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Articles

Interregional analysis using a bi-regional input-output matrix for Argentina

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ABSTRACT:

This paper presents a regional case study using a Bi-Regional Input-Output (BRIO) matrix of Buenos Aires City (BAC) and the Rest of Argentina (ROA), constructed from the Argentinian Input-Output matrix. A hybrid approach was applied to obtain the BRIO matrix, which combines pure non-survey methods with matrix-balancing methods like RAS or Cross-Entropy. Once the BRIO matrix was obtained, our study has focused on analyzing the BAC regional structure and the interconnections between regions. We have also estimated the regional and national carbon footprint for the BAC and Argentina, respectively. Results show that service and industry sectors play an important role in the economy of BAC and some of them have strong interregional spillover effects over the rest of the country. In addition, the results also show that sectors on BAC with the highest regional multipliers are also the ones with highest emissions.

KEYWORDS: Interregional input-output model; carbon footprint; bi-regional input-output tables; location quotients; cross entropy.

JEL CLASSIFICATION: C67; D57; R15; R58.

Análisis interregional utilizando una matriz Insumo-Producto bi-regional de Argentina

RESUMEN:

Este artículo presenta un caso de estudio regional utilizando una matriz Bi-Regional Input-Output (BRIO) de la Ciudad de Buenos Aires (BAC) y el Resto de Argentina (ROA), construida a partir de la matriz Input-Output de Argentina. Se ha utilizado una metodología híbrida para obtener la matriz BRIO, la cual combina métodos indirectos puros y métodos de calibración de matrices como RAS y Entropía Cruzada. Una vez obtenida la matriz BRIO, nuestro estudio se ha centrado en analizar la estructura regional de la BAC y las interconexiones entre regiones. También hemos realizado la estimación de la huella de carbono nacional y regional para Argentina y en la BAC, respectivamente. Los resultados muestran que los sectores de servicios e industria juegan un papel importante en la economía de la BAC y algunos de ellos tienen fuertes efectos indirectos interregionales sobre el resto del país. Además, los resultados también muestran que los sectores de la BAC con los multiplicadores regionales más altos también son los que tienen las emisiones más altas.

PALABRAS CLAVE: Modelo insumo-producto interregional; huella de carbono; matrices insumo-producto bi-regionales; coeficientes de localización; entropía cruzada.

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1. Introduction

Interregional Input-Output (IRIO) models are a valuable tool to study a particular region of interest considering the interconnections with the rest of the country. Due to the dramatics socio-economic and political differences between the Buenos Aires City (BAC) and the Rest of Argentina (ROA), implementing an interregional approach becomes essential. In this sense, a Bi-Regional Input-Output (BRIO) matrix is necessary to carry out such analysis (Boero et. Al, 2018 and Round, 1983). As there are no available regional matrices in Argentina, regionalization process has been performed to regionalize Argentina's national Input-Output (IO) matrix into a Bi-Regional one.

Leaving the Regional IO matrices problem aside, our efforts were placed on BAC which is adhered to the 2030 Agenda for Sustainable Development Goals (SDG's). This assumed commitment generates the need for policy makers to have a methodology to quantify the effects of their decisions. This work intends to contribute in that way presenting a case study mainly related to the 8th and 13th SDGs, in which the Buenos Aires City takes on the commitment to boost the local economic developments through incentives to strategic economic sectors and to be a carbon neutral by 2050, respectively.

The economic structure of the BAC differs completely from the national average and considering the interconnections with the ROA is relevant for its study. The BAC is the richest region of the country with the core businesses concentrated on it. It has an approximated area of 203 square kilometers and approximately three million inhabitants that represent 7% of the Argentina population. The political division between BAC and ROA are not implying economical division and companies are integrated between regions with significant "imports" and "exports" between them. National headquarters of the most important companies of the country are centered in this region, especially in the service sectors. Finally, the structure of the BAC job market is inherently interconnected with the ROA because BAC has many commuters from Greater Buenos Aires (GBA), that is the name to call the suburbs of BAC.

Considering the mentioned, the interregional approach using a Bi-Regional IO matrix is essential to perform regional studies on the BAC.

Our main objective is to present a case study of the BAC where the regional structure, the interconnections between regions and carbon footprint are analyzed using a BRIO matrix of Argentina made up by the BAC and the ROA regions. However, as the regional structure was not available, we first had to obtain the BRIO matrix. To go through this first step, we have used a hybrid non-survey approach which combines two of the most frequently used techniques in the field of Input-Output matrices (Mastronardi and Romero, 2012). They are the Location Quotients (LQs), (Flegg et al., 1995; Flegg and Webber, 1997, 2000) and, additionally, the well-known matrix balancing methods like RAS and Cross Entropy.

Considering Lamonica (2020), we built, in a practical case and with other point of view, a regional estimation inside a country when is not common to have a lot of information about intermediate purchases and sales between regions, final regional consumption, exports, national taxes, etc.

In absence of primary data, researcher would probably construct the most important regional internal intermediate consumption with secondary data, with an important focus on specific sector that she will analyze before in a sectoral economic analysis. Considering the specific case of Buenos Aires City, we used specific estimations for intermediate purchases and sales developed in a specific academic project to study its economic structure[1].

This article could be the first stone to continue contributing to the analysis of the impacts of public policies that are defined within the framework of the SDGs, such as the initiative to create green jobs. Interregional analysis of other economic problems could be also extensions of this work, such as

[1] Modelos regionales: Desarrollo de un modelo de equilibrio general para CABA – UADE PID IE-10D1, Universidad Argentina de la Empresa, 2010-2012

applications for tourism in the Province of Salta in Haslop et. al (2020) or for green energy in the Misiones province in Perrota et. al (2020).

Finally, we have decided to make the regionalization methodology explicit in this paper. With this, it is intended to help colleagues from different disciplines in economics to be able to estimate the BRIO matrix in a relatively simple way.

The paper is organized as follows. Section 2 presents a brief introduction of the non-survey methods based on Location Quotients which are important to understand the regionalization methodology and constitute the first step of our regionalization process. Section 3 presents an initial Regionalized National Input-Output matrix which includes intra-regional and inter-regional sub-matrices. Section 4 introduces two calibration methods (RAS and Cross Entropy) which could by applied over the initial matrix obtained in the previous section. The end of this section shows only the results obtained by applying the Cross-Entropy method. Section 5 present the case study using the BRIO matrix obtained in the previous sections. Finally, Section 6 provides final remarks and potential extensions.

2. Intra-regional input-output: The use of location quotients

2.1. Overview

As we have mentioned before, we first need to build a BRIO matrix to perform the regional study. In this sense, the regionalization process consists of separating Argentina into two regions, the BAC and the ROA. Therefore, the national input-output table is broken down into four regional tables, which represent: [A] intra-regional commerce (within each region) and [B] inter-regional commerce between regions (exports and imports from/to another region). The construction procedure of [A] will be detailed in this section while the construction procedure of [B] will be detailed in section 3.

Table 1 shows a scheme for "n" sectors of the economy in each region to describe the tables.

Table 1.
An example of Regional Input-Output Table for N sectors

		BAC activity sectors	ROA activity sectors
		S_1 … S_n	S_1 … S_n
BAC activity sectors	S_1 … S_n	BAC Input-Output [A]	BAC Exports- ROA Imports [B]
ROA activity sectors	S_1 … S_n	ROA Exports- BAC Imports [B]	ROA Input-Output [A]

Source: Own elaboration.

Having computed matrices A and B, it is necessary to combine them to find an initial bi-regional table. After that, matrix balancing methods adjust that initial bi-regional table to find the final bi-regional matrix that can be used to perform regional analysis.

Non-survey or indirect methods, including Location Quotients (LQs) methods, are used to estimate a regional (r) IO matrix from a national (n) IO one by adjusting national coefficients to reflect regional production structures. In order to estimate a IO matrix of a single region, it can be applied the regional technical coefficients ($a_{ij}^{r} = \alpha_{ij}^{r} a_{ij}^{n}$) and the regional input coefficients ($a_{ij}^{rr} = \beta_{ij}^{r} a_{ij}^{r}$). The first one does not distinguish the local or imported origin of inputs (i) to produce a unit of output (j), but the second does identify local input requirements per unit of output.

The assumptions behind the regional input coefficients estimation are:

- Identical technologies between the nation and the region ($a_{ij}^{r} = a_{ij}^{n}$), which implies $a_{ij}^{rr} = \beta_{ij}^{rr} a_{ij}^{n}$; then $\alpha_{ij}^{r} = 1$
- Regional demand preferences for regional production, and
- Positive regional exports after regional demand satisfaction.

In this work, both [A] matrices (BAC and ROA), were constructed by means of indirect methods based on (LQs) which are the most frequently used to estimate a single-region IO matrix. Some of them are Simple LQ (SLQ), Cross Industry LQ (CILQ), Flegg's LQ (FLQ) and Augmented FLQ (AFLQ) (Flegg et al., 1995; Flegg and Webber, 1997, 2000). Several empirical studies on different countries' regions, such as Argentina (Flegg et al., 2015), Finland (Flegg and Tohmo, 2013), Germany (Kowalewski, 2015), Greece (Psaltopoulos and Balamou, 2005; Lampiris et al., 2018), Ireland (Morrissey and O'Donoghue, 2013; Morrissey, 2016), Northern Australia (Stoeckl, 2012), Scotland (Johns and Leat, 1987), South Korea (Zhao and Choi, 2015; Flegg and Tohmo, 2016) and the United States (New York State Department of Labor, 2017), have used this methodology.

LQ methodology, has assumed that the regional input coefficient (a_{ij}^{rr}) differ from the national coefficients (a_{ij}^{n}) only by a share, which has explained the regional trade (lq_{ij}) (Jensen *et. al*, 1979). Thus, lq_{ij} measures the proportion of regional requirements of input i that can be satisfied by firms located within the region and, for this reason, $lq_{ij} \in [0,1]$ by definition (Flegg and Tohmo, 2013).

The regional input coefficient has been defined as follows:

$$\begin{cases} a_{ij}^{rr} = lq_{ij}.a_{ij}^{n} & if \quad lq_{ij} < 1 \\ a_{ij}^{rr} = a_{ij}^{n} & if \quad lq_{ij} > 1 \end{cases} \tag{1}$$

that, in general terms, if $lq_{ij} < 1$ then $\beta_{ij}^{r} = lq_{ij}$ and $\alpha_{ij}^{r} = 1$. On the other hand, when q_{ij} is greater than 1, then $\beta_{ij} = 1$.

The constraint to one implies that if the regional sector is self-sufficient or a net exporter ($lq_{ij} < 1$) the regional input coefficient is exactly the national technical coefficient. Instead, if the regional sector is a net importer ($lq_{ij} > 1$) the regional input coefficient will be a share of the national coefficient.

In this work we have built the intra-regional matrices using the Augmented Flegg Location Quotient (AFLQ) (Flegg and Webber, 2000), which is a theoretical improvement of the Flegg Location Quotient (FLQ) (Flegg et al., 1995; Flegg and Webber, 1997).

We first introduce the FLQ and then, from there, arrive at the AFLQ by introducing an adjustment.

The FLQ can be computed as follow:

$$\begin{cases} FLQ_{ij} = \lambda^{*}.CILQ_{ij} & for \quad i \neq j \\ FLQ_{ij} = \lambda^{*}.SLQ_{i} & for \quad i = j \end{cases} \tag{2}$$

where the λ is the parameter estimated by the equation (3), with which the FLQ consider the region's size in relation compared to country size.

$$\lambda^{*} = [\log_2\left(1 + \frac{x^r}{x^n}\right)]^{\delta}, \quad with \quad 0 < \delta < 1 \tag{3}$$

In this sense, it can be seen that if $\delta = 0$, then the FLQ equals:

- The $SLQ_i = \frac{x_i^r/x^r}{x_i^n/x^n}$ when $i = j$, where the x_i^r and x^r correspond to the region r gross output of the sector i and total regional gross output, respectively, while x_i^n and x^n have the same meaning but at national level.

- The SLQ has been viewed as a measure of the ability of regional industry i to supply the demand placed in that region. So, if the industry i is less specialized in the region than in the nation ($SLQ_i < 1$), it's seen as less capable of satisfying regional demand with it production. Conversely, if the industry i is more specialized ($SLQ_i > 1$), then it is assumed that the national technical coefficient of industry i is appropriate to represent the region's structure, and that the regional surplus produced by i will be export to the rest of the country;
- The $CILQ_{ij} = \frac{SLQ_i}{SLQ_j}$ when $i \neq j$ and it measures the relative importance of the supplying industry i with respect to the demanding industry j, in the same region. It is important to notice that if the regional production of the supplying industry i (in terms of its national production) is greater than the regional production of the purchasing industry j (in terms of its national production), the $CILQ_{ij}$ is greater than one and the input requirements of j sector could be satisfied within the region. On the other hand, if $CILQ_{ij}$ is lower than one, the inputs needed by the purchasing industry might not be produced by the supplying sector and, consequently, they would need to import the inputs from another region.

However, if $\delta > 0$ then the FLQ accounts the size of the region by means of the value of λ, for instance, the greater the region the lower the need for imports.

The value of δ is intensely discussed in the literature [we could mention Lampiris et. al (2019), Lamonica et.al (2018), Flegg and Webber (1997), Flegg and Tohmo (2013) and Kowalewski (2015), among others] but, in this case, for simplicity, we have used the definition derived from Flegg and Tohmo, 2014:

$$\delta = \frac{\log[(x^r/x^n)/\log_2\{1+(x^r/x^n)\}]}{\log[\log_2(1+(x^r/x^n))]} \tag{4}$$

Flegg and Webber (1997) have acknowledged that a standard and a reference value of δ could be 0.3, with smaller (greater) value than that for smaller (bigger) regions (Miller and Blair, 2009).

The AFLQ have theoretically improved the FLQ by allowing the regional technical coefficients of a particular industry to be greater than the national one. This version of LQ includes the regional specialization effect of each industry (Miller and Blair, 2009), by means of a correction of the equation (2) if and only if the industry is self-sufficient in that region ($SLQ_i > 1$). If that occurs, $AFLQ > FLQ$ and, consequently, the regional import are lower. As with the FLQ, the constraint AFLQij ≤ 1 is imposed.

$$AFLQ_{ij} = \lambda^* . CILQ_{ij}. [\log_2(1 + SLQ_i)] = FLQ_{ij}. [\log_2(1 + SLQ_i) \tag{5}$$

Either FLQ and AFLQ significate an improvement of previous LQs. Lampiris et al. (2019) highlights that FLQ and AFLQ, are preferable quotients and provide satisfactory results, even for small regions.

Although the AFLQ has some theoretical merits relative to the FLQ, its empirical performance is typically very similar (Flegg and Tohmo, 2019). For instance, in the Monte Carlo study by Bonfiglio and Chelli (2008), the AFLQ gave only slightly more accurate results than the FLQ. This outcome was confirmed by Flegg et. al. (2016) and Kowalewski (2015). In this work we have used the AFLQ.

It is worth mentioning the contribution of Pereira et al. (2020) which generalizes Flegg`s methodology by using a bidimensional approach, the 2D-LQ. This methodology yields better results than FLQ or AFLQ since it takes advantage of the available information and overcomes the fact that Flegg`s methodology makes the adjustment of purchasing sectors proportionally to the productive specialization.

Table 2 shows the production value of 14 sectors[2] in each region and the corresponding SLQ, using national data.

TABLE 2.
Production values (PV) and Simple Location Quotient for BAC and ROA

N°	Sectors	PV of Argentina	PV of BAC	SLQ	PV of ROA	SLQ
1	Agriculture, forestry and hunting	64,594	1,282	**0,09**	63,312	**1,27**
2	Fishing	2,792	75	**0,12**	2,716	**1,27**
3	Mining and quarrying	47,229	4,586	**0,42**	42,643	**1,17**
4	Industry	403,266	62,122	**0,67**	341,145	**1,10**
5	Water, Electricity and gas	23,048	4,412	**0,83**	18,636	**1,05**
6	Construction	96,792	13,99	**0,63**	82,802	**1,11**
7	Commerce	93,114	24,346	**1,13**	68,768	**0,96**
8	Hotels and restaurants	31,432	12,821	**1,77**	18,611	**0,77**
9	Transport and communication	102,246	34,321	**1,45**	67,925	**0,86**
10	Financial intermediation	40,411	21,863	**2,34**	18,548	**0,60**
11	Real estate, renting and business	77,833	45,272	**2,52**	32,561	**0,54**
12	Public administration	50,727	11,554	**0,99**	39,172	**1,00**
13	Education, health and social services	78,117	17,635	**0,98**	60,482	**1,01**
14	Other services	50,489	14,051	**1,21**	36,438	**0,94**
	Total	**1,162,089**	**268,329**		**893,759**	

Source: Own elaboration based on INDEC, Ministerio de Hacienda GCBA and Chisari et. al (2010).

It must be remarked that non-survey methods use only production figures. In our case, we also have information on intermediate consumption and value added. Hence, we have a more precise notion about the existent technology at the sectorial level. These are included as additional constraints that our estimation of the RIO tables must enforce. In the next sections we will show calibration techniques to deal with these constraints

Once the $AFLQ_{ij}$ is computed over the national matrix (see Annex), we can estimate the regional input coefficients a_{ij}^{rr} and build the intra-regional technical coefficient matrix for each region. Then, these coefficients could be used to estimate the intra-regional transaction matrix corresponding to each region by multiplying them by the regional production value. Table 3 shows BAC´s intra-regional technical coefficient matrix[3].

[2] Given that the available gross output disaggregation of BAC was only 14 sectors and we took this as our primary regional data, we had to use a small disaggregation.

[3] The ROA´s intra-regional I-O matrix can be constructed by following the same procedure.

TABLE 3.
BAC´s Intra-regional technical coefficient matrix

	Sectores	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	Agriculture, forestry and hunting	0,0058	0,0016	0,0000	0,0109	0,0000	0,0000	0,0000	0,0001	0,0000	0,0000	0,0000	0,0000	0,0000	0,0001
2	Fishing	0,0000	0,0021	0,0000	0,0002	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000
3	Mining and quarrying	0,0001	0,0000	0,0141	0,0208	0,0545	0,0818	0,0000	0,0000	0,0002	0,0000	0,0000	0,0001	0,0000	0,0000
4	Industry	0,1769	0,1813	0,0693	0,1469	0,0331	0,2101	0,0172	0,1599	0,0510	0,0102	0,0138	0,0304	0,0364	0,0599
5	Water, Electricity and gas	0,0027	0,0012	0,0158	0,0075	0,1458	0,0024	0,0065	0,0101	0,0033	0,0027	0,0041	0,0131	0,0034	0,0101
6	Construction	0,0109	0,0000	0,0363	0,0011	0,0004	0,0000	0,0000	0,0186	0,0014	0,0000	0,0211	0,0079	0,0045	0,0034
7	Commerce	0,0174	0,0291	0,0022	0,0208	0,0011	0,0391	0,0117	0,0121	0,0106	0,0012	0,0007	0,0035	0,0029	0,0091
8	Hotels and restaurants	0,0020	0,0159	0,0000	0,0070	0,0001	0,0000	0,0008	0,0006	0,0053	0,0176	0,0071	0,0582	0,0273	0,0102
9	Transport and communication	0,0209	0,0681	0,0143	0,0793	0,0387	0,0968	0,0576	0,0126	0,1319	0,0680	0,0153	0,0394	0,0126	0,1208
10	Financial intermediation	0,0217	0,0173	0,0124	0,0107	0,0171	0,0604	0,0952	0,0088	0,0480	0,1297	0,0215	0,0854	0,0032	0,0436
11	Real estate, renting and business	0,0013	0,0374	0,0202	0,0191	0,0260	0,0566	0,0796	0,0233	0,0530	0,0666	0,0130	0,0360	0,0090	0,0923
12	Public administration	0,0013	0,0050	0,0019	0,0024	0,0085	0,0002	0,0009	0,0000	0,0082	0,0020	0,0005	0,0010	0,0009	0,0026
13	Education, health and social services	0,0005	0,0006	0,0298	0,0028	0,0233	0,0000	0,0004	0,0030	0,0014	0,0022	0,0126	0,0191	0,0964	0,0129
14	Other services	0,0009	0,0001	0,0317	0,0049	0,0138	0,0001	0,0005	0,0012	0,0140	0,0052	0,0022	0,0086	0,0077	0,0125

Source: Own elaboration.

3. Construction of the inter-regional input-output table

As we mentioned, a BRIO national matrix includes both intra-regional and inter-regional sub-matrices (see Table 1). While in the previous section, we have estimated the intra-regional sub-matrices, both for BAC and ROA, in this section we discuss how to estimate the inter-regional sub-matrices.

It is known that the SLQ_i indicates whether the region is a net-exporter ($SLQ_i > 1$) or net-importer ($SLQ_i < 1$). In this way, BAC region is considered as net-exporter of service sectors and the ROA the importer of those services (see Table 2).

From these assumptions it follows that the sum of transactions by sector, must reproduce the transactional value of national sector in terms of the intermediate consumption and intermediate sales. In other words, the sum of regional *ij*'s transactions for a particular sector must reproduce the *ij* national transaction for that sector. This constraint implies enforcing the national technical coefficients and it can be summarized by following the equation:

$$t_{ij}^{n} = \sum_p \sum_s t_{ij}^{ps}, \forall ij \tag{6}$$

Where t_{ij}^{ps} is the regional *ij* transaction from the purchasing region "p" and the supplying region "s", and t_{ij}^{n} is the national *ij* transaction.

Considering the mentioned, we have estimated the inter-regional matrices under the following assumptions:

a. A regional sector is exporter if and only if its SLQ_i is greater than one. Therefore, the sectors that do not comply with this rule have a 0 in the export matrix.

b. Given the equation (6) and that one sector can be net-exporter or net-importer but not both, it follows that ${t_{ij}}^{BAC,ROA} = 0$ or ${t_{ij}}^{ROA,BAC} = 0$ and the initial export transaction value for ${t_{ij}}^{BAC,ROA}$ (if ${t_{ij}}^{ROA,BAC} = 0$) or vice versa is:

$${t_{ij}}^{BAC,ROA} = t_{ij}^{n} - t_{ij}^{BAC,BAC} - t_{ij}^{ROA,ROA} \tag{7}$$

Once we have obtained the inter-regional matrices for BAC and ROA, the BRIO matrix was built by joining the inter-regional and intra-regional matrices (obtained in the previous section) as in Table 1

4. Calibration methods

4.1. Preliminary comments about the initial table

Pure indirect methods like LQs theory only needs production data to perform a regionalization. However, if there were additional regional information (i.e. intermediate consumption of one region), this methods would not take advantage of that extra information. In this sense, calibration methods could be a helpful tool by allowing us to improve our estimation with some extra information. The objective of these methods is to fit the internal values of the analyzed matrix such that their sum (by rows or columns) equals the values of the Intermediate Consumption and Sales vectors with information from external sources.

In the case of Argentina, we have taken advantage of the availability of Intermediate Consumption information of BAC which has been introduced through a control vector. This control vector of Intermediate Consumption [IC*] probably differ from the Intermediate Consumption vector [IC] obtained by our BRIO matrix estimated. This vector was built such that $IC_i^{BAC} + IC_i^{ROA} = IC_i^{ARG}$, where IC_i^{BAC} and IC_i^{ARG} come from external sources and IC_i^{ROA} was estimates as the difference between these vectores. Additionaly, it is important to mention that information about regional intermediate sales (IS) was not available. In this case, we have used the estimated intermediate as the control vector.

To adjust the differences between the information and our estimation, Cross Entropy (CE) was applied, but RAS could be a reasonable alternative. In this way, the use of borders ensures the resolution of the problem above.

Table 4 presents the initial matrix with the control vectors. This table have been used as the basis for the application of the calibration methods described in the following subsections. To clarify the understanding of the table, note that the row sum of each sector [IC] differs from the intermediate consumption control vector [IC*], but only in its internal structure since the total sum of IC and IC * is identical.

It is important to mention that this complementary method presented on our contribution in a hybrid technique requires information that it could not be available as a primary source. In our case, if the additional information were not available, we would not be able to use calibration methods to improve our first estimate with pure LQs.

TABLE 4.
Initial Regionalized National Input-Output Table for Argentina in 2006 (transactions)

		BAC Activity Sectors													
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**
BAC Activity Sectors	**1**	7,5	0,1	0,0	676,9	0,0	0,4	0,0	0,8	0,1	0,0	0,0	0,2	0,1	1,7
	2	0,0	0,2	0,0	15,1	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
	3	0,2	0,0	64,6	1.293,3	240,6	1.144,4	0,0	0,0	5,5	0,0	0,1	0,6	0,3	0,2
	4	226,8	13,6	318,0	9.124,6	146,0	2.938,6	418,9	2.050,0	1.750,1	222,1	623,9	350,8	642,5	841,0
	5	3,4	0,1	72,4	468,1	643,2	32,9	158,8	128,9	112,1	58,7	187,7	151,2	60,5	141,2
	6	14,0	0,0	166,6	67,6	1,6	0,0	0,1	238,3	47,8	0,0	954,1	90,9	79,5	48,4
	7	22,3	2,2	9,9	1.293,2	5,1	547,1	284,6	154,7	364,0	26,7	30,3	39,9	51,5	128,2
	8	2,6	1,2	0,0	433,1	0,5	0,0	20,5	7,1	181,6	384,6	323,0	671,9	480,7	143,3
	9	26,8	5,1	65,8	4.924,3	170,9	1.354,2	1.401,9	161,9	4.526,6	1.485,8	692,7	454,9	221,9	1.697,7
	10	27,8	1,3	57,0	663,9	75,4	845,7	2.318,5	113,4	1.648,6	2.834,6	974,1	986,4	56,7	612,8
	11	1,7	2,8	92,6	1.184,8	114,7	791,4	1.939,1	299,3	1.818,0	1.457,0	590,3	416,0	159,0	1.296,4
	12	1,7	0,4	8,8	146,3	37,4	3,0	21,5	0,0	281,9	42,8	22,0	11,3	15,6	36,2
	13	0,7	0,0	136,5	172,8	102,7	0,0	10,8	39,1	48,0	48,7	568,5	220,6	1.699,3	181,6
	14	1,1	0,0	145,3	302,3	60,8	1,4	12,8	15,0	481,7	113,4	100,0	99,5	135,8	175,0
ROC Activity Sectors	**1**	105,3	0,1	0,2	6.142,9	0,0	3,7	0,0	14,3	1,0	0,0	0,1	2,1	1,2	24,8
	2	0,0	1,6	0,0	97,1	0,0	0,0	0,0	0,1	0,0	0,0	0,0	0,0	0,0	0,0
	3	0,0	0,0	134,8	1.370,0	375,2	1.066,8	0,0	0,0	13,5	0,0	0,4	1,3	0,6	0,5
	4	547,5	23,0	71,7	8.628,4	89,5	816,7	425,9	2.749,4	2.072,3	359,5	1.060,6	322,5	579,7	887,5
	5	15,5	0,3	45,4	152,5	363,8	10,2	98,9	113,9	84,9	65,0	220,1	101,2	39,9	92,4
	6	26,4	0,0	20,6	25,9	1,2	0,0	0,1	356,3	63,5	0,0	1.791,5	95,0	81,6	57,7
	7	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
	8	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
	9	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
	10	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
	11	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
	12	10,8	1,8	9,0	73,7	17,2	1,7	10,1	0,0	134,5	33,0	18,2	6,8	9,2	14,8
	13	4,3	0,2	135,8	84,8	47,3	0,0	5,1	23,4	23,5	38,3	478,9	132,2	1.018,7	74,9
	14	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
	IC	1.046,4	53,9	1.554,9	37.341,6	2.492,9	9.558,3	7.127,7	6.465,8	13.659,1	7.170,1	8.636,4	4.155,1	5.334,2	6.456,3
	IC*	475,0	30,6	1.051,6	35.667,4	2.473,3	6.510,0	8.272,1	5.611,9	15.862,4	7.149,0	13.499,4	3.720,3	6.708,7	7.355,4

Table 4. cont.
Initial Regionalized National Input-Output Table for Argentina in 2006 (transactions)

		ROC Activity Sectors													
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**
BAC Activity Sectors	**1**	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
	2	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
	3	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
	4	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
	5	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
	6	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
	7	186,7	13,3	13,6	933,1	2,6	434,7	104,6	58,7	104,4	14,5	17,9	21,8	27,8	46,7
	8	43,3	14,4	0,0	722,1	0,6	0,0	14,8	2,9	61,6	0,0	6,4	649,7	471,0	88,2
	9	334,9	46,5	143,0	5.913,1	150,4	1.773,3	648,8	12,0	1.765,4	299,4	165,6	305,3	151,1	635,5
	10	665,2	22,7	249,5	1.677,8	144,2	2.312,2	2.765,6	46,0	1.167,3	1.070,8	0,0	1.491,2	86,8	649,7
	11	44,6	53,8	445,4	3.305,0	243,0	2.387,1	2.593,2	149,1	1.491,9	188,8	209,9	698,1	270,1	1.550,4
	12	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
	13	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0	0,0
	14	10,4	0,0	226,5	251,0	36,0	1,3	5,2	4,4	100,7	50,9	49,4	52,3	70,6	58,0
ROC Activity Sectors	**1**	5.571,6	7,5	2,0	37.451,2	0,0	24,8	0,0	21,9	2,0	0,0	0,1	7,7	4,3	68,6
	2	0,1	63,4	0,0	616,0	0,0	0,0	0,0	0,2	0,0	0,0	0,0	0,0	0,1	0,0
	3	8,4	0,0	1.853,9	14.625,6	2.601,1	13.087,3	0,0	0,0	37,5	0,0	0,4	6,5	3,3	1,7
	4	10.651,6	469,6	2.884,8	97.490,6	994,4	21.006,0	2.386,3	6.966,9	7.565,0	493,4	1.211,5	2.282,7	4.191,5	4.482,7
	5	154,6	3,0	627,7	2.553,5	4.253,6	184,5	728,0	352,4	389,8	104,9	293,3	772,6	309,9	605,8
	6	664,6	0,0	1.528,5	513,5	12,0	0,0	0,5	863,1	220,1	0,0	1.974,7	630,1	552,6	275,2
	7	913,6	65,7	78,3	6.168,7	18,8	2.803,4	753,1	309,7	927,1	35,0	34,6	136,4	176,3	382,9
	8	86,1	28,9	0,0	1.656,3	1,4	0,0	43,2	7,4	297,8	326,3	236,9	1.628,5	1.177,7	283,4
	9	988,4	138,5	468,8	21.128,6	571,5	6.241,9	3.311,0	252,4	7.193,1	1.514,5	617,3	1.236,9	609,9	3.767,2
	10	709,3	24,3	280,6	1.968,2	174,1	2.693,0	3.783,3	118,6	2.095,5	1.334,1	700,6	1.853,2	107,6	939,4
	11	39,6	47,9	415,3	3.201,3	241,6	2.297,2	2.884,0	285,3	2.106,2	1.047,3	214,7	712,3	275,2	1.811,5
	12	71,3	11,7	73,1	729,6	158,7	16,2	80,4	0,0	824,3	64,3	28,9	47,0	64,2	129,6
	13	29,0	1,5	1.133,7	864,3	440,3	0,0	41,0	90,6	141,5	73,7	753,4	915,5	7.275,6	658,8
	14	44,7	0,1	1.125,0	1.409,2	221,0	7,1	36,6	28,2	1.152,6	139,4	107,4	312,3	426,9	395,8
	IC	21.218,2	1.012,9	11.549,6	203.178,5	10.265,3	55.270,0	20.179,5	9.570,0	27.643,8	6.757,4	6.623,0	13.760,1	16.252,3	16.831,0
	IC*	21.789,5	1.036,3	12.053,0	204.852,7	10.284,9	58.318,4	19.035,1	10.423,8	25.440,5	6.778,5	1.759,9	14.194,9	14.877,7	15.931,8

Source: Own elaboration.

4.2. The RAS method

Biproportional Adjustment, usually called RAS method (Stone, 1962 and Bacharach, 1970) is a well-known technique widely used by analysts to adjust and/or update IO tables. Although the literature covers this topic in detail, we can say that basically the technique takes an initial matrix and a set of row and column vectors as a benchmark to enforce. After several iterations, the method offers a new table with transactions that has a similar structure to the initial matrix, but it enforces the constraints (at rows and columns level)[4].

4.3. Regional Cross-Entropy: additional constraints for the regional problem

The principle of minimum Cross-Entropy (CE) is an inference statistic application based on information theory that consists of estimating an unknown probability density of q when there exists a prior estimate of the density p and new information in the form of constraints on expected values (Shore, John E. et. al, 1981).

The procedure implies to minimize a cross-entropy measure of distance (Kullback-Leibler, 1951) between the initial and the new probabilities. This principle implies that we should choose the posterior q with the least cross-entropy, between all densities that satisfy the constraints.

It could be considered that this method as more flexible than RAS because it allows updating the tables starting from inconsistent data. Moreover, it allows including additional constraints like non-linear constraints of information on each transaction or a set of them (not necessarily total row or column).

In our case, once the BRIO matrix was estimated, the problem has become to find a new set of coefficients (new BRIO matrix) close to the already existing ones (initial BRIO matrix), minimizing the cross-entropy distance but enforcing the constraints.

Thus, let a^*_{ij} and a_{ij} denote the original coefficient and the new coefficient, respectively. Then,

$$\min \sum_i \sum_j a_{ij} \ln \frac{a_{ij}}{a^*_{ij}} \tag{8}$$

such that,

$$\sum_i a_{ij} = 1; \qquad \sum_j a_{ij} x_j = y_i \tag{9}$$

with $0 \leq a_{ij} \leq 1$, where x and y are vectors of known data (in our case, production and IC data). The solution is obtained by solving a Lagrangian that includes equations (8) and (9). The results combine information about the new coefficients matrix and the initial one:

$$a_{ij} = \frac{a_{ij}\, exp\left(\varphi_i y^*_j\right)}{\sum_{ij} a^*_{ij}\left(\varphi_i y^*_{ij}\right)} \tag{10}$$

Where φ_i are the Lagrange multipliers associated with the row-columns sum and the denominator is the normalization factor. This methodology is used to update the social accounting matrices.[5]

Furthermore, this paper introduces additional transaction and transversality constraints in the minimizing program. The first one has been introduced by means of equation (6). On the other hand, the transversality constraint (which consider the assumptions in the previous Section 3), has been introduced as follow,

$$\prod_{p \neq s} t^{p,s}_{ij}\, 0. \tag{11}$$

where p and s are the purchasing and supplying region and ij are the specific sectors.

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[4] It has been shown by Bacharach (1971) that RAS converges under some necessary and sufficient conditions.

[5] A methodological approach has been shown by Chisari *et. al* (2010) and Romero (2009). In addition, it could also be seen in Arndt, Robinson and Tarp (2002) to view application focuses on computable general equilibrium models.

It is important to mention that the transaction constraint cannot be applied for the entire matrix because the BAC intra-regional table have been fixed, being the loss of degrees of freedom the main problem. Instead, the equation (11) was enforced for each interregional transaction.

Enforcing these constraints implies less distance between transaction values of our estimated national IO matrix (constructed from the BRIO matrix) and the values of the original one.

One of the advantages of cross entropy is that we have some degrees of freedom in some values from the total column/row. Lamonica (2020) presents an hybrid method combining constrained matrix-balancing methods for the case of the world input-output table. He found that Cross Entropy method boosted by de FLQ has better estimators. Our paper is in line with this method, but, unlike Lamonica (2020), we applied it to adjust a Bi-Regional table.

4.4. Cross-entropy method applied over the initial BRIO matrix.

CE method has been run in GAMS (General Algebraic Modeling System) with different quantities and combination of restrictions at the sectoral level to find the best fit between the original national IO matrix and the estimated one.

Firstly, the program was run without these constraints. Secondly, the first principal purchasing transaction for each sector at national level was fixed. Finally, the second purchasing transaction was computed. This procedure was followed until all possible restrictions were applied without neglecting the objective of maximum approximation in the aggregation.

The final BRIO transaction matrix is shown in the following Table 5.

TABLE 5.
Final BRIO Transaction Matrix for Argentina (2006)

		BAC Activity Sectors													
		1	2	3	4	5	6	7	8	9	10	11	12	13	14
BAC Activity Sectors	1	3,4	0,1	0,0	681,0		0,3		0,7	0,1		0,0	0,1	0,1	1,9
	2	0,0	0,1		15,1				0,0					0,0	
	3	0,1	0,0	45,0	1.627,6	244,4	823,7			7,6		0,3	0,6	0,5	0,3
	4	103,1	7,7	218,1	9.300,5	146,0	2.017,0	505,7	1.810,7	2.137,2	230,3	1.005,1	323,0	879,8	982,5
	5	1,6	0,1	48,8	390,7	634,5	21,6	177,9	109,7	124,1	56,9	282,9	134,0	78,3	158,1
	6	6,3		109,1	37,3	1,6		0,1	187,4	42,1		1.109,7	74,6	91,4	49,3
	7	10,1	1,2	6,7	1.219,8	5,0	368,9	335,9	134,2	432,5	27,2	50,2	36,3	69,2	147,6
	8	1,2	0,7		382,3	0,5		23,5	6,1	207,5	380,1	507,0	603,0	633,7	162,4
	9	12,2	2,9	44,7	4.493,4	169,6	906,2	1.626,1	139,2	5.237,8	1.483,8	1.255,1	410,4	294,7	1.937,2
	10	12,6	0,7	38,7	593,3	74,6	563,7	2.672,3	97,0	1.888,9	2.824,4	1.542,7	887,6	74,8	696,7
	11	0,8	1,6	62,9	1.086,0	113,9	530,2	2.253,2	257,9	2.106,2	1.454,7	908,7	376,0	211,7	1.480,8
	12	0,8	0,2	5,9	114,9	36,7	2,0	23,5		302,9	40,6	31,8	9,9	19,9	39,9
	13	0,3	0,0	88,4	77,3	97,2		9,7	29,4	39,0	38,7	643,7	175,5	1.851,5	178,6
	14	0,5	0,0	98,7	267,8	60,3	0,9	14,8	12,9	553,8	113,5	161,1	89,8	180,3	199,7
ROC Activity Sectors	1	47,8	0,1	0,1	5.705,0		2,5		12,3	1,1		0,1	1,9	1,5	28,4
	2		0,9		90,2				0,1					0,0	
	3			91,7	1.265,9	372,8	716,2			15,8		0,7	1,2	0,9	0,5
	4	248,5	13,1	48,9	8.003,1	88,9	548,8	495,5	2.381,7	2.402,3	360,5	1.595,2	291,8	772,8	1.015,0
	5	7,0	0,2	30,9	142,3	361,8	6,8	115,8	99,2	100,1	65,5	359,9	91,6	53,3	106,0
	6	12,0		14,0	24,5	1,2		0,1	312,9	75,2		3.080,0	86,2	109,4	66,3
	7														
	8														
	9														
	10														
	11														
	12	4,9	1,0	6,1	69,1	17,1	1,1	11,9		159,3	33,3	29,8	6,1	12,3	17,0
	13	2,0	0,1	92,9	80,2	47,2		6,2	20,5	28,9	39,6	935,3	120,9	1.372,6	87,3
	14														

	IC	475,0	30,6	1.051,6	35.667,4	2.473,3	6.510,0	8.272,1	5.611,9	15.862,4	7.149,0	13.499,4	3.720,3	6.708,7	7.355,4
	IC*	475,0	30,6	1.051,6	35.667,4	2.473,3	6.510,0	8.272,1	5.611,9	15.862,4	7.149,0	13.499,4	3.720,3	6.708,7	7.355,4

Table 5. cont.
Final BRIO Transaction Matrix for Argentina (2006)

		ROC Activity Sectors													
		1	2	3	4	5	6	7	8	9	10	11	12	13	14
BAC Activity Sectors	1														
	2														
	3														
	4														
	5														
	6														
	7	191,7	13,5	14,2	1.027,9	2,6	468,4	101,4	63,9	99,2	14,7	4,7	22,7	25,6	44,7
	8	41,7	14,6		552,5	0,6		13,2	3,1	54,2		1,6	648,1	406,6	81,0
	9	335,1	47,0	145,6	5.430,5	149,4	1.827,7	599,0	13,0	1.592,4	298,0	46,2	310,0	133,9	593,9
	10	649,5	23,0	249,8	1.373,3	142,2	2.328,9	2.507,9	49,1	1.032,5	1.063,7		1.500,5	75,1	601,5
	11	45,1	54,4	456,6	3.111,5	242,1	2.475,9	2.406,1	160,9	1.348,8	187,9	52,1	713,0	241,5	1.452,9
	12														
	13														
	14	10,4	0,0	230,5	195,9	35,7	1,4	4,8	4,8	89,6	50,8	12,7	53,1	62,6	54,2
ROC Activity Sectors	1	5.633,2	7,7	2,0	37.885,1		26,5		23,7	1,9		0,0	7,9	3,8	64,7
	2	0,1	64,4		622,6				0,2					0,1	
	3	8,5	0,0	1.916,6	14.393,6	2.599,7	13.758,6			34,7		0,1	6,7	2,9	1,6
	4	11.074,3	485,5	3.007,6	97.939,9	994,9	22.195,5	2.221,4	7.573,9	6.847,9	492,8	295,6	2.341,1	3.761,0	4.213,7
	5	157,8	3,1	647,6	2.655,5	4.264,4	198,5	689,0	386,3	364,5	105,2	76,0	794,2	279,8	575,3
	6	686,0	0,0	1.592,6	567,1	12,0		0,5	957,4	208,3		530,5	652,2	504,3	261,9
	7	920,8	66,8	80,9	6.147,2	18,8	2.948,0	715,0	335,5	863,7	35,1	9,0	140,4	159,6	362,6
	8	89,3	29,4		1.870,9	1,4		41,6	8,0	283,1	328,8	61,9	1.698,9	1.089,2	271,5
	9	1.012,5	140,2	484,8	22.042,1	571,6	6.635,6	3.136,5	273,5	6.654,9	1.517,9	174,3	1.274,3	552,7	3.569,2
	10	740,0	24,7	293,8	2.302,9	175,1	2.958,3	3.687,1	129,2	1.990,1	1.351,3	183,6	1.942,8	99,3	903,7
	11	41,2	48,5	433,7	3.493,6	242,6	2.469,7	2.756,9	310,3	1.961,1	1.050,6	54,0	740,0	252,6	1.724,6
	12	73,1	11,9	75,7	777,4	158,8	17,6	76,5		778,5	64,6	7,5	48,4	58,2	122,9
	13	32,0	1,6	1.230,8	964,4	449,9		42,1	100,3	143,5	75,6	221,8	972,0	6.769,5	649,5
	14	47,3	0,1	1.190,2	1.498,7	223,2	8,0	36,1	30,8	1.091,5	141,4	28,4	328,5	399,5	382,4
	IC	21.789,5	1.036,3	12.053,0	204.852,7	10.284,9	58.318,4	19.035,1	10.423,8	25.440,5	6.778,5	1.759,9	14.194,9	14.877,7	15.931,8
	IC*	21.789,5	1.036,3	12.053,0	204.852,7	10.284,9	58.318,4	19.035,1	10.423,8	25.440,5	6.778,5	1.759,9	14.194,9	14.877,7	15.931,8

Source: Own elaboration.

5. Case study of Buenos Aires City – multipliers, Rasmussen indicators and footprint analysis

Once the BRIO matrix is obtained, we are able to undertake any kinds of regional studies using an interregional approach, which allows us to take into account the interconnections between the regions.

Considering the objective of the 8th SDG we compute the intraregional and interregional multipliers to analyze sectoral structure of BAC and understand its interregional spillover effects. In addition, we follow the Rasmussen (1956)'s methodology to identify the relevance of each sector in the regional economy network. On the other hand, taking into account the objective of the 13th SDG we compute the BAC regional carbon footprint to determine the sectoral emissions responsibilities.

We present the methodology insights in section 5.1 and then we briefly interpret the results in section 5.2.

5.1. Methodology insights

To analyze the interdependencies between sectors of each region, considering the interregional spillover effects, we follow Rasmussen's methodology. This methodology consists of computing two indices at sector level: the Power of Dispersion index (PD) and the Sensitivity of Dispersion index (SD), which allow us to identify the relevance of each sector for the regional economic network.

To compute these indices, we first have to calculate the Leontief (L) matrix associated with the estimated BRIO matrix. It should be noted that, since it is an IRIO model, we have:

$$L = (I - A)^{-1} = \begin{bmatrix} L^{BAC,BAC} & L^{BAC,ROA} \\ L^{ROA,BAC} & L^{ROA,ROA} \end{bmatrix} = \left(\begin{bmatrix} I & \theta \\ \theta & I \end{bmatrix} - \begin{bmatrix} A^{BAC,BAC} & A^{BAC,ROA} \\ A^{ROA,BAC} & A^{ROA,ROA} \end{bmatrix} \right)^{-1} \quad (12)$$

where,

- $A^{BAC,BAC}$ and $A^{ROA,ROA}$ matrices are the intraregional technical coefficient matrix estimated before,
- $A^{BAC,ROA}$ and $A^{BAC,ROA}$ matrices are the interregional technical coefficient matrix estimated before, and
- I and θ are the identity matrix and null matrix, respectively.

The PD indicator is defined as the relative extent to which an increase in final demand for the products of industry j is dispersed throughout the total system of sectors:

$$PD_j = \frac{\frac{1}{n}\sum_i l_{ij}}{\frac{1}{n^2}\sum_i \sum_j l_{ij}} \quad (13)$$

where l_{ij} are the elements of the Leontief matrix. If the $PD_j > 1$, the intermediate input requirements increase generated by one unit increase in final demand of sector j, will be greater for such sector than for the economy's average. Thus, such sector has a robust backward drag. Conversely, if $PD_j < 1$, the j sector will have a low carry-forward and insignificant effects on the economy.

On the other hand, the SD indicator describes the extent to which the industry system draws on the given i industry, generating forward linkages:

$$SD_i = \frac{\frac{1}{n}\sum_j l_{ij}}{\frac{1}{n^2}\sum_i \sum_j l_{ij}} \quad (14)$$

If the $SD_i > 1$, the increase in the production of sector i will be greater than in the productive system's average; and if $SD_i < 1$, the system average increase will be higher than in sector i, denoting slight effects on the productive system. This index represents a measure of forward linkages.

Considering both indices for each sector, Rasmussen proposes a four-way classification according to the results of both indicators:

- Key sectors when $PD_j > 1$ and $SD_i > 1$, indicating that such sector have an above-average drag with strong forward and backward linkages.

- Strategic sectors when only $SD_i > 1$, indicating that such sector have little effect on the rest of the sectors but highly affected by them.
- Pushing sectors when only $PD_j > 1$, indicating that such sector have significantly affect the rest of the sectors.
- Independent sectors when $PD_j < 1$ and $SD_i < 1$, indicating that such sector have little drag both backward and forwards.

We use this four-way classification to interpret the role of each sector for the two regions. Results are presented in Table 6.

In addition, following Miller and Blair (2009), to analyze the sectoral structure and understand the interregional spillover with IRIO model, we compute various types of multipliers using the Leontief submatrices in (12):

- Intraregional multipliers: are obtained as the column sum of the BAC intraregional Leontief matrix ($L^{BAC,BAC}$) elements. It represents the total value of output from all sectors in the region BAC used to satisfy a dollar's worth of final demand for sector j in the same region. Sectors in BAC with a high intraregional multiplier induce the development of other sectors of the region on the demand side.
- Interregional multipliers: are obtained as the column sum of the ROA,BAC interregional Leontief matrix ($L^{ROA,BAC}$) elements. It represents the total value of output from all sectors in the region ROA used to satisfy a dollar's worth of final demand for sector j in the BAC. Sectors in BAC with a high interregional multiplier induce the development of other sectors on the other region on the demand side.
- Regional multipliers: are obtained as the column sum of $L^{BAC,BAC}$ and $L^{ROA,BAC}$ elements.

TABLE 6.
Rasmussen classification criteria, multipliers and production value (PV) of BAC

Nº	Sector	Classification	Multipliers			PV of BAC (%)
			Intraregional	Interregional	Regional	
1	Agriculture, forestry and hunting	Pushing	1,20	0,54	1,75	0,5%
2	Fishing	Pushing	1,32	0,49	1,81	0,0%
3	Mining and quarrying	Independent	1,25	0,16	1,41	1,7%
4	Industry	Key	1,50	0,58	2,08	23,2%
5	Water, Electricity and gas	Pushing	1,54	0,47	2,01	1,6%
6	Construction	Pushing	1,55	0,29	1,83	5,2%
7	Commerce	Independent	1,45	0,13	1,58	9,1%
8	Hotels and restaurants	Pushing	1,35	0,55	1,89	4,8%
9	Transport and communication	Key	1,57	0,28	1,85	12,8%
10	Financial intermediation	Strategic	1,44	0,12	1,55	8,1%
11	Real estate, renting and business	Strategic	1,26	0,31	1,57	16,9%
12	Public administration	Independent	1,39	0,19	1,58	4,3%
13	Education, health and social services	Pushing	1,36	0,31	1,68	6,6%
14	Other services	Pushing	1,63	0,32	1,96	5,2%

Source: Own elaboration.

It is worth noting that intraregional Leontief matrices ($L^{BAC,BAC}$ and $L^{ROA,ROA}$) represent the intraregional effects, both intra- and interindustry, of an exogenous change in the final demand of the region. On the other hand, interregional Leontief matrices ($L^{ROA,BAC}$and $L^{BAC,ROA}$) represent the interregional spillover effects and its elements accounts a measure of the impacts, both direct and indirect, in one region caused by changes in the final demand in another region.

The result of the mentioned multipliers is also presented in Table 6and interpreted further.

Finally, a footprint analysis allows us to complete the sectoral analysis with an environmental dimension. By computing the footprint analysis, we can identify and quantify the generation of carbon emissions (CO2) associated with each sector of each region, given a fixed productive structure and a precise moment in time.

Technically, to compute the CO2 multipliers for each sector of the BAC and ROA, we post-multiply the Leontief inverse matrix - L in (12) - that contains intraregional and interregional, both direct and indirect relationships between sectors, with the CO2 emissions vector from Chisari et al. (2020b).

Then, we compute the CO2 footprints for both regions by multiplying the multiplier vector and the final demand. The aggregate national sectoral results and BAC's share of the carbon footprint are presented in Table 7.

TABLE 7.
National and BAC Carbon footprint in MtCO2eq, percentages and BAC's share

Nº	Sector	Original Emissions	National FP (MtCO2eq)	National FP (%)	BAC FP MtCO2eq	BAC FP (%)	BAC's share (%)
1	Agriculture, forestry and hunting	139,24	36,96	10,1%	1,50	2,0%	4%
2	Fishing	0,34	0,71	0,2%	0,02	0,0%	3%
3	Mining and quarrying	17,74	5,31	1,5%	1,01	1,3%	19%
4	Industry	58,81	158,10	43,4%	32,26	42,3%	20%
5	Water, Electricity and gas	70,98	34,08	9,4%	9,22	12,1%	27%
6	Construction	5,38	38,90	10,7%	4,16	5,5%	11%
7	Commerce	2,91	13,41	3,7%	4,05	5,3%	30%
8	Hotels and restaurants	0,09	8,85	2,4%	2,94	3,8%	33%
9	Transport and communication	50,22	17,97	4,9%	3,75	4,9%	21%
10	Financial intermediation	0,00	0,24	0,1%	0,01	0,0%	4%
11	Real estate, renting and business	4,35	6,75	1,9%	5,24	6,9%	78%
12	Public administration	1,36	11,73	3,2%	2,53	3,3%	22%
13	Education, health and social services	0,00	7,57	2,1%	2,49	3,3%	33%
14	Other services	13,02	23,88	6,6%	7,08	9,3%	30%
	Total	**364,44**	**364,44**	**100%**	**76,27**	**100%**	**21%**

Source: Own elaboration.

5.2. Analysis of results

As was mentioned above, Rasmussen classification enable us to analyze, given the interregional connections, the role of each sector of the BAC and identify key sectors that depend on inter-industrial supply and demand or even their independency from the other sectors of the region. In addition, the intraregional and interregional multipliers, allow us to understand the behavior of the economy's internal structure and its interregional spillover effects.

The Key sectors identified in the economy of BAC (also with strong regional multipliers) are Industry and, Transport and Communication Services representing 36% of the BAC's PV. The Financial Intermediation services and Real estate, renting and business appear to be Strategics sectors for the inter-industrial interactions, concentrating 25% of the regional PV (see Table 6). The Pushing sectors of the BAC concentrates 24% of the regional production value and are mainly represented by service sectors (Construction, Hotels and Restaurants and, Education, Health and Social Services). Independent sectors in the BAC are Commerce and Public Administration which accumulate the remaining 13.4% of the BAC's PV.

Regarding the multipliers, Table 6 shows that Industry and various service sector (mainly Water, electricity and gas, Construction and Transport and communication) have the highest intraregional multipliers of BAC. On the other hand, the primary sector, Industry and only one service sector (Hotel and Restaurants) have the highest interregional multipliers. This result shows the economic structure differences and interconnections between regions

Concerning carbon footprint, Industry and Service sectors (mainly Water, Electricity and gas, Real Estate and Construction) are the responsible for the BAC carbon emissions.

For instance, we can say that the Industry and Water, Electricity and Gas sectors in the BAC are Key and Pushing sectors, respectively, and they have the highest regional multiplier for this regional economy. However, they are carbon-intensive activities. According to Argentina's climate change commitments, these sectors (very important in the BAC) should switch to the use of low-carbon technology.

6. Conclusions

In the light of the assumed commitment by the Buenos Aires City in the 2030 Agenda for Sustainable Development Goals (SDG's), policy makers require a methodology to quantify the effects of their decisions. This paper contributes to these requirements by presenting an interregional Input-Output analysis of two-region economy, the Buenos Aires City, and the Rest of Argentina.

Since the lack of regional matrices in Argentina, to carry out the interregional analysis we had to build a Bi-Regional Input-Output matrix using a hybrid approach that combines the non-survey methods based on Location Quotients and the well-known matrix balancing methods. Considering the contribution of Lamonica et. al (2020) we prefer to boost the preliminary estimation with the cross-entropy method over the RAS method. The former is also capable of replicate more accurately the national input-output table and takes advantage of the information the researcher has.

Once the BRIO matrix was obtained, we analyze sectoral structure of BAC, its interregional connections and we identify the relevance of each sector in the regional economy network. In addition, we estimate the carbon footprint of Argentina and the share of the Buenos Aires city to analyze the responsibilities of the regional sectors.

As expected, results show that service and industry sectors play an important role in the economy of BAC and some of them have strong interregional spillover effects over the rest of the country. In addition, the results also show that sectors on BAC with the highest regional multipliers are also the ones with highest emissions.

It is important to mention that this analysis could be extended for more sectors and to analyze regional matters in other regions. It also could be extended to the analysis of the impacts of environmental policies, such as the initiative to create local green jobs, the deployment of distributed generation or energy efficiency measures.

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Annex

Technical coefficients of national Input-Output table for Argentina in 2006

	Sectores	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	Agriculture, forestry and hunting	0,0880	0,0028	0,0000	0,1098	0,0000	0,0003	0,0000	0,0012	0,0000	0,0000	0,0000	0,0002	0,0001	0,0019
2	Fishing	0,0000	0,0233	0,0000	0,0018	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000	0,0000
3	Mining and quarrying	0,0001	0,0000	0,0435	0,0429	0,1396	0,1581	0,0000	0,0000	0,0006	0,0000	0,0000	0,0002	0,0001	0,0000
4	Industry	0,1769	0,1813	0,0693	0,2858	0,0534	0,2558	0,0347	0,3743	0,1114	0,0266	0,0372	0,0583	0,0693	0,1230
5	Water, Electricity and gas	0,0027	0,0012	0,0158	0,0079	0,2282	0,0024	0,0106	0,0189	0,0057	0,0057	0,0090	0,0202	0,0053	0,0166
6	Construction	0,0109	0,0000	0,0363	0,0015	0,0006	0,0000	0,0000	0,0464	0,0032	0,0000	0,0606	0,0161	0,0091	0,0076
7	Commerce	0,0174	0,0291	0,0022	0,0208	0,0011	0,0391	0,0123	0,0166	0,0136	0,0019	0,0011	0,0039	0,0033	0,0110
8	Hotels and restaurants	0,0020	0,0159	0,0000	0,0070	0,0001	0,0000	0,0008	0,0006	0,0053	0,0176	0,0073	0,0582	0,0273	0,0102
9	Transport and communication	0,0209	0,0681	0,0143	0,0793	0,0387	0,0968	0,0576	0,0136	0,1319	0,0817	0,0190	0,0394	0,0126	0,1208
10	Financial intermediation	0,0217	0,0173	0,0124	0,0107	0,0171	0,0604	0,0952	0,0088	0,0480	0,1297	0,0215	0,0854	0,0032	0,0436
11	Real estate, renting and business	0,0013	0,0374	0,0202	0,0191	0,0260	0,0566	0,0796	0,0233	0,0530	0,0666	0,0130	0,0360	0,0090	0,0923
12	Public administration	0,0013	0,0050	0,0019	0,0024	0,0093	0,0002	0,0012	0,0000	0,0121	0,0035	0,0009	0,0013	0,0011	0,0036
13	Education, health and social services	0,0005	0,0006	0,0298	0,0028	0,0256	0,0000	0,0006	0,0049	0,0021	0,0040	0,0231	0,0250	0,1279	0,0181
14	Other services	0,0009	0,0001	0,0317	0,0049	0,0138	0,0001	0,0006	0,0015	0,0170	0,0075	0,0033	0,0091	0,0081	0,0125

Source: Own elaboration based on Instituto Nacional de Estadísticas y Censos (INDEC).