities to be considered.

This paper outlined an integral and systematic approach to the analysis of employment transitions data at a high level of disaggregation and provided a specific application of SR indicator data through the adoption of a network science approach. In contrast to a traditional approach of employment analysis, usually performed at the aggregated economic sectors level, the approach used here included disaggregated sectors and their interactions, a dataset that is usually very complex to study. In conclusion, that type of analysis is a first step towards the interpretation and understanding of data at a more detailed and profound level, and it presents both challenges and great opportunities in the development of SR networks and supportive policy frameworks.

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Annex

HC Groups: Top 30 sectors by group in descending order by average employment, 2021-22

Group hc1

Sector	Description	Direct links	Employment R2
C.1010	Processing and preserving of meat	196	84,878
A.0141	Raising of cattle and buffaloes	112	58,708
A.0161	Support activities for crop production	106	54,838
A.0112	Growing of rice	104	34,334
A.0111	Growing of cereals (except rice), leguminous crops and oil seeds	82	33,925
C.1030	Processing and preserving of fruit and vegetables	84	29,300
A.0123	Growing of citrus fruits	52	22,844
C.1040	Manufacture of vegetable and animal oils and fats	150	22,195
A.0121	Growing of grapes	50	17,561
A.0113	Growing of vegetables and melons, roots and tubers	60	15,279
C.1061	Manufacture of grain mill products	130	14,883
A.0146	Raising of poultry	68	13,894
A.0114	Growing of sugar cane	58	12,336
A.0130	Plant propagation	78	10,080
A.0148	Raising of poultry (fowls) and egg production	84	10,064
A.0122	Growing of tropical and subtropical fruits	48	9,087
A.0124	Growing of pome fruits and stone fruits	52	7,812
A.0127	Growing of beverage crops	30	6,461
A.0145	Raising of swine/pigs	58	4,767
A.0220	Logging	60	3,874
A.0125	Growing of other tree and bush fruits and nuts	36	3,118
A.0144	Raising of sheep and goats	40	2,780
A.0240	Support services to forestry	46	2,770
A.0162	Support activities for animal production	48	2,696
A.0142	Raising of horses and other equines	34	1,971
A.0115	Growing of tobacco	16	1,684
A.0119	Growing of other non-perennial crops	26	1,634
A.0149	Raising of other animals	18	1,220
A.0210	Silviculture and other forestry activities	18	1,112
A.0126	Growing of oleaginous fruits	12	1,010

Group *hc2*

Sector	Description	Direct links	Employment R2
B.0910	Support activities for petroleum and natural gas extraction	118	44,074
C.1079	Manufacture of other food products n.e.c.	178	41,786
C.1411	Manufacture of wearing apparel (clothing)	142	34,271
C.1050	Manufacture of dairy products	176	32,319
C.1104	Manufacture of soft drinks; production of mineral waters and other bottled waters	148	25,554
B.0610	Extraction of crude petroleum	108	22,318
C.2023	Manufacture of soap and detergents, cleaning and polishing preparations, perfumes and toilet preparations	160	19,032
C.2029	Manufacture of other chemical products n.e.c.	162	15,053
C.1709	Manufacture of other articles of paper and paperboard	152	14,486
C.1399	Manufacture of other textiles n.e.c.	100	14,320
C.1020	Processing and preserving of fish, crustaceans and molluscs	30	12,498
A.0311	Marine fishing	38	11,558
C.1702	Manufacture of corrugated paper and paperboard and of containers of paper and paperboard	114	11,335
B.0729	Mining of other non-ferrous metal ores	64	10,091
C.1392	Manufacture of made-up textile articles, except apparel	106	9,856
C.1312	Weaving of textiles	70	9,014
C.2011	Manufacture of basic chemicals	108	8,425
C.1701	Manufacture of pulp, paper and paperboard	112	8,328
C.2022	Manufacture of paints, varnishes and similar coatings, printing ink and mastics	98	7,479
B.0899	Other mining and quarrying n.e.c.	70	6,198
C.1313	Finishing of textiles	72	5,912
C.2014	Manufacture of synthetic resins and synthetic rubber and plastics in primary forms N.E.C.	76	5,368
B.0813	Extraction of sand, pebbles, and crushed stone	80	4,818
C.1430	Manufacture of knitted and crocheted apparel	56	4,366
B.0990	Support activities for other mining and quarrying	80	3,930
C.1920	Manufacture of refined petroleum products	86	3,920
C.2012	Manufacture of fertilizers and nitrogen compounds	80	3,874
C.1812	Service activities related to printing	52	3,536
C.1391	Manufacture of knitted and crocheted fabrics	54	2,730
A.0313	Inland fishing: river (fluvial) and lake (lacustrine)	14	300

Group hc3

Sector	Description	Direct links	Employment R2
C.1071	Manufacture of bakery products	142	45,212
C.1073	Manufacture of cocoa, chocolate and sugar confectionery	114	16,690
C.1311	Preparation and spinning of textile fibres	90	9,791
C.1103	Manufacture of malt liquors and malt	110	9,782
C.1074	Manufacture of macaroni, noodles, couscous and similar farinaceous products	76	9,278
C.1200	Manufacture of tobacco products	60	5,068
C.1101	Distilling, rectifying and blending of spirits	50	1,712
C.1062	Manufacture of starches and starch products	16	1,335
B.0812	Extraction of limestone and gypsum	18	1,168
C.1075	Manufacture of prepared meals and dishes	24	1,105
B.0893	Extraction of salt	8	933
B.0891	Mining of chemical and fertilizer minerals	14	916
B.0814	Extraction of clay and kaolin	12	898
C.1394	Manufacture of cordage, rope, twine and netting	4	856
B.0620	Extraction of natural gas	12	827
C.1090	Industrial services for the processing of food and beverages	28	630
A.0312	Freshwater fishing	8	388
A.0147	Production of sheep and goat wool	12	372
C.1412	Manufacture of leather accessories	4	372
C.1393	Manufacture of carpets and rugs	2	318
A.0129	Growing of other perennial crops	2	290
B.0811	Extraction of ornamental stones	8	281
A.0320	Support services to fishing	2	156
A.0128	Growing of spices, aromatic, drug and pharmaceutical crops	2	96
A.0170	Hunting, trapping and related service activities	0	80
B.0510	Mining of hard coal	0	74
B.0892	Extraction of peat	0	66
B.0710	Mining of iron ores	0	42
C.1420	Manufacture of articles of fur	0	20
B.0721	Mining of uranium and thorium ores	0	1

Group *hc4*

Sector	Description	Direct links	Employment R2
H.4921	Urban and suburban passenger land transport	178	130,212
G.4773	Other retail sale of new goods in specialized stores	164	72,023
C.2220	Manufacture of plastics products	234	54,752
C.2599	Manufacture of other fabricated metal products n.e.c.	232	47,664
G.4511	Sale of new cars, vans, and utility vehicles	216	43,814
C.2930	Manufacture of parts and accessories for motor vehicles	166	40,730
K.6513	Social security schemes and social welfare fund services	78	40,132
J.6110	Wired telecommunications activities	68	33,811
C.2511	Manufacture of structural metal products	166	26,982
C.2410	Manufacture of basic iron and steel	194	25,245
G.4532	Retail sale of parts, pieces, and accessories N.E.C.	138	23,370
G.4753	Retail sale of carpets, rugs, wall and floor coverings in specialized stores	154	22,769
C.2750	Manufacture of domestic appliances	178	16,426
G.4531	Wholesale trade of parts, pieces, and accessories for motor vehicles	158	15,376
C.2821	Manufacture of agricultural and forestry machinery	142	14,143
G.4659	Wholesale of other machinery and equipment	208	13,516
G.4740	Retail sale of information and communications equipment in specialized stores	168	11,210
C.2829	Manufacture of other special-purpose machinery	158	10,924
C.2710	Manufacture of electric motors, generators, transformers and electricity distribution and control apparatus	144	9,690
K.6511	Life insurance	72	8,950
J.6120	Wireless telecommunications activities	54	7,688
J.6311	Data processing, hosting and related activities	92	7,038
G.4540	Sale, maintenance and repair of motorcycles and related parts and accessories	88	6,387
J.6022	Subscription television operators	52	5,998
C.2790	Manufacture of other electrical equipment	104	5,864
C.2660	Manufacture of irradiation, electromedical and electrotherapeutic equipment	94	4,886
C.2512	Manufacture of tanks, reservoirs and containers of metal	86	4,788
J.5811	Book publishing	54	4,124
J.6203	Information technology (IT) consultancy services	78	2,458
J.6312	Web portals	50	1,348

Group hc5

Sector	Description	Direct links	Employment R2
J.6201	Computer programming activities	182	74,816
K.6419	Other monetary intermediation	114	63,628
N.8220	Activities of call centres	170	51,116
J.6209	Other information technology and computer service activities	150	49,920
M.6920	Accounting, bookkeeping and auditing activities; tax consultancy	216	32,344
M.7310	Advertising	164	19,054
K.6492	Other credit granting	108	16,794
K.6620	Reinsurance	98	12,472
J.6023	Subscription television signal emission and television program production	78	12,002
J.5911	Motion picture, video and television programme production activities	56	8,410
J.5813	Publishing of newspapers, journals and periodicals	64	8,328
K.6619	Other activities auxiliary to financial service activities	80	6,542
N.8291	Activities of collection agencies and credit bureaus	92	6,277
G.4651	Wholesale of computers, computer peripheral equipment and software	102	6,126
J.6021	Open television broadcasting and retransmission	40	4,929
J.6140	Internet telecommunication services	82	4,754
K.6499	Other financial service activities, except insurance and pension funding activities, n.e.c.	66	4,658
J.6010	Radio broadcasting	48	4,316
J.6190	Other telecommunications activities	74	4,299
G.4652	Wholesale of electronic and telecommunications equipment and parts	86	3,117
J.6029	Television services N.E.C.	20	1,704
K.6630	Fund management activities	42	1,422

First 30 links with $SR > 0.75$ in descending order by SR

SR	Origin	O.desc	O.eps	O.hc	O.pci	Dest.	D.desc	D.eps	D.hc	D.pci
0.999	A.0144	Raising of sheep and goats	(0,5]	hc.1	A.0147	A.0147	Production of sheep and goat wool	(-1,0]	hc.3	
0.999	A.0147	Production of sheep and goat wool	(-1,0]	hc.3	A.0144	A.0144	Raising of sheep and goats	(0,5]	hc.1	
0.996	A.0128	Growing of spices, aromatic, drug and pharmaceutical crops	(-1,0]	hc.3	A.0130	A.0130	Plant propagation	(10,100]	hc.1	
0.996	A.0130	Plant propagation	(10,100]	hc.1	A.0128	A.0128	Growing of spices, aromatic, drug and pharmaceutical crops	(-1,0]	hc.3	
0.996	A.0311	Marine fishing	(10,100]	hc.2	A.0312	A.0312	Freshwater fishing	(5,10]	hc.3	
0.996	A.0312	Freshwater fishing	(5,10]	hc.3	A.0311	A.0311	Marine fishing	(10,100]	hc.2	
0.995	A.0312	Freshwater fishing	(5,10]	hc.3	A.0313	A.0313	Inland fishing: river (fluvial) and lake (lacustrine)	(0,5]	hc.2	
0.995	A.0313	Inland fishing: river (fluvial) and lake (lacustrine)	(0,5]	hc.2	A.0312	A.0312	Freshwater fishing	(5,10]	hc.3	
0.995	H.5012	Sea and coastal freight water transport	(5,10]	hc.2	H.5022	H.5022	Inland freight water transport	(0,5]	hc.2	
0.995	H.5022	Inland freight water transport	(0,5]	hc.2	H.5012	H.5012	Sea and coastal freight water transport	(5,10]	hc.2	
0.994	A.0311	Marine fishing	(10,100]	hc.2	C.1020	C.1020	Processing and preserving of fish, crustaceans and molluscs	(10,100]	hc.2	
0.994	C.1020	Processing and preserving of fish, crustaceans and molluscs	(10,100]	hc.2	A.0311	A.0311	Marine fishing	(10,100]	hc.2	
0.994	C.1490	Industrial services for the clothing industry	(0,5]	hc.3	S.9601	S.9601	Washing and (dry-) cleaning of textile and fur products	(-1,0]	hc.3	
0.994	S.9601	Washing and (dry-) cleaning of textile and fur products	(-1,0]	hc.3	C.1490	C.1490	Industrial services for the clothing industry	(0,5]	hc.3	
0.992	A.0210	Silviculture and other forestry activities	(0,5]	hc.1	A.0240	A.0240	Support services to forestry	(0,5]	hc.1	
0.992	A.0220	Logging	(0,5]	hc.1	A.0240	A.0240	Support services to forestry	(0,5]	hc.1	
0.992	A.0240	Support services to forestry	(0,5]	hc.1	A.0210	A.0210	Silviculture and other forestry activities	(0,5]	hc.1	

SR	Origin	O.desc	O.eps	O.hc	O.pci	Dest.	D.desc	D.eps	D.hc	D.pci
0.992	A.0240	Support services to forestry	(0,5]	hc.1		A.0220	Logging	(0,5]	hc.1	
0.992	A.0311	Marine fishing	(10,100]	hc.2		A.0313	Inland fishing: river (fluvial) and lake (lacustrine)	(0,5]	hc.2	
0.992	A.0313	Inland fishing: river (fluvial) and lake (lacustrine)	(0,5]	hc.2		A.0311	Marine fishing	(10,100]	hc.2	
0.992	B.0812	Extraction of limestone and gypsum	(10,100]	hc.3		C.2394	Manufacture of cement, lime and plaster	(10,100]	hc.2	
0.992	C.2394	Manufacture of cement, lime and plaster	(10,100]	hc.2		B.0812	Extraction of limestone and gypsum	(10,100]	hc.3	
0.992	C.3030	Manufacture of air and spacecraft and related machinery	(10,100]	hc.3		H.5110	Passenger air transport	(5,10]	hc.3	
0.992	H.5110	Passenger air transport	(5,10]	hc.3		C.3030	Manufacture of air and spacecraft and related machinery	(10,100]	hc.3	
0.992	J.5813	Publishing of newspapers, journals and periodicals	(0,5]	hc.5	TRUE	J.6391	News agency activities	(-1,0]	hc.3	
0.992	J.6391	News agency activities	(-1,0]	hc.3		J.5813	Publishing of newspapers, journals and periodicals	(0,5]	hc.5	TRUE
0.991	H.5110	Passenger air transport	(5,10]	hc.3		H.5120	Freight air transport	(0,5]	hc.3	
0.991	H.5120	Freight air transport	(0,5]	hc.3		H.5110	Passenger air transport	(5,10]	hc.3	
0.990	J.5911	Motion picture, video and television programme production activities	(0,5]	hc.5		J.6023	Subscription television signal emission and television program production	(0,5]	hc.5	
0.990	J.6023	Subscription television signal emission and television program production	(0,5]	hc.5		J.5911	Motion picture, video and television programme production activities	(0,5]	hc.5	

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