AN EMPIRICAL TYPOLOGY OF TRAVEL-TO-WORK AREAS IN ARGENTINA BASED ON SECTORAL PROFILES OF TERRITORIAL COAGGLOMERATION[1]

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1. Introduction

Spatial location of economic activities is a central aspect for the analysis of a country's productive structure and the design of productive development policies. In developed countries there is a large number of investigations that describe regional specialization profiles within a single country and explain the observed patterns based on different factors, such as the existence of economies of scale, the endowment of natural resources or fiscal incentives. The specialization profile is also typically used as an input to explain the economic performance of the regions in terms of employment growth, productivity or value added (Frenken *et al*., 2007; Bishop and Gripaios, 2010; van Oort *et al.*, 2015; Cortinovis and van Oort, 2015). Besides, the evolution of regional specialization profiles can be used to illustrate or describe processes of structural change.

In Latin America, a set of studies calculate and analyze the type of regional specialization, linking it with the degree of diversification and regional development in Uruguay, Chile, Paraguay and El Salvador (Rodríguez Miranda *et al*., 2019). In Argentina some contributions quantify and describe the type of productive specialization at the regional level (provinces), either for manufacturing (Jaramillo *et al*., 2017) or for all sectors (Keogan *et al*., 2020). Other studies link the type of specialization of Travel-to-Work Areas[2] (TWA) with productive diversity (Rotondo *et al*., forthcoming) or with their ability to recover from crises (Otegui Banno *et al*., 2019).

All these contributions -both for developed and developing countries- use basic specialization measures (relative indices[3]) that usually have several limitations. On the one hand, calculations with a low level of sectoral disaggregation do not allow distinguishing specializations that may be qualitatively different within the same category, such as regions specialized in "trade and services". On the other hand, if the level of disaggregation is high, a large number of specializations are identified in each region, which difficults a clear exposition of results, and

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[1] We thank the Employment and Business Dynamics Observatory (EBDO/OEDE), under the Ministry of Production and Labor, for facilitating access to the database and for the valuable suggestions to this preliminary version. We are also grateful to Santiago Otegui Banno and Manuela Coppola Goyhenespe for research assistance.

[2] A Travel-to-Work Area is a geographical area which is delimited by daily displacements (the so-called pendulum movements) that people make to go to (and back from) their work (Borello, 2002).

[3] The relative specialization index measures the proportion of employment or value added in a certain activity in a region over the proportion of employment or value added that the same activity has in the whole country. The region will be specialized in those activities with indexes higher than one.

into account the interdependencies between activities. That is, the fact that certain activities are frequently located near (or developed alongside) others, such as the set of "heavy industries" or activities that are part of the same production network or value chain, is ignored.

We propose to overcome these limitations by using a combination of multivariate analysis techniques. First, we empirically build a set of sectoral profiles that group economic activities according to their proximity or joint development, without taking into account *ad-hoc* classifications. Unlike the idea of value chains or production networks, these sectoral co-agglomeration profiles show what kind of activities tend to be developed jointly in a specific territory, and do not necessarily indicate the existence of backward or forward linkages. Secondly, we use these sectoral profiles to classify the main 85 Travel-to-Work Areas (TWA) in Argentina, thus defining an empirical typology based on their patterns of productive specialization. Our results indicate that in some TWA a single set of co-agglomerated sectors stands out, while in others several co-agglomeration profiles coexist.

2. Literature Review

The pattern of specialization can be explained by various approaches. For example, according to the Ricardian model and the Heckscher-Ohlin model, a country's specialization is determined by its comparative advantages. They are explained, respectively, by productivity differentials or by the relative abundance of resources and the relative intensity with which they are used. However, Capello (2007) argues that within a country the pattern of specialization is rather explained by the absolute advantages of each region. They mainly depend on the availability of natural resources, the level of real wages and the degree of technological development (Shaikh, 2009). The first factor explains regional specialization in primary activities (oil, mining, agriculture, livestock, forestry, etc.) and related industries or services. The second factor explains the specialization of regions with lower wages in (unskilled) labor-intensive activities. The last factor, emphasized by evolutionary theory, explains specialization in industries or services according to their technological content. Since technology is not equally accessible to all regions, only a few can specialize in activities that require a certain level of technological capabilities. These capabilities are generated in the productive process itself -they depend on production and investment- and are created slowly due to the tacit nature of the knowledge incorporated in them (Dosi *et al*., 1990).

The New Economic Geography (NEG), on the other hand, explains how population and economic activity are distributed within a country. According to this approach, internal economies of scale and other centrifugal forces attract companies and individuals and explain the concentration of economic activity in central regions, while centripetal forces (immobile factors such as natural resources, competition between companies and other external diseconomies) explain the location of economic activity in peripheral regions (Krugman, 1991). Thus, NEG explains the development of highly developed urban centers and less developed (rural or agricultural) regions. It can also account for regional inequalities by considering capital and skilled labor as mobile factors and unskilled labor as immobile (Krugman, 1991). By integrating the evolutionary and NEG approaches, we can expect that more developed regions -i.e. more densely populated regions with higher capabilities- will attract companies whose

production is subject to scale economies and requires rapid and effective transmission of knowledge and information.

Another aspect of interest is the interrelation between economic activities. Since the middle of the last century, the pioneering contributions of Leontief, Perroux and Hirschman showed the importance of the interrelationship between sectors and between firms. From these seminal contributions, a set of articles have analyzed the geographical space in which firms or sectors co-localize as well as the type of relationships generated between them, thus shaping the notions of linkages, value chains or production networks (ECLAC, 2015). The approaches that explain the pattern of specialization may also explain the co-location of activities. For example, regions where labor is abundant and cheap will specialize in many different labor-intensive activities. Likewise, large regions will specialize in many different scale-intensive activities.

The concept of Product Space (Hausmann and Hidalgo, 2010) also explains the co-agglomeration of economic activities. The production of complex goods and services requires numerous capacities (productive, institutional, technological), so that only those regions with these capacities can produce certain products. This may explain the specialization of a region in seemingly unrelated activities, such as software and pharmaceutical products. Additionally, the capacities developed for the production of goods located in the periphery of the Product Space may only be applicable to a limited range of other products, while the capacities developed for the production of other goods (located in the center of the Product Space) can be used for the elaboration of many others. This may explain that, in Argentina, regions with the highest capabilities have a greater number of specializations, while lagging regions are highly specialized in a few branches, usually related to natural resources (Jaramillo *et al*., 2017; Keogan *et al*., 2020).

Regarding the empirical background, our contribution is located at a point of confluence between studies that, on the one hand, analyze the sectoral distribution of employment and the regional productive specialization in Argentina and, on the other, try to define regional typologies. Within the first group, the Permanent Observatory of the Argentinean Pymis (1999; 2001) calculates sectoral specialization at the department level, based on census data of small and medium industrial companies for the years 1984 and 1994. Mazorra and Beccaria (2007) evaluate the sectoral productive specialization in some TWAs of Buenos Aires Province, while Rojo and Rotondo (2006) focus on the municipalities of Greater Buenos Aires. In contrast, Jaramillo *et al*. (2017) and Keogan *et al*. (2020) cover the entire national territory and all firms (not only small and medium-sized industrial companies). As mentioned, all of them use relative specialization indices (2 and/or 4 digits of the ISIC classification) and analyze the first specializations of each region.

In relation to the second group of studies, Nuñez Miñana (1972) develops an empirical typology of regions (provinces) which has been a reference point in the literature, for example, to compare the evolution over time of the classifications obtained. In line with the methodology adopted in this paper, Cicowiez (2003) uses Principal Components Analysis to prepare a ranking of provinces based on a series of synthetic socioeconomic indicators. On the other hand, Figueras *et al*. (2009) use an average-linkage hierarchical clustering to obtain typologies applicable to different years (1970, 1991 and 2001). UNDP (2002) combines

conceptual and empirical typologies, and classifies provinces into seven groups according to competitiveness indicators, characteristics of the productive structure and the Expanded Human Development Index. As can be seen, the development of regional typologies has usually been carried out at the provincial level, largely due to the greater availability of data.

Finally, it is worth noting the studies of ECLAC (2015) and Borello *et al*. (2016), which divide the country into 55 micro-regions and then, using Ward's hierarchical clustering method, classify them and define an empirical typology. To do this, they use data at the micro-region level referring to the number of companies, percentage of export firms, average salaries and type of productive specialization. The latter is approximated through the participation of agricultural-based and manufacturing-based chains in the Hirschman-Herfindahl concentration index. Although this measure of specialization has an important conceptual richness, since it encompasses the set of activities that are part of the same production network, it only distinguishes two very aggregate types of specialization.

3. Data and Method

As usual, we analyze productive specialization by using employment data. For Argentina, these data are more reliable and have greater temporal and regional coverage than alternative indicators such as value added. Data come from the information system of Travel-to-Work Areas, elaborated by the Employment and Business Dynamics Observatory (EBDO), which depends from the Ministry of Production and Labor. This database includes the total of salaried employment registered in the private sector over the main 85 TWAs in the country (this accounts for 86% of the population and 95% of private registered employment). The data is disaggregated into 24 sectors (primary products, manufacturing, commerce and services). In order to prevent the results from being affected by short-term changes, we work with average information for the 2010-2015 period.

Regarding the methodology, we first build sectoral profiles (that take into account the co-agglomeration of activities) by using Principal Components Analysis (PCA). Given the weight of the 24 sectors in the employment of each TWA, the PCA allows us to synthesize the information or variability shared by variables that are highly correlated in a smaller number of common dimensions. Subsequently, we use the estimated factor scores to perform a Cluster Analysis of the 85 TWAs and, in this way, we build a TWA typology based on their productive patterns. The Cluster Analysis seeks to maximize both the homogeneity between the cases included within the same cluster and the heterogeneity between clusters, which makes it possible to distinguish the particularities of each group. In line with the empirical literature, we use Ward's hierarchical method and, to define the number of clusters, we analyze the changes in heterogeneity at each stage, in this case, the within-cluster error sum of squares (Hair *et al*., 2010).

As both the PCA and Cluster Analysis are sensitive to changes in scale, variables are usually standardized as Z scores (Johnson and Wichern, 2008; Hair *et al*., 2010). The components estimated from the PCA, which are the basis for the subsequent Cluster Analysis, are already standardized by default. Another notable property of the components is that they are not correlated with each other, which is desirable for Cluster Analysis.

4. Results

4.1. Sectoral profiles and TWA typology

Based on the exploration of the results and some preliminary statistical tests such as the Bartlett's test of sphericity and the Kaiser-Meyer-Olkin (KMO) measure of sample adequacy, we divide the original 24 sectors into two subgroups, and we then perform the PCA in each one of them: on the one hand, 9 primary and manufacturing branches; and on the other hand, 15 branches related to service sectors. To define how many components to retain, we apply the Kaiser -or eigenvalue- criterion, which consists of maintaining all principal components whose eigenvalues are greater than one. Thus, from the first subgroup we extract 3 components and from the second one, another 5. For its interpretation, we analyze the factor loadings (the correlation of the different variables with each principal component), after applying the VARIMAX orthogonal rotation (Hair *et al*., 2010).

PCA allows us to identify the following sectoral profiles (Table 1):

1. Agro-industries: agricultural activities, food industry and wood and paper (negative values in this component indicate extractive profiles);
2. Light industries: textile, clothing and leather;
3. Heavy industries: automotive, metalworking and chemical;
4. Urban services: health, education, commerce, community, financial and other services;
5. Tourism: hotels, cultural and real estate services;
6. Software and business services;
7. Construction;
8. Logistic services.

Table 1: Sectoral profiles defined from PCA

	Heavy industries	**Agro-industy**	**Light industry**
	Comp. 1	Comp. 2	Comp. 3
Agriculture, hunting, forestry and fishing	-0,39	0,62	-0,04
Mining and quarrying	-0,25	-0,57	-0,17
Food products	0,00	0,48	-0,46
Textile, clothing and leather	-0,03	0,03	0,82
Wood and paper	0,04	0,54	0,41
Chemical	0,74	-0,17	0,17
Metalworking	0,76	0,05	-0,12
Automotive	0,86	-0,03	-0,04
Other manufacturing	0,20	-0,54	0,21

	Urban services	**Tourism**	**Software and business ss**	**Construction**	**Logistic services**
	Comp. 4	Comp. 5	Comp. 6	Comp. 7	Comp. 8
Construction	0,17	-0,07	0,04	0,87	0,06
Wholesale trade	0,12	-0,33	-0,12	-0,67	0,01
Retail trade	0,62	0,47	-0,22	0,22	-0,13
Hotels	0,02	0,88	0,02	0,03	-0,02
Transport	-0,02	0,21	0,18	0,09	0,80
Community ss	0,54	0,17	0,51	0,14	-0,09
Financial ss	0,50	-0,33	0,19	0,06	0,12
Real state ss	0,04	0,57	0,52	-0,09	-0,32
Software	0,17	-0,10	0,83	-0,07	0,15
Business ss	0,10	0,00	0,70	0,45	0,26
Education	0,57	0,14	0,20	-0,39	0,00
Health	0,81	-0,07	0,22	0,09	0,11
Other personal ss	0,03	0,39	-0,12	0,02	-0,56
Cultural ss	0,15	0,79	-0,07	0,03	0,29
Other ss	0,76	0,15	0,09	0,04	-0,09

Source: authors. Note: highest factor loads are highlighted

The final typology of TWA we proposed is composed by 11 clusters (Table 2). The details of their conformation are described in Annex 1, while Annex 2 shows the distribution of the 85 TWAs in each cluster and their respective values in the sectoral components. In order to verify that these 11 clusters do indeed differ from each other, we turn to the analysis of variance (ANOVA, Annex 3). We show that in 7 of the 8 components the means of the different clusters are significantly different from each other[4].

Table 2 shows the means of each sectoral component in the 11 clusters that make up our TWA typology. Since these are Z scores, the values show how many standard deviations from the general average (zero) are the average of the TWAs that compose each cluster. The main relative specializations of each cluster are shaded in green. For example, both clusters 1 and 4 show a greater degree of specialization (in relation to all the TWAs) in heavy industries and business services, but comparatively the first cluster is strongly specialized in services and the other one in manufacturing. This is reflected in the order in which both activities appear in the name assigned to each cluster.

Table 2. Average of sectoral components in each (type of) cluster

Cluster	TWA typology	Sectorial components								Numer of TWA
		Heavy industries	Agro-industy and mining	Light industry	Urban services	Tourism	Software and business ss	Construction	Logistics	
1	Software, business ss and heavy industry	1,0	-0,5	0,1	0,0	-0,2	3,5	-0,2	0,5	3
2	Business services	-0,2	-0,2	-0,2	0,3	0,0	1,4	-0,3	0,5	5
3	Urban services and construction	-0,5	-0,4	0,1	1,4	-0,1	-0,2	0,7	0,1	15
4	Heavy industries and supporting services	2,2	-0,3	0,2	-0,9	-0,2	0,7	0,6	0,3	6
5	Agro industries and supporting industries	1,4	0,5	-0,3	-0,3	-0,6	-0,4	-1,1	-0,2	9
6	Food products and urban services	-0,1	0,3	-0,2	0,4	-0,6	-0,2	-1,0	-0,2	8
7	Tourism and related activities	-0,6	-0,3	-0,1	-0,2	2,2	-0,4	-0,1	0,0	10
8	Primary sector and food products	-0,6	1,1	-0,5	-0,8	-0,4	-0,5	0,0	-0,1	17
9	Light industry	-0,3	0,8	3,1	-0,3	-0,3	-0,2	0,1	-0,6	4
10	Extractive activities and construction	-1,1	**-1,8**	-0,8	-0,1	-0,2	0,2	1,6	0,0	4
11	Oter industries and extractive activities	0,1	**-1,9**	0,7	-0,4	0,2	-0,1	0,6	0,5	4

Source: authors.

As the last column of Table 2 shows, the most numerous regional productive patterns in Argentina are linked to agriculture and related industries, since clusters 5, 6 and 8 account for 34 of the 85 TWAs. Another large cluster is “urban services” (cluster 3), which includes 14 of the 24 provincial capital cities. Continuing with services, another 10 TWAs have a touristic pattern, while in 5 TWAs (cluster 2) computer and business services are the outstanding aspect.

As regards the rest of manufacturing, as we mentioned before, in cluster 4 heavy industries predominate over business services, while in 1 the opposite occurs. Heavy industries are also present in the aforementioned cluster 5, presumably as support for the primary and agro-

[4] The only non-significant result (logistics services component), owes to the union and simplification of the two touristic TWA clusters in a single group, since one of them had a greater weight of transport services than the other one (see details in Annex 2).

industrial activity of the TWAs. A similar coexistence occurs in cluster 9, where although light industries (textiles, clothing, leather, etc.) stand out, there is also agro-industrial activity in some of these clusters. Finally, the development of "other industries", together with some extractive activities (mining and hydrocarbons), is evidenced in cluster 11, while the TWAs with the highest extractive profile are found in cluster 10.

Although the proposed typology overcomes some limitations of traditional specialization indexes, it also presents some problems, mainly related to the type of data employed. Our calculations are based on data of total salaried employment registered in private companies, ignoring public organizations, non-salaried employment and informal employment. It should be noted that the patterns of specialization thus formed may differ from others calculated from value-added data, or from the total of workers (formal and informal). This could undoubtedly modify the proposed specialization for some TWAs, since not all branches use labour factor with the same intensity. In addition, informal employment is not distributed homogeneously in all economic activities. However, in Argentina there are no official, continuous, updated and disaggregated data on added value or total employment by province. Additionally, the typology has been built based on the distribution of employment in 24 sectors. Greater sectoral disaggregation would allow accounting for a greater number of profiles, especially in the primary and manufacturing sectors.

4.2 Comparison between typologies

The proposed typology can be contrasted with other previous classifications of Argentinean TWAs, such as the one carried out and used by the EBDO/OEDE team (Rotondo *et al*., forthcoming), which consists in taking the first specialization that arises from the calculation of the traditional relative specialization index (see footnote 3). According to Table 5, the crossings between the two classifications are relatively coincident for a good number of TWAs around agro and agroindustrial, extractive, industrial, commerce and services and tourism activities. However, there are also differences between taxonomies, especially among the TWAs classified by EBDO as agricultural and agroindustrial. In our typology, 12 of these TWAs show a pattern of specialization focused on different branches of services, while another 6 lean towards light industries, other industries and extractive activities. We also observe that the proposed typology provides a greater disaggregation in industrial, commercial and service activities.

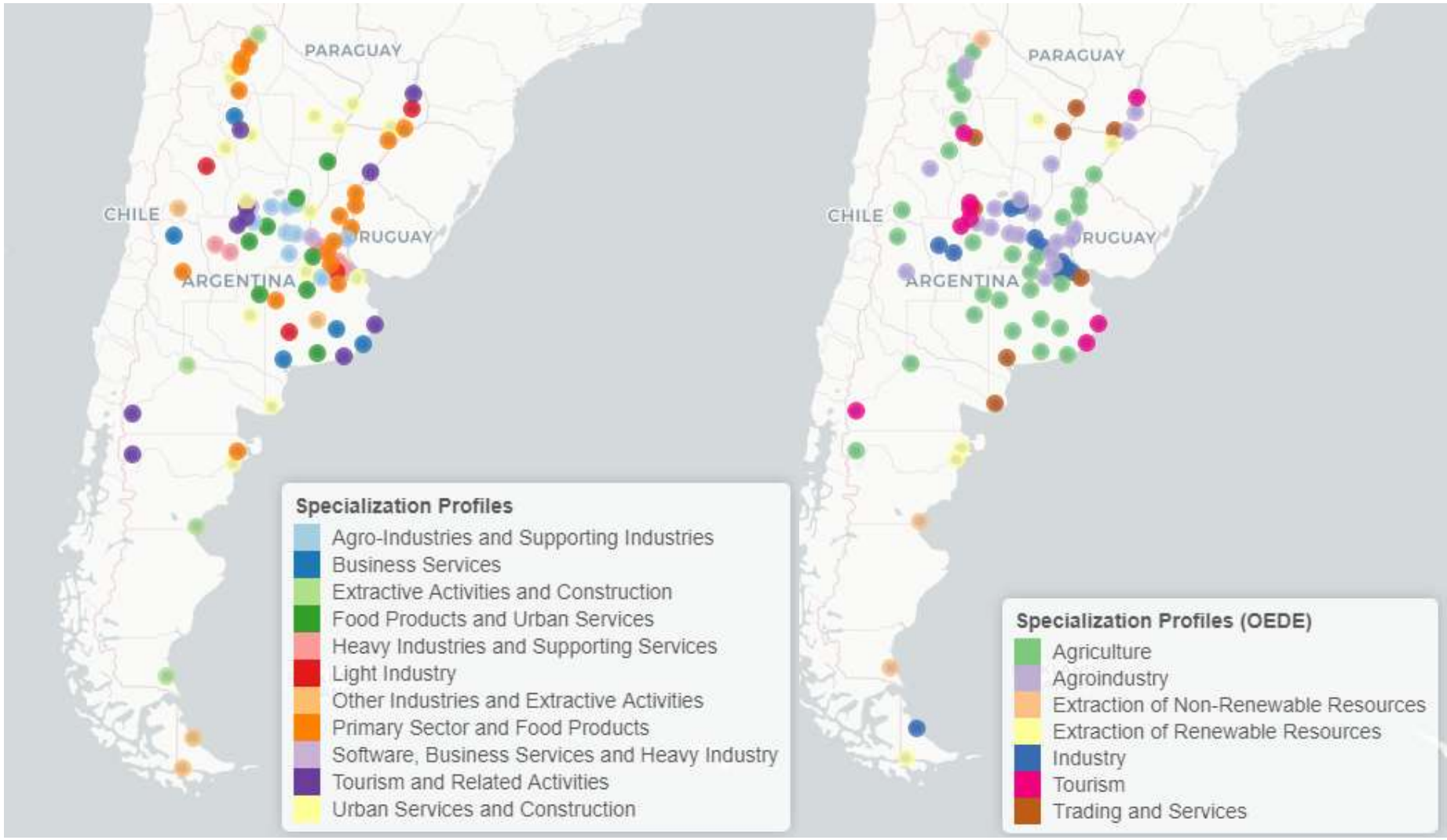
Table 5: Comparison between TWA classifications

		TWA typology of productive patterns										Total
		Primary sector & food products	Food products & urban services	Agro industries & supporting industries	Extractive activities & construction	Other industries & extractive activities	Light industry	Heavy ind. & supporting services	Software, business ss & heavy ind.	Business services	Urban services & construction	Tourism & related activities	
Traditional classification (Rotondo et al.)	Primary secor	7	5	1	1	2	1			3	5	3	28
	Agro-industries	8	3	6			2				1		20
	Extractive (renewable)	2				1					2		5
	Extractive (non-renewable)				3								3
	Manufacturing	2				1	1	6	2				12
	Commerce and services								1	1	6		8
	Tourism									1	1	7	9
Total		19	8	7	4	4	4	6	3	5	15	10	85

Source: authors

Figure 1 displays these differences on a map. An initial analysis shows some preliminary results. Firstly, we can see that agricultural TWAs (according to EBDO classification) can be actually divided into to two different profiles spatially distinguishable: TWAs that combine food products and urban services, shaded in green, located in the center of the country (Buenos Aires province, Córdoba and Santa Fe) and TWA that combine primary sectors with food product elaboration, shaded in orange, located in eastern and north-western provinces. Secondly, our typology captures better the unique profile of the capital cities of the provinces (mainly included in the cluster of Urban services and construction). Thirdly, like EBDO classification, the proposed typology also shows a heavy industries corridor from Greater Buenos Aires to Rosario (Santa Fe), Córdoba and San Luis, but together with the development of business services. Interestingly, the typology also captures some TWAs outside this area with software and business services profile (such as Mendoza, Tucumán or the hinterland of Buenos Aires province) that are ignored by EBDO classification. Finally, our typology enables to distinguish a higher degree of productive diversity in Buenos Aires Province (and a lower degree of diversity in Chaco or Tierra del Fuego).

Figure 1: TWA map by specialization profiles (cluster typology vs. traditional specialization index)



The greater disaggregation of our typology is also valuable, for example, to analyze the evolution of the total employment at the TWA level in recent years. Table 6 shows the average percentage of employment variation in the TWAs included in each cluster in the 2010-2015 period (coinciding with the data used to define our typology) and in 2015-2017 (latest data published by OEDE, matching with the change in the National government). Obviously, the periods cover a different number of years and also different realities regarding the evolution of formal private employment. Beyond these differences, the TWA groups are sorted or ranked from the highest employment growth rates to the lowest and, in addition, the relative position changes between the rankings of each period are plotted with coloured arrows (highlighting with green and red the movements of more than one position).

Table 6: Evolution of employment according to TWA classifications

Typology based on cluster analysis

	2010-2015		2015-2017
Other industries and extractive activities	20,84	Food products and urban services	3,07
Extractive activities and construction	14,98	Business services	3,03
Urban services and construction	12,72	Urban services and construction	1,87
Tourism and related activities	12,53	Tourism and related activities	1,31
Business services	9,59	Heavy industries and supporting services	1,23
Heavy industries and supporting services	9,38	Agro industries and supporting industries	1,19
Software, business ss and heavy industry	8,46	Primary sector and food products	1,14
Primary sector and food products	7,42	Software, business ss and heavy industry	0,85
Food products and urban services	7,37	Other industries and extractive activities	-2,02
Agro industries and supporting industries	5,25	Light industry	-2,77
Light industry	1,73	Extractive activities and construction	-7,37

Traditional classification (EBDO/OEDE)

	2010-2015		2015-2017
Commerce and services	15,87	Tourism	2,84
Tourism	15,77	Extractive (renewable)	2,11
Extractive (renewable)	12,37	Commerce and services	1,59
Extractive (non-renewable)	11,50	Primary secor	1,06
Manufacturing	10,50	Manufacturing	0,93
Agro-industries	9,08	Agro-industries	0,63
Primary secor	5,49	Extractive (non-renewable)	-9,98

Source: authors

Thus, according to the OEDE classification, the most dynamic TWAs between 2010 and 2015 are the ones specialized in commerce and services. However, a greater disaggregation shows that TWAs specialized in urban services and construction are more dynamic than the ones specialized in business services or software. Likewise, our typology shows some heterogeneity within manufacturing: employment in TWAs specialized in heavy industries grew substantially more than employment of TWAs devoted to light industry.

When comparing 2010-2015 and 2015-2017 we can see more differences. For example, taking the traditional classification, the group of agricultural TWAs is the one that climbs more positions from one period to another, while the typology proposed here makes it possible to distinguish that the most dynamic TWAs are not those of agricultural type (or strictly primary),

but those ones that combine agribusiness with urban services or with support industries. Likewise, the classification that emerges from the traditional specialization index indicates that the TWAs specialized in non-renewable extractive activities and in commerce and services are the ones that descend the most in the ranking. Although the first fact is also observed in the alternative classification, we can see that our typology allows to distinguish different dynamics among different types of services (ascending for business services, stable for urban services and construction, and slightly descending for business services that are developed in conjunction with heavy industry).

5. Concluding remarks

In this paper we build an empirical typology that allows to classify the main 85 Travel-to-Work Areas of Argentina based on their patterns of productive specialization. We use a combination of multivariate analysis techniques. First, we empirically obtain a set of sectoral profiles that group the economic activities according to their proximity or joint development, without resorting to previous or *ad-hoc* classifications. Secondly, we use these sectoral profiles to identify 11 groups or clusters of TWA: a) agricultural and food products; b) food products and urban services; c) agro industries and support industries; d) extractive and construction; e) other industries and extractive activities; f) light industries; g) heavy industries and supporting services; h) software, business and heavy industry services; i) business services; j) urban services and construction; k) tourism.

We believe this classification overcomes the limitations of traditional specialization measures for several reasons. On the one hand, it allows to distinguish within the same category, such as "manufacturing", several specializations that are different not only in qualitative but in empirical terms, that is, referring to how economic activity is effectively distributed and agglomerated in our country (eg. light industry; heavy industry; agribusiness and others). On the other hand, it takes into account the interdependencies between activities, contemplating the co-location or joint development of activities that are part of the same production network, or that are based on similar capacities at the local level.

Despite the limitations that our typology faces, empirical applications seem to account for greater analytical richness. Although a greater sectoral disaggregation would probably give more precise results, we believe that typologies of productive patterns developed by means of multivariate analysis techniques can be useful for future applications on regional economics and regional structural change in Argentina and many other countries.

As future extensions, we propose to employ the TWA typology to analyze structural change at the regional level in Argentina. In particular, we aim at analysing changes in specialization profiles under different macroeconomic conditions and during economic crises, as well as tracking changes of TWAs between clusters and identifying stylized facts.

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Annex 1: Methodological note

Originally, the evaluation of the change in the heterogeneity for each stage of the Cluster Analysis suggested an initial conformation of 9 clusters. However, after a detailed evaluation of the TWAs included in each cluster and their respective values in the 8 sectoral components, we made the following changes:

- we collapsed 2 clusters with a marked touristic specialization into one (the "original" clusters 5 and 6, according to Ward's method, see Annex 2);
- we subdivided another 2 clusters for greater analytical richness (the original clusters 1 and 4);
- we created an *ad-hoc* cluster to account for the special cases associated with "other manufactures";
- in the latter we included 2 TWAs initially classified as extractive (original cluster 9), along with another pair of TWAs coming from the most numerous and heterogeneous original cluster (number 2);
- we moved another 6 TWAs from cluster 2 to other more relevant cluster, based on the comparison of the values of the TWAs in the different sectoral components.

All these changes can be seen in Annex 2.

Annex 2: TWAs by cluster and values of sectoral components.

TWA	Capital city	Classification		Sectoral component								Typology
		9 Cluster (Ward)	11 Cluster	Heavy industries	Agro-ind & mining	Light industry	Urban services	Tourism	Software & business ss	Constr uction	Logistics	
GRAN BUENOS AIRES	X	1	1	0,7	**-0,7**	0,6	-0,2	0,0	4,6	-0,7	0,5	Software, business ss and heavy industry
CORDOBA	X	1	1	1,1	-0,5	-0,2	-0,1	-0,4	3,9	0,2	0,2	
ROSARIO		1	1	1,2	-0,4	-0,1	0,2	-0,3	2,0	-0,3	0,9	
TANDIL		1	2	-0,3	-0,1	-0,2	0,0	-0,2	1,9	-1,0	-0,1	Business services
MAR DEL PLATA		1	2	-0,3	-0,2	-0,2	0,8	0,7	1,5	-0,6	-0,2	
BAHIA BLANCA		1	2	0,1	**-0,6**	-0,1	0,7	0,4	1,5	0,0	1,4	
MENDOZA	X	1	2	-0,3	-0,1	-0,5	-0,1	-0,3	1,1	0,1	0,8	
SAN MIGUEL DE TUCUMAN	X	1	2	-0,4	0,0	0,0	0,1	-0,4	0,9	0,2	0,7	
LA FALDA		2	3	-0,5	**-0,7**	-0,1	3,5	0,9	-1,4	-0,9	-0,1	Urban services and construction
VIEDMA	X	2	3	-0,7	**-0,7**	-0,2	2,2	0,2	-0,5	1,2	-0,6	
SANTIAGO DEL ESTERO	X	2	3	-0,6	**-0,9**	0,4	1,8	-0,5	-0,2	1,1	-0,2	
LA PLATA	X	2	3	0,0	**-0,8**	0,0	1,7	-0,1	0,8	0,3	0,0	
SANTA FE - PARANA	X (2)	2	3	0,1	-0,2	-0,2	1,6	-0,3	0,3	-0,6	0,3	
SAENZ PEÑA		2	3	-0,8	0,2	0,9	1,4	-0,1	-1,6	0,2	0,2	
JUNIN		2	3	-0,2	0,2	-0,3	1,3	-0,4	-0,1	-0,7	0,0	
CATAMARCA	X	2	3	-0,5	-0,2	1,2	1,3	-0,4	-0,3	0,0	-0,5	
RESISTENCIA-CORRIENTES	X (2)	2	3	-0,4	**-0,6**	0,2	1,1	-0,3	0,7	1,3	0,4	
TRELEW-RAWSON	X	2	3	-0,6	-0,5	0,9	1,0	0,0	-1,0	1,3	0,5	
POSADAS	X	2	3	-0,5	-0,5	0,0	1,0	-0,1	0,2	1,1	1,4	
SAN SALVADOR DE JUJUY	X	2	3	-0,7	0,1	-0,3	1,0	-0,3	0,1	0,5	0,4	
FORMOSA	X	2	3	-0,5	**-0,6**	-0,1	0,9	-0,4	-0,9	3,5	-0,6	
SANTA ROSA	X	2	3	-0,7	**-0,6**	0,1	0,9	0,2	-0,1	1,2	-0,1	
SALTA	X	2	3	-0,6	-0,3	-0,3	0,6	-0,1	0,6	0,5	0,4	
ESCOBAR		3	4	3,6	-0,5	0,2	-1,0	0,2	0,9	-0,1	1,0	Heavy industries and supporting services
ZÁRATE-CAMPANA		3	4	3,1	0,1	-0,3	-1,6	-0,2	0,7	1,4	0,4	
PILAR		3	4	2,2	**-0,7**	0,9	-0,8	0,3	1,0	-0,6	0,0	
SAN LUIS	X	3	4	1,6	**-0,6**	0,7	0,1	-0,5	0,7	1,1	-0,3	
SAN NICOLAS		3	4	1,4	-0,3	-0,5	-0,6	-0,4	0,4	0,7	1,0	
MERCEDES		3	4	1,4	0,3	-0,2	-1,3	-0,6	0,5	0,9	-0,4	
RAFAELA		4	5	2,9	0,6	-0,7	-0,2	-0,9	0,2	-0,5	-0,5	Agro industries and supporting industries
ARMSTRONG		4	5	2,2	0,8	-0,1	-0,8	-0,8	-0,7	-1,4	0,0	
MARCOS JUAREZ		4	5	1,8	0,6	-0,6	-0,5	-1,0	-0,8	**-2,4**	-0,1	
SAN FRANCISCO		4	5	1,5	0,6	-0,7	0,4	-0,9	-0,5	-1,4	-0,2	
ARROYITO		4	5	1,2	1,4	-0,3	-1,2	-0,7	-0,6	-1,2	-0,6	
RIO TERCERO		4	5	1,0	-0,3	-0,3	-0,1	-0,5	-0,5	-0,8	-0,7	
VENADO TUERTO		4	5	0,9	0,4	-0,4	0,1	-0,7	-0,2	-1,2	0,1	
GUALEGUAYCHU		4	5	0,8	0,3	-0,6	0,0	-0,1	0,3	-0,8	-0,2	
CHIVILCOY		4	5	0,6	0,1	0,6	-0,1	-0,2	-0,5	-0,4	0,1	
RECONQUISTA		4	6	0,3	0,1	0,0	-0,1	-0,9	-0,5	-0,7	0,3	Food products and urban services
PERGAMINO		4	6	0,2	0,3	1,2	-0,5	-0,3	-0,3	-0,7	-0,1	
SUNCHALES		4	6	0,0	0,7	-0,8	1,4	-1,9	0,0	-0,8	-0,1	
9 DEJULIO		4	6	-0,1	0,6	-0,2	0,0	-0,5	-0,3	-1,6	-0,8	
VILLA MARIA		4	6	-0,2	0,2	-0,6	0,4	-0,5	-0,2	**-2,1**	0,4	
TRES ARROYOS		4	6	-0,3	0,4	-0,8	0,6	-0,5	0,0	-1,0	-0,6	
RIO CUARTO		4	6	-0,4	0,1	-0,5	0,7	-0,3	-0,1	-1,2	-0,3	
GENERAL PICO		4	6	-0,4	0,2	-0,2	0,6	-0,2	-0,5	-0,3	-0,7	
PINAMAR - VILLA GESELL		**6**	7	-0,6	**-0,6**	-0,1	-0,4	4,0	2,2	-0,3	**-3,5**	Tourism and related activities
IGUAZÚ		5	7	-0,7	0,0	0,1	-1,2	3,9	-1,2	-0,3	4,3	
MERLO		5	7	-0,1	-0,5	1,0	0,8	2,8	-0,9	-0,9	-0,7	
VILLA GENERAL BELGRANO		**6**	7	-0,3	-0,3	-0,4	-1,2	2,5	-0,7	0,3	**-3,9**	
BARILOCHE		5	7	-0,6	**-0,6**	-0,3	0,2	2,4	0,7	-0,5	0,5	
TERMAS DE RIO HONDO		5	7	-0,8	-0,1	-0,2	-1,1	2,4	-1,0	0,5	0,6	
CARLOS PAZ		5	7	-0,4	**-0,8**	0,1	1,1	2,3	-0,7	-0,9	-0,3	
NECOCHEA		5	7	-0,6	-0,1	-0,2	0,1	0,9	-0,5	-0,6	1,5	
ESQUEL		**2**	7	-0,7	-0,2	-0,2	0,4	0,6	-0,6	1,8	-1,7	
PASO DE LOS LIBRES		5	7	-0,8	0,4	-0,3	-0,4	0,5	-1,3	-0,1	2,9	

TWA	Capital city	Classification		Sectoral component								Typology
		9 Cluster (Ward)	11 Cluster	Heavy industries	Agro-ind & min	Light industry	Urban services	Tourism	Software & business ss	Constr uction	Logistics	
GOBERNADOR VIRASORO		7	8	-0,7	2,5	0,1	-1,7	-0,4	-0,9	-0,2	-0,2	Primary sector and food products
CHAJARÍ		7	8	-0,7	1,9	1,1	-0,6	-0,6	-0,5	-1,4	-0,4	
ORAN		7	8	-0,8	1,6	-0,8	-1,0	-0,9	-0,6	0,5	-0,3	
LIBERTADOR GRAL SAN MARTIN		7	8	-0,2	1,6	**-3,0**	**-2,1**	-0,8	-0,2	0,4	-0,1	
OBERÁ		7	8	-0,4	1,4	-0,4	-0,7	-0,4	-0,9	-0,1	0,2	
METAN		7	8	-1,2	1,2	-0,4	-0,9	-0,8	-0,6	0,5	-0,7	
CONCORDIA		7	8	-0,8	1,1	0,2	-0,3	-0,7	0,0	0,1	0,0	
SAN PEDRO DE JUJUY		7	8	-0,6	1,1	-1,4	-1,2	-0,6	-0,9	0,5	0,1	
SAN ANTONIO DE ARECO		7	8	-0,6	1,0	0,0	-1,2	-0,2	-0,4	-0,5	-0,1	
VILLAGUAY		7	8	-0,9	0,9	-0,6	0,0	-0,4	-0,3	-0,2	-1,3	
LOBOS		7	8	-0,3	0,9	-0,5	-0,7	0,2	0,1	-0,7	-0,6	
GUALEGUAY		7	8	-0,4	0,8	-1,1	-1,1	-0,4	-0,7	-0,2	0,2	
SAN PEDRO		7	8	-0,4	0,8	0,3	-0,6	-0,2	-0,2	-0,2	0,2	
TRENQUE LAUQUEN		7	8	-0,8	0,7	-0,5	0,1	-0,2	-0,8	-0,7	0,0	
CONCEPCIÓN DEL URUGUAY		7	8	-0,3	0,5	-0,6	0,3	-0,4	-0,7	-0,1	0,4	
SAN RAFAEL		7	8	-0,3	0,2	-0,9	0,1	0,1	-0,3	0,4	0,2	
PUERTO MADRYN		7	8	-0,2	0,1	-0,6	-1,6	0,1	-0,1	1,6	0,0	
CORONEL SUAREZ		8	9	-1,0	0,6	5,1	-0,9	-0,4	-0,4	-0,8	-0,9	Light industry
ELDORADO		8	9	-0,4	2,5	3,6	-1,7	-0,5	0,0	0,4	-0,7	
LA RIOJA	X	**2**	9	-0,4	0,0	2,6	0,2	-0,6	-0,5	1,2	-0,7	
LUJAN		**2**	9	0,5	0,0	1,2	0,9	0,2	0,2	-0,5	-0,2	
GOLFO SAN JORGE		9	10	-1,8	**-4,2**	-1,5	-1,1	-0,2	0,4	1,7	0,2	Extractive activities and construction
RIO GALLEGOS	X	**2**	10	-0,9	**-1,3**	-0,5	0,9	-0,1	0,3	2,0	0,5	
TARTAGAL-MOSCONI		**2**	10	-0,8	**-1,1**	-0,5	-0,2	-0,3	-0,4	1,9	-1,0	
ALTO VALLE DEL RÍO NEGRO	X	**2**	10	-0,8	**-0,9**	-0,5	-0,2	-0,2	0,5	0,6	0,2	
RIO GRANDE		9	11	1,4	**-3,0**	1,6	-1,4	0,1	0,1	0,8	-0,3	Other industries and extractive activities
USHUAIA	X	9	11	-0,4	**-2,6**	0,6	-0,7	1,1	-0,3	0,4	1,8	
OLAVARRIA		**2**	11	-0,5	**-1,4**	0,3	0,5	0,0	-0,3	0,2	0,3	
SAN JUAN	X	**2**	11	0,1	-0,5	0,3	0,1	-0,4	0,1	0,8	0,3	

Source: authors

Annex 3: Analysis of variance

Component	Sum of squares	Degrees of freedom	Mean square	F
Heavy industries	67,391	10	6,739	30,025***
Agro-industy and mining	57,151	10	5,715	15,751***
Light industry	50,619	10	5,062	11,221***
Urban services	48,248	10	4,825	9,986***
Tourism	60,414	10	6,041	18,955***
Software and business ss	57,325	10	5,733	15,903***
Construction	40,586	10	4,059	6,918***
Logistics	6,610	10	0,661	0,632

Source: authors. Significance level: *p<0,05; **p<0,01; ***p<0,001