

# Análisis meso-estructural de redes intersectoriales de movilidad laboral de alta granularidad en Argentina

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**Abstract.** En este trabajo exploramos sistemáticamente datos de flujos laborales por actividad económica con alta granularidad utilizando una técnica de reducción de redes, centrándonos en un análisis de meso-estructura de grupos relevantes de actividades económicas. A partir de datos administrativos de flujos laborales interindustriales para 1996-2020, construimos las redes, extrajimos sus “backbones” representativos y aplicamos un algoritmo de detección de comunidades. Los resultados desenmascaran una conectividad interindustrial con estructuras persistentes y comunidades bien identificadas, organizadas en una estructura centro-periferia.

**Keywords:** movilidad laboral, análisis de redes, datos desagregados, Disparity Filter, comunidades.

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# Meso-structure Analysis of High Granularity Inter-sectoral Labor Mobility Networks in Argentina

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**Abstract.** In this paper we systematically explore high granularity economic activity data of labor flows using a network filtering reduction technique, focusing on a meso-structure analysis of relevant groups of economic activities. Using administrative data of interindustry labor flows for 1996-2020, we built the networks, extracted their representative backbones and applied a community detection algorithm. The results unmask inter-industry connectivity with persistent structures and well-identified communities organized in a core-periphery structure.

**Keywords:** labor mobility, network analysis, disaggregated data, disparity filter, communities

## 1 Introduction

The aggregate information on labor markets segmented by sectors of economic activity is usually analyzed by economists on a reduced set of categories (at the level of sectoral letters A to U or two-digit ISIC classifications). These categories are well-established and widely used by economists, analysts and public policy decision makers, because they offer a tractable, interpretable view of the economy and are compatible with conventional statistical methods and macroeconomic modeling approaches. Thus, they serve as a useful starting point for diagnostics, cross-reference comparison and routine monitoring (Causa et al., 2021).

However, these levels of aggregation also present consequential limitations. Key economic dynamics, such as structural transformations, technological upgrading, emergent vulnerabilities, which often take place, can be seen and explored only at a more granular level of economic activity (e.g. at the four-digit

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level) and may be completely obscured in aggregate categories. For example, combining all manufacturing sectors under one label may cover the different trajectories of high-tech versus low-tech industries, or the rise of niche sub-sectors critical for employment or exports. Consequently, when policymakers, researchers, or institutions need very specific and useful information, they often require on-demand analyses that break down economic sectors into much finer detail. These in-depth studies usually involve sophisticated methods such as combining complex data, network analysis, machine learning, or heterogeneous agent-based models. They also require a high level of specialized expertise to correctly understand the results. Although these highly detailed studies might not apply broadly to every situation, they are absolutely essential for designing policies based on solid evidence, developing industrial strategies, and real-time monitoring of economic transformations.

Therefore, there is a dual challenge. On the one hand, the data itself, drawn from administrative labor records, identifies employers' activities at a highly disaggregated level. While this granularity offers rich potential, it also poses significant challenges related to the selection of appropriate analytical methods and the interpretation of sectoral structures in terms of their economic significance and relevance for public policy. On the other hand, the network-based analytical framework is particularly well suited for studying labor mobility, as the data can be represented as a bipartite network of interactions between workers and industries. This structure enables the analysis of the underlying patterns and dynamics of mobility. However, these networks are inherently complex, often presenting dense structures. To extract meaningful insights while preserving the informative scale of labor mobility, it becomes necessary to apply dimensionality reduction techniques and other network simplification strategies that maintain the core structural properties of the system.

In this paper, we explore and systematically analyze intersectoral labor flows in Argentina at a highly detailed level of disaggregation. Specifically, we utilize administrative data provided by the Undersecretariat for Employment and Job Training, which classifies economic activity according to the four-digit level of the ISIC Rev. 3 industrial classification system. The dataset spans the period from 1996 to 2020, offering a rich and largely untapped resource for economic research at this level of granularity. We aim to uncover the structural characteristics of sectoral interdependencies, analyze how these relationships evolve over time, and identify the meso-structures that emerge from these dynamic patterns. Specifically, we investigate sector-specific labor mobility patterns, the formation and transformation of sectoral clusters, and the persistence of these structures across different periods.

Previously, we analyzed these data and demonstrated that intersectoral relationships, as evidenced by employment transitions between industries, form highly connected and persistent networks. These interconnections create dense networks characterized by a single connected component and short average path lengths. This structure is a key feature of a small-world network, meaning that labor can move between any two sectors through a surprisingly small number

of intermediaries (De Raco and Semeshenko, 2019a, 2019b). Our analysis also revealed a distinct core-periphery structure within the sectoral organization of the economy. This structure reflects the functional roles of different sectors as mediated by labor flows. We identified two large, densely connected cores, along with several peripheral sectoral groups that have remained relatively stable over time. Over the medium term, we observed notable shifts in the network's architecture, which correspond to different connectivity regimes of labor mobility. These regimes appear to correlate with changes in aggregate economic activity, suggesting that the dynamics of labor mobility networks are highly sensitive to macroeconomic fluctuations and broader structural transitions within the economy, as shown in De Raco and Semeshenko, 2024.

Analyzing data at such a high level of detail means that we are dealing with a large number of sectors, which makes the system highly complex. This complexity requires more sophisticated methods to extract useful information and understand how the system works at this fine level of granularity. To handle this, we need techniques that can reduce complexity while still keeping all the important information. In particular, in our specific case of study, the resulting networks are dense, not sparse, and are directed and weighted. This adds another layer of challenge for simplification. Any method we use to reduce the complexity of the network must carefully preserve its essential structure and connectivity patterns. Extracting the network backbone, the most relevant and informative connections, is especially complex in this context. We need methods that can extract its fundamental network structure without distorting it or losing significant information. There are many different network reducing techniques that exist, each having its pros and cons, well described in Serrano et al., 2009, Itzkovitz et al., 2005. In this paper, we are using the Disparity Filter for weighted networks (Serrano et al., 2009), a method designed to operate across all scales inherent to the network's weight distribution. This approach helps us extract the network backbone by keeping only the most statistically important connections, which allows us to preserve most of the total flow within the network while discarding a fair number of links.

In pursuit of our objective of uncovering the structural characteristics of sectoral interdependencies, examining their evolution over time, and identifying the meso-structures that emerge from these dynamics, we apply community detection techniques, using the Leiden algorithm (Traag et al., 2019). This method allows us to identify sector clusterings that exhibit a higher intensity of labor transitions among themselves than with the rest of the network. By focusing on patterns of intra-group connectivity, community detection provides valuable insights into the latent organization of the labor mobility network and the functional groupings that shape the dynamics of the productive system.

Analyzing communities in the different periods makes it possible to identify sector clusterings that may not align strictly with formal classification codes (such as ISIC letter categories), but are nonetheless closely related in terms of their functional roles in the broadest sense of productive organization. These groupings often reveal underlying economic interdependencies and shared labor

dynamics that are not immediately apparent from the official taxonomy. We are interested to know its persistence and its evolution over time in order to identify those sectors that determine the main groupings and sectors that can be associated with different communities over time. Specifically, we want to identify sectors that consistently anchor the main clusters and show stable relationships over time. At the same time, we are looking at peripheral or transitional sectors whose connections change between periods. These shifts could point to changing roles within the economy, new connections emerging, or innovation processes in production technologies. This long-term perspective gives us valuable insight into how productive structures are reconfiguring. This can help both with building theoretical models of economic complexity and designing practical sectoral policies.

As the main results, we highlight the following findings: a) the backbones of labor flow networks are shown to be representative and informative; and, b) there is a persistent structure of communities with two well identified cores.

In light of these results, the contribution of this work consists in the development of a general framework for the systematic analysis of high-granularity inter-industrial data, which allows us to extract the fundamental structure of the interactions of the system it represents, as well as to examine its functional meso-structure, and analyze its temporal dynamics. Thus, and given that the analysis is based on data from administrative records, this methodology is a toolbox at the disposal of policy makers for the analysis, monitoring and design of public policies on labor and production. Particularly, the analysis framework developed herein enables the analyst to delve into complex heterogeneities of productive interactions. For example, by identifying from which other distinct productive activities the labor force demanded by a particular industry is coming from, which in turn can shed light to some (hidden) pool of skills relating any particular pair of industries. To the best of our knowledge, we consider our contribution to be innovative in addressing practical and analytical issues posed by complex data like the high-granularity labor transitions, with potential as an analytical tool for labor and productive public policy design and evaluation.

The paper is organized as follows: the data and methods used for the analysis are presented in section 2. The results are presented in section 3. In section 4, we present conclusions.

## 2 Data and Methods

**Data.** We used data from the Argentinian Integrated Pension System (SIPA)<sup>3</sup>, provided by the Undersecretariat for Employment and Job Training at four digits of detail of the ISIC Rev. 3 of industrial activity classification code for the periods between 1996 and 2020. The Observatory of Business and Employment Dynamics (OEDE)<sup>4</sup> provided these data on private sector employment, received from affidavits submitted by employers to the Revenue Collection and Customs

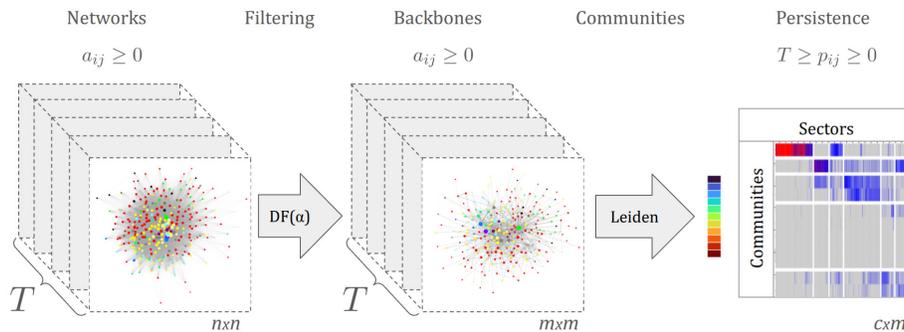
<sup>3</sup>Spanish: Sistema Integrado Previsional Argentino (SIPA).

<sup>4</sup>Spanish: Observatorio de Empleo y Dinámica Empresarial (OEDE).

Control agency. These administrative records express the relationship between the employer and its payroll and contain information on the economic and social characteristics of both actors. This information is processed and interannual transition matrices are built, recording the individual switches in employment between the different economic activities.

In this work, only the flows of inter-industrial employment transactions are used, which represent the aggregate of individuals who are employed in one period and in the next one are employed in another company belonging to a different activity sector. So far, the set of productive activities includes approximately 300 sectors or branches of activity at 4 digits organized in 14 sections (i.e.: letters).

**Methods.** From the transition matrices, we construct dense, directed, and weighted flow networks, which serve as the foundation for the subsequent analysis. To analyze these networks, we employ two complementary methods: the Disparity Filter (Serrano et al., 2009), which extracts the statistically significant backbone of the network by preserving the most relevant edges, and the Leiden algorithm (Traag et al., 2019), which is used to uncover the meso-structural organization and identify the main community structures within the network. Below, we briefly describe each of these methods and present the corresponding results from their implementation. The network analysis workflow follows a systematic process presented schematically in Figure 1.



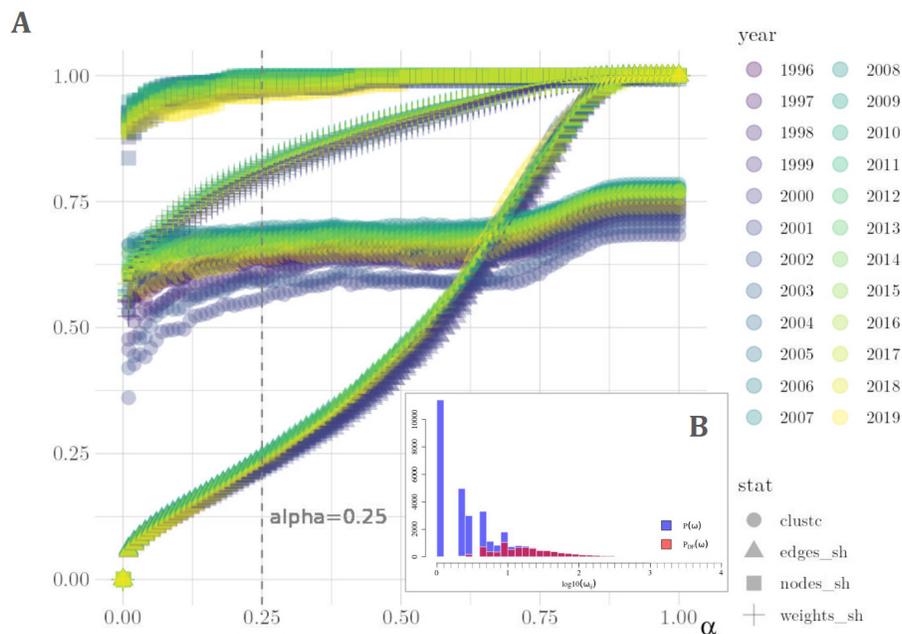
**Fig. 1.** Network analysis 4-step workflow. 1. Networks are constructed from observed inter-industry employment transitions data across the  $T = 24$  available yearly periods. 2. A filtering procedure using the  $DF$  (Serrano et al., 2009) is then applied to each network. With a significance parameter of  $\alpha = 0.25$ , this step extracts the network backbone, retaining only the most significant connections and filtering out less relevant noise. 3. The Leiden algorithm (Blondel et al., 2008) is applied to each backbone to perform community detection. This provides a functional representation of the network’s mesostructure by clustering connected sectors. 4. To evaluate community persistence a contingency table is calculated. This table is then organized using hierarchical clustering to find stable groups of sectors that frequently belong to the same community.

**Disparity Filter.** The original flow networks are dense and contain a large number of small flows, some of which may carry significant informational value. This is particularly important because emerging flow patterns often begin as low-volume transitions. If a global threshold were applied, these early signals could be excluded and thus remain undetected. Moreover, small flows may hold strategic relevance from a public policy perspective, especially when targeting vulnerable sectors or promoting new areas of economic activity. To address this challenge, we adopt the Disparity Filter ( $DF$ ) as a network reduction technique. Unlike global threshold methods, which indiscriminately remove all edges below a fixed value, the disparity filter evaluates the statistical significance of each edge relative to the node's local distribution of weights. This approach allows us to retain both large and small flows, as long as they are significant in context, thereby preserving structurally meaningful connections and enabling a more nuanced representation of the flow distribution within the network.

The Disparity Filter algorithm identifies the backbone structure of a weighted network without destroying its multi-scale nature. The algorithm operates like a statistical significance test for the weighted edges of a network: given a distribution of edge weights, the algorithm singles out those forming the backbone of the network, using the equivalent of a statistical significance threshold to identify them. In Figure 2 we plot the histogram of weights of the original network versus the weights that have been retained by the backbone after the filtering. The method locally identifies statistically relevant weight (links) heterogeneities, filters out the backbone of dominant connections that are not compatible with the significance level  $\alpha$  and preserves the structural properties that are important.

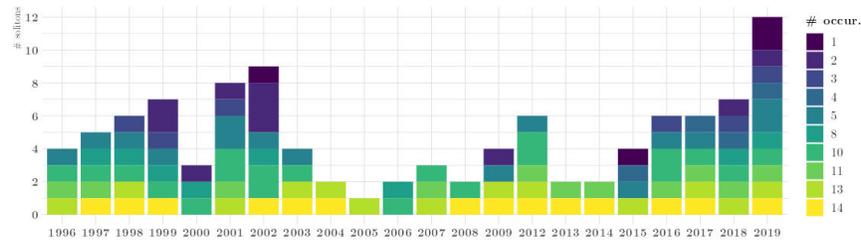
We explored different values for  $\alpha$  with respect to fundamental elements of the network, such as the shares of the number of nodes,  $N_B/N$ , the number of edges,  $E_B/E$ , the accumulated weights,  $W_B/W$ , and the average (local) clustering coefficient,  $\langle C_{Df} \rangle$  (see Figure 2.B). We selected  $\alpha = 0.25$  to carry out the analysis, such that it guarantees networks with almost all nodes, with few left as isolates, and despite the fact that  $DF$  reduces the number of edges significantly (almost to 24%), at the same time keeps almost all the weights that are significant, and a high clustering coefficient. Taking into account the results of the simulation in Figure 2, we can conclude that the backbones obtained for this values of  $\alpha$  for all periods are good for considering for further analysis because they retain a large proportion of nodes and weights, similar clustering of the original networks, and with a very small number of connections compared to the original network.

A more detailed view of the isolated sectors, those left out of the network backbones after applying  $DF$ , is provided in Figure 3. This visualization highlights the sectors that are consistently disconnected from the backbone across different time periods. Notably there are several sectors (marked in yellow) that appear as isolates in 14 out of the 24 periods analyzed, suggesting a persistent marginality in terms of intersectoral labor mobility. The evolution of these isolates can be directly linked to broader labor market dynamics and macroeconomic conditions. We can distinguish four main phases that help contextualize



**Fig. 2.** Disparity filter process and selection of significance parameter  $\alpha$ . A.  $\alpha$  and key network statistics. Shares of nodes kept in the backbone  $N_B/N$ , edges  $E_B/E$ , total weights  $W_B/W$ , and average (local) clustering coefficient  $\langle C_{DF} \rangle$  retained by the filter, for different values of  $\alpha$ . Based on this analysis,  $\alpha = 0.25$  was selected to extract the network backbones, for which, edges are reduced significantly to 24% (on average) of the original networks, while preserving almost all the nodes (with 4 isolates left, on average) and more than 75% of weights, including all the edges in the right tail of  $\omega$  (subfigure B) in the extracted backbones. B. Weights ( $\log_{10}$  flows) histogram of original network and extracted backbone ( $\alpha = 0.25$ ), for 2006. Weights  $\omega$  show a large proportion of connections concentrated in very small flows. While global thresholding (absolute range cutoff) would drastically remove all the information (flows) below the cutoff scale, the *DF* technique preserves statistically significant links weights. Here, the backbone retains transitions of 4 (lower bound) and more individuals, see  $\omega^{DF}$ .

the labor dynamics: 1996-2002 (a period of economic decline associated with the final phase of the Convertibility Plan and the onset of the 2001-2002 crisis); 2002-2011 (a recovery and post-crisis growth phase); 2012-2017 (a phase of macroeconomic stagnation with limited structural change); and 2018-2020 a period of sharp economic decline coinciding with a political transition and the COVID-19 pandemic). This exploration suggests that sectors isolates found in networks are not just statistical artifacts but can serve as indicators of structural segmentation in the economy. Their persistence or reappearance over time provides valuable insights into the resilience or fragility of labor connections and mobility under changing macroeconomic conditions.



**Fig. 3.** Occurrence of isolates (sectors that become disconnected from the network) in the backbone for each period after filtering with  $DF$  using  $\alpha = 0.25$ . Colors of the data points reveals the accumulated frequency of occurrence, highlighting which sectors are most consistently observed as isolates over time.

**Leiden algorithm.** After accounting for the persistence of isolated sectors, a natural step is to examine the presence of industries characterized by a higher frequency of employment exchanges within the group (community) than with industries in the rest of the network. This involves identifying clusters of sectors that exhibit intense internal labor mobility (job transitions between these sectors), which indicates the existence of underlying structural or functional linkages. This refers to the exploration of the network’s meso-structure, specifically by detecting communities that represent consistent patterns of labor transitions between sectors. Using community detection algorithms we aim to find sectoral clusters that are not only meaningful in their structure but also stable over time. This allows to tell the difference between core sectors that always stay in their communities and others that shift their affiliations. Persistent core sectors are reliable, central players, tightly connected (e.g. connected to manufacturing or finance). Shifting sectors are more dynamic players, might be part of one community in one period (e.g. connected to manufacturing) and then shift to another in a different period (connected to tech or services). This is why their affiliation is changing. Looking at these dynamics gives us valuable insight into how labor mobility is organized and how it evolves within the broader economic system.

We apply the Leiden algorithm (Traag et al., 2019), a node partitioning one, to backbone networks. This algorithm builds upon and improves the widely used Louvain method (Blondel et al., 2008), which is based on the modularity optimization framework. The Leiden algorithm introduces several enhancements over Louvain, including a more refined and accurate method for local movement of nodes, a refinement phase that guarantees well-connected communities, and an aggregation phase that improves convergence and ensure that the resulting partitions are both meaningful and stable. To ensure the stability and consistency of the resulting community structures, we perform 1,000 iterations of the algorithm on each extracted backbone network.

### 3 Results

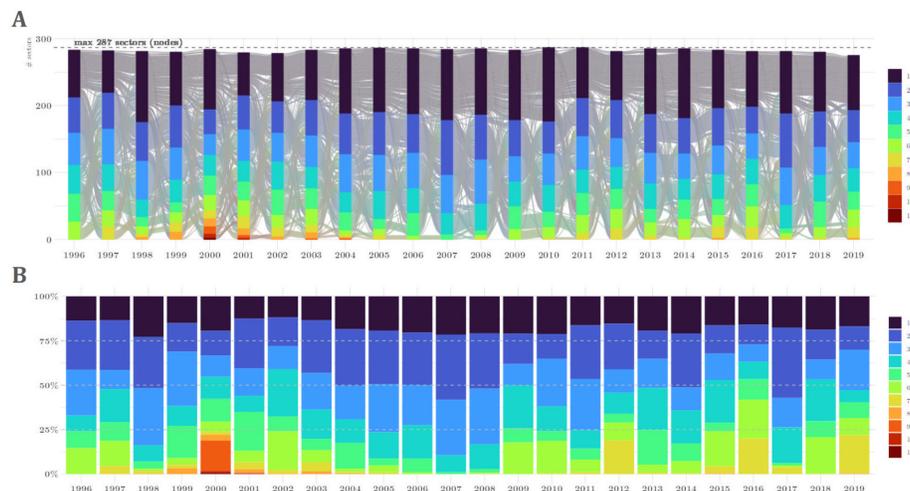
In this section, we present the key findings derived from the two analytical methods detailed previously in section 2. After extracting 24 yearly network backbones, each representing a comprehensive depiction of intersectoral labor flows, we applied the Leiden community detection algorithm. This analysis revealed that the community structures within the network are not only consistent but also remarkably stable over time. These communities highlight persistent, embedded patterns of sectoral dependencies and labor mobility, allowing us to effectively trace how the productive system's meso-structure evolves. This stability is a crucial insight, suggesting a robust underlying organization despite continuous labor mobility.

To effectively visualize these results, we use a Sankey diagram (see Figure 4.A). This powerful visualization is particularly well-suited for illustrating the transitions and persistence of sectoral aggregation (clusters) from one year to the next. The Sankey diagram clearly shows which communities remain cohesive and which sectors change their category, offering a dynamic view of the system's evolution. This allows us to see how the overall structure adapts or fragments in response to macroeconomic shifts. Observing these shifts can reveal emerging linkages and transformations in production structures, providing valuable insights into the evolving and dynamic nature of the economic landscape over time.

The core structure breaks down these networks into a maximum of eleven communities of economic activity sectors, organized in descending order according to their clustering stability during the re-labeling phase of the community detection algorithm. A higher number of communities emerges in years when macroeconomic downturns impacted labor market performance for example, during 1998-2004 period associated with the end of the Convertibility regime, and in 2015 and 2019 (years marked by political transitions to opposition parties). By definition, the communities derived from the backbone networks exclude isolated nodes, which themselves exhibit a positive correlation with the economic cycle, showing similar dynamics observed in community formation (see Figure 3).

Notably, the first two communities, ( $C1 - C2$ ), encompass between 40-65% of the sectors analyzed and, on average, account for over than 40% of total employment. Furthermore, the first four communities, ( $C1 - C4$ ), include between 66-97% of the sectors and together capture on average of 77% of total employment across nearly all years in the period under study (see Figure 4.B).

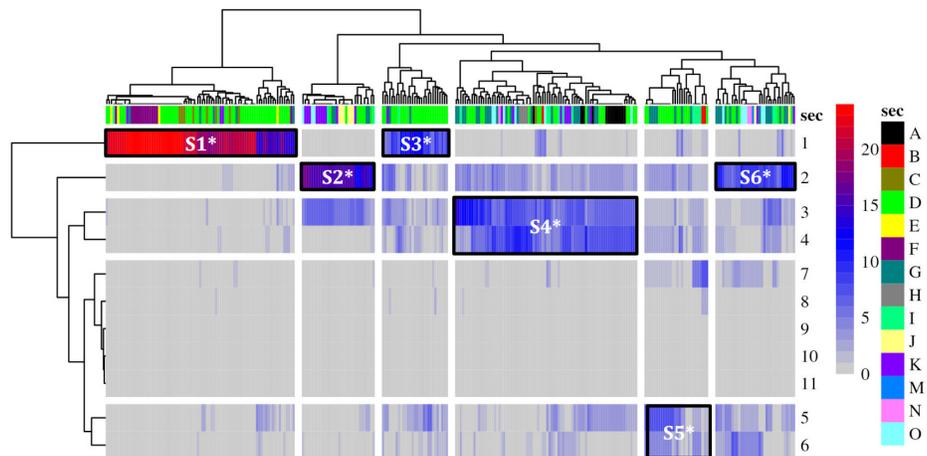
To evaluate the *persistence* of the extracted communities, we construct a matrix that records the community assignment of each sector across all time periods. This matrix is then analyzed using a heatmap, with rows (sectors) ordered by a hierarchical clustering algorithm employing complete linkage. As shown in Figure 5, the resulting dendrogram is cut into six groups ( $S1-S6$ ), reflecting natural clusters of sectors that consistently share similar community labels over time. We can appreciate an interesting structure reflecting a clear core-periphery pattern in sectoral organization. Two central groups emerge (cores), predominantly



**Fig. 4.** Communities. Color for each detected community (Leiden). A. Sankey diagram for flow dynamics on backbones of the 24 periods showing communities detected by Leiden algorithm after 1000 iterations (sectors on left axis). Communities numbered in decreasing order of stability with respect to the Leiden labeling process.  $C1$  and  $C2$  reflect the more stable cores, in the text referred respectively as “industrial” and “services” because of their main function or systemic role.  $C3 - C4$  represent “close periphery” functional groups, interacting closely with sectors of the cores, while  $C5 - C6$  represent “less-close periphery”, referring to sectors showing lesser interactions with the mentioned cores and close periphery sectors.  $C7 - C11$  are deemed “far periphery”, sectors showing low interactions with the other functional groups. Years with more macroeconomic instability (i.e.: 2000-2004, 2015, 2019) show more groups reflecting systemic stress and changes in recent patterns of interactions. Details in the text. B. Employment share by community (shares on left axis). Per sector average annual share of total employment.  $C1 - C2$  account on average for over than 40% of total employment, while the aggregate of  $C1 - C4$  capture about 77% of total employment across nearly all years in the whole period under study.

associated with communities  $C1$  and  $C2$ , while communities  $C3$  and  $C4$  form the periphery. In contrast, communities  $C5$  and  $C6$  demonstrate lower persistence, and communities  $C7$  through  $C11$  tend to be small, functioning more as residual groups in the community detection phase. These latter communities show weak identification and limited temporal stability in their sectoral composition.

The first and most relevant community,  $C1$ , referred to as the “industrial” core, accounts for an average of 18% of total employment and stands out as the most stable in terms of sectoral membership over time. As illustrated in Figure 5,  $C1$  is primarily composed of activities from cluster  $S1^*$ , which include mining and extractive activities, manufacturing of metals, machinery and tools, water and electricity infrastructure and services, construction, and associated transport and commerce services. It also incorporates sectors from cluster  $S3^*$ ,



**Fig. 5.** Community persistence. Heatmap representation of co-occurrence of sectors (columns) in each community (rows), both sorted using a hierarchical clustering algorithm with complete linkage. Intensity scale red-blue-gray (max. 24, min. 0 periods). “Sec” colors refers to the letter ISIC Rev 3 classification code of the 4 digits sectors used. *Vertical tree (sectors)*, is cut into 6 groups of sectors showing more persistence (more density in their co-occurrence) in defined community labels (rows), each group referred as  $S1 - S6$ . Selected sectors with major contribution marked with  $S1^* - S6^*$ . *Horizontal tree (communities)*, cut into 5 groups representing “levels” of persistence of their members, explained in the text as cores  $C1$  and  $C2$ , followed by the “close periphery”  $C3 - C4$ , the “less-close periphery”  $C5 - C6$ , and the lesser stable (with respect to Leiden labeling process) “far periphery”  $C7 - C11$  groups.

including manufacturing of motor vehicles, furniture, plastic, paper, and other machinery.

Community  $C2$ , referred to as the “services” core, is primarily composed of activities from cluster  $S2^*$  and cluster  $S6^*$ . Cluster  $S2^*$  includes sectors such as legal, merchandising, news and related services, telecommunication infrastructure and services, financial and computing services (v.g.: Information Technology services), publication and printing services, radio and television services, and travel-related services. Cluster  $S6$  encompasses insurance, education, health, social work, aerial transportation, motor vehicles sale services, as well as pharmaceutical manufacturing and associated manufacturing and services.

Communities  $C3$  and  $C4$  can be classified as forming a “close periphery” within the overall network structure. These communities consist of sectors that demonstrate intermediate levels of persistence, typically appearing in approximately one-third of the periods analyzed (8 out of 24). While not as consistently present as the core communities ( $C1$  and  $C2$ ), they nonetheless represent a recurring and structurally relevant component of the system. The sectors comprising these communities are mainly drawn from cluster  $S4^*$  and are characterized by a mix of service-oriented and primary economic activities: tourism, entertainment,

retail, security, cleaning, real estate services, as well as agricultural and forestry sector activities, with associated services. The positioning of these communities as “close periphery” highlights their intermediate role in the network: while not central in terms of connectivity or persistence, they are nonetheless important conduits of labor mobility and economic interaction, particularly in periods of economic transition or restructuring.

Communities  $C5$  and  $C6$  can be classified as a “less-close periphery”, comprising sectors with lower temporal persistence across the observed periods. These communities primarily include activities from cluster  $S5^*$ , such as: textile, shoe and footwear manufacturing and associated commercialization and repair services, cargo and aquatic transportation, and phishing. In addition, they incorporate sectors from cluster  $S6^*$ , such as: optics and furniture manufacturing and associated services. In contrast, communities  $C7$  through  $C11$ , represent what can be considered the “far periphery” of the system. These groups do not contain sectors with consistently recurring membership across periods and display high variability and low coherence. Their emergence is likely the result of residual partitioning during community detection. However, while less stable and harder to be interpreted in terms of sectoral function and transitional labor dynamics, their identification is nonetheless important, as it highlights the existence of dynamic areas of economy that might require different tools for the analysis.

## 4 Conclusions

In this paper we present the analysis of the structural characteristics of sectoral interdependencies, their evolution, and the meso-structures that emerge from these dynamic patterns in the Argentine interindustrial labor market. We use administrative data from the Undersecretariat for Employment and Job Training, at the 4-digits level of classification of the ISIC Rev.3 of Industrial classification system. Covering the period from 1996 to 2020, this dataset offers a rich and largely underutilized resource for economic analysis, unexplored at this level of high granularity.

We introduce a systematic approach to analyze these high granular labor data by combining two complementary methods: the disparity filter and a community detection algorithm. Our objective is to investigate sector-specific labor mobility patterns, the formation and transformation of sectoral clusters, and the persistence of these structures across different time periods. The methodology integrates network filtering technique, which extracts backbone structures based on statistical significance with meso-structural analysis to identify key clusters of economic activities. The results provide novel insights into the organization of the productive system, revealing persistent interindustry connectivity and clearly defined community structures within the economic networks.

We identified persistent communities organized within a core-periphery structure. Two stable core communities emerged: the first predominantly consisting of industrial activities and associated services, and the second composed mainly

of specialized services along with certain manufacturing activities. Additionally, we detected four communities functioning as a “close periphery” around these cores, characterized by lower persistence and grouping diverse subsets of activities. Beyond these, we observed other communities representing less connected sectors, which we classify as the “far periphery”.

These findings are promising for two main reasons. First, the observed persistence in the connectivity structure of productive activities through labor flows brings new insights, provides a deeper understanding of the economic system that complements and challenges existing knowledge derived from more aggregated data analyses. While traditional labor economics, macroeconomics, and real sector studies often rely on broader sectoral classifications and overlook the finer details, our approach reveals stable and intricate patterns of interdependence at a much higher level of granularity. This allows for a more precise examination of how specific sectors interact over time, how labor mobility shapes the productive structure, and how these relationships evolve in response to economic cycles and shocks. Such detailed insights can enhance the accuracy of economic models, improve the interpretation of sectoral dynamics, and ultimately contribute to more informed policy design targeted at specific industries or clusters within the economy.

Second, our work contributes methodologically by introducing a systematic analytical framework specifically designed to handle highly disaggregated economic data. Traditional economic analyses often rely on aggregated data due to computational constraints or data limitations, which can obscure important sector-specific dynamics and interdependencies. Our approach integrates advanced network techniques, enabling the extraction of meaningful meso-structures and their analysis from complex, large-scale datasets. This framework not only enhances the clarity and interpretability of high-resolution economic information but also provides a versatile toolbox applicable across different contexts and datasets. We believe that this methodological approach holds considerable potential to advance the analysis of economic systems by allowing researchers and policymakers to explore detailed interactions within the economy, identify emerging trends, and tailor interventions more precisely to the needs of specific sectors or clusters.

However, as mentioned in the introduction, the complexity of working with high granularity data poses challenges regarding its application to public policies. From the point of view of the technology transference for such uses, the adoption of this approach requires certain minimum knowledge of network science to understand the technical tools involved and skills to communicate and interpret the results. Nevertheless, network science approaches have now proliferated in their uses and applications, along with the increased availability of computational means and data science positions, both required to develop complex data analysis workflows. These factors appear favorable to the implementation and use of methodologies such as those developed here.

## References

- Blondel, V. D., Guillaume, J. L., Lambiotte, R., & Lefebvre, E. (2008). Fast unfolding of communities in large networks. *J. Stat. Mech.*, *P10008*, 12.
- Causa, O., Luu, N., & Abendschein, M. (2021). *Labour market transitions across oecd countries: Stylised facts* (tech. rep.). OECD. <https://doi.org/10.1787/62c85872-en>
- De Raco, S., & Semeshenko, V. (2019a). Labor mobility and industrial space in Argentina. *Journal of Dynamics & Games*, *6*(2), 107. <https://doi.org/10.3934/jdg.2019008>
- De Raco, S., & Semeshenko, V. (2019b). The network structure of inter-industry labor mobility in Argentina. *6th Regulating for Decent Work Conference*.
- De Raco, S., & Semeshenko, V. (2024). Identificación de diferencias y similitudes estructurales de las redes interindustriales del empleo de argentina. *Electronic Journal of SADIO (EJS)*, *23*, 200–220.
- Itzkovitz, S., Levitt, R., Kashtan, N., Milo, R., Itzkovitz, M., & Alon, U. (2005). Coarse-graining and self-dissimilarity of complex networks. *Phys. Rev E*, *71*, 016127.
- Serrano, A. M., Boguñá, M., & Vespignani, A. (2009). Extracting the multiscale backbone of complex weighted networks. *PNAS*, *106*, 6483–6488.
- Traag, V., Waltman, L., & van Eck, N. (2019). From louvain to leiden: Guaranteeing well-connected communities. *Sci Rep*, *9*, 5233.