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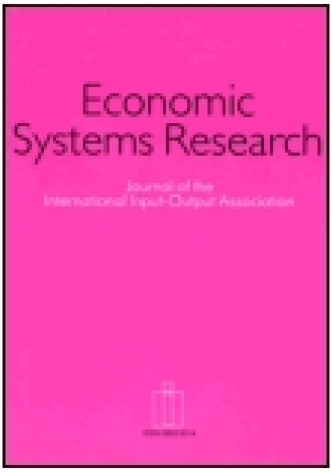

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TESTING ASSUMPTIONS MADE IN THE CONSTRUCTION OF INPUT-OUTPUT TABLES

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TESTING ASSUMPTIONS MADE IN THE CONSTRUCTION OF INPUT–OUTPUT TABLES

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Product input–output (IO) tables are mainly constructed on the basis of product and/or industry technology assumptions. The choice is not trivial and deserves empirical analysis using input and output data at the level of establishments. This paper offers input–output compilers econometric tests to facilitate the construction of tailored hybrid technology-based product IO tables. We provide weighted likelihood ratios of the product and industry technology assumptions. Although the proposed econometric tests are aimed to be used *ex ante*, we construct four variants of hybrid technology-based product IO tables using establishment data from Andalusia (Spain) and contrast them to the official product IO table and the pure product and industry technology-based tables. Our econometric tests are not valid for industry IO tables.

Keywords: Input–output tables; Econometric tests

1. INTRODUCTION

There are two types of input–output (IO) tables and each type has two main methods of construction. *Product IO tables* are conceptually clean and their construction has nice theoretical foundations, but *industry IO tables* make a comeback (Yamano and Ahmad, 2006). Product IO tables are chiefly constructed according to the product technology assumption (the favorite of theorists, Kop Jansen and ten Raa, 1990; ten Raa and Rueda-Cantuche, 2003, and of statistical offices) or the industry technology assumption (which yield no negative coefficients and have been adopted by the US Bureau of Economic Analysis and other offices). Industry IO tables are constructed chiefly according to the fixed product sales structure assumption (Canada, Denmark, Finland, The Netherlands and Norway) or the fixed industry sales structure model (criticized as unrealistic by Eurostat, 2008, but defended on theoretical grounds by Rueda-Cantuche and ten Raa, 2009). In this paper, we take a pragmatic look at product IO tables, letting the data decide which of the two competing assumptions is better for each product. We thus construct a hybrid technology-based IO table. We also explain why this approach is not applicable to industry IO tables.

Most statistical offices already use hybrid product and industry technology assumptions to construct product IO tables (and also hybrid fixed product and fixed industry sales structure

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*Corresponding author. E-mail: jmruecan@upo.es assumptions to construct industry tables), but on the basis of expert judgments. Our purpose is to supplement the judgment with econometric analysis of establishment data, which are unlikely to become publicly available, but can be used in-house.

The product and industry technology assumptions are the main competitors (albeit not the only ones). One of the two assumptions is not the alternative to the other in the sense of hypothesis testing. The assumptions are not even nested. Our strategy, therefore, is to determine the level of confidence of each assumption and then to select one of them accordingly, on a product-by-product basis.

2. TESTING THE ASSUMPTIONS IN PRODUCT INPUT–OUTPUT TABLES

2.1. The Tests

Product IO tables[1] describe the technological relations between products: how to produce products by means of products. In contrast, industry IO tables[2] depict inter-industry relations, displaying the industries' use of each other's products.

To construct a product IO table, secondary outputs must be transferred out to the industries for which they are primary outputs, along with the associated inputs. (And to construct an industry IO table, secondary products must be transferred into the primary output of the industry, see Rueda-Cantuche and ten Raa, 2009.) The question is how to associate inputs with the transferred outputs. This can be handled in different ways and these distinguish the competing construction models.

Primes denote transposition, $^{-1}$ inversion of a matrix and $^\wedge$ diagonalization, whether by suppression of the off-diagonal elements of a square matrix or by placement of the elements of a vector. A use matrix $\mathbf{U} = (u_{ij})$ comprises commodities i $(= 1, \ldots, n)$ consumed by industries j $(= 1, \ldots, n)$ and a make matrix $\mathbf{V} = (v_{ji})$ shows the produce of commodities i in terms of industries j; it is the transposed of a supply matrix (Eurostat, 2008). Following Rueda-Cantuche and ten Raa (2009), product input–output coefficients can be defined generically by

$$a_{ij} = \frac{u_{ij} - \sum_{k \neq j} a_{ijk} v_{jk} + \sum_{k \neq j} a_{ikj} v_{kj}}{\sum_k v_{kj}}, \tag{1}$$

where product coefficient a_{ijk} is the amount of product i used by industry j to make one unit of product k. The product technology assumption postulates that all products have unique input structures irrespective of the industry of fabrication (removal of the second subscript) and can be written as follows:

$$a_{ijk} = a_{ik}^{PT} \text{ for all } j. \tag{2}$$

Substitution of Equation 2 into Equation 1 confirms the well-known product technology formula (Rueda-Cantuche and ten Raa, 2009)

$$u_{ij} = \sum_k a_{ik}^{PT} v_{jk}. \tag{3}$$

---

[1] Hereafter, product IO tables will refer to 'product-by-product symmetric input–output tables'.

[2] Hereafter, industry IO tables will refer to 'industry-by-industry symmetric input–output tables'.

The industry technology assumption postulates that every industry has its own specific input structure irrespective of the product-mix of that industry (removal of the third subscript) and can be written as follows:

$$a_{ijk} = a_{ij}^{IT} \text{ for all } k. \tag{4}$$

Substitution of Equation 4 into Equation 1 confirms the well-known industry technology formula (Rueda-Cantuche and ten Raa, 2009)

$$u_{ij} = a_{ij}^{IT} \sum_{k} v_{jk}. \tag{5}$$

The idea of this paper is to add error terms to Equations 3 and 5 and thus to consider the input–output coefficients as regression coefficients (Mattey and ten Raa, 1997). The regressions of the inputs on outputs are performed at the level of establishments. If this is done for the subsets of establishments which constitute the industries, the product technology assumption is confirmed if the input coefficients are the same across subsets. The imposition of this equality will increase the residual sums of squares and the increase is measured by the F-statistic. A modification of this procedure is used to test the industry technology assumption.

To explain the basic idea, imagine 100 establishments produce cheese, of which 25 in agriculture, 15 in the meat industry and 60 in the cheese industry. All establishments are supposed to use milk as input in their production process. Therefore, if cheese is supposed to be produced with the same input structure irrespective of the industry of production (the product technology assumption), the input share of milk across the 100 establishments must be similar. However, if we admit different cheese technologies, the input shares will differ between industries.

To test the industry technology assumption, imagine 100 establishments whose main business is the production of meat and meat products. Some establishments also feature livestock activities and production of animal fats. All establishments use plastic materials. If the industry technology holds for livestock and animal fats, the input ratio of plastic materials to the total output of the meat industry (including primary and secondary activities) across all establishments must be similar to the input ratio accounting only for the primary output (meat production). The larger the difference between these two input shares, the more likely it is that the industry technology assumption is rejected.

Let m $(>c)^3$ be the total number of establishments, m_1 the number of establishments populating industry 1, m_2 the number of establishments populating industry 2, …, so that $m = m_1 + m_2 + \ldots\ m_n$. We propose the following null hypothesis, where $a_{ik}^{PT}(j)$ is the technical coefficient a_{ik}^{PT} of the jth term of Equation 3:

$$\text{H}_0 : a_{ik}^{PT}(j) = a_{ik}^{PT}, \text{ for } j = 1, 2, \ldots, n \tag{H1}$$

---

[3] Notice that m should be greater than c (= number of non-zero product inputs) to get positive degrees of freedom in the econometric regression. Besides, c is always different from n provided that industries do not use all types of products as inputs but only a few of them. Also, m might be also referred to a more detailed breakdown of n industries and not necessarily to establishment micro-data, which would be the highest detail level. We also assume that firms of the same industry operate with the same technology.

under which the product technology assumption is fulfilled. Running the corresponding regressions for the product and industry technology assumptions yields estimations of the associated inputs (left-hand side of equation), which by difference with respect to their actual values lead to the so-called residuals. They are subsequently made square and summed over all observations, i.e. the residual sum of squares (RSS). Next, we will use the RSS of two different models to construct a standard F-statistic that would allow us for testing H1. On the one hand, we will take for granted (H1) and assume that for all industries, we have the same input structures and consequently one single regression shall be run using all the considered observations, namely r (or establishments). This is the so-called restricted model. On the other hand, the so-called unrestricted model consists of regressions with n restrictions or equations, all of which must be estimated independently with a subset of m_j observations in each case (only those establishments producing effectively product k). By using the F-test[4] based on the residual sum of squares of the restricted ($\mathrm{RSS_C}$) and unrestricted (RSS) models

$$F_{(n-1),m-n} = \frac{(\mathrm{RSS_C} - (\mathrm{RSS}_1 + \mathrm{RSS}_2 + \cdots + \mathrm{RSS}_n))\,/(n-1)}{(\mathrm{RSS}_1 + \mathrm{RSS}_2 + \cdots + \mathrm{RSS}_n)\,/(r-n)},$$

we will be able to test the statistical significance of the product technology assumption for each of the inputs. As long as we accept the null hypothesis in most of them, we may eventually accept the product technology assumption on the basis of a weighted ratio of the number of accepted inputs over the total number of inputs used. The weights would correspond to the input structure of those surveyed establishments that produce product k independently of the industry to which they belong. The so-called probability values (usually abbreviated as p-values) provide the minimum significance levels to reject the null hypothesis. For example, if a p-value equals 0.05, then the imposition of the product technology model pushes the error terms in the tail with 5% mass, i.e. we shall accept H1.

For the industry technology assumption, the following null hypothesis can be proposed, where $a_{ij}^{IT}(k)$ is the technical coefficient a_{ij}^{IT} of the kth term of Equation 5:

$$\mathrm{H}_0 : a_{ij}^{IT}(k) = a_{ij}^{IT}, \ \text{for}\, k = 1, 2, \ldots, m_s \qquad \text{(H2)}$$

under which the industry technology model is fulfilled. Next, we regress input i's use of industry j's establishments on their primary and secondary outputs. In standard econometrics, the F-test (Johnston and Di Nardo, 1997) is frequently used to test the equality of regression coefficients in a flexible manner. With $q = (m_s - 1)$ independent equations in H2, m_j number of observations (number of establishments populating industry j) and m_s explanatory variables (number of different secondary outputs), we may define the F-statistic as

$$F_{(m_s-1),m_j-m_s} = \frac{(\mathbf{R}\hat{\boldsymbol{\beta}} - \mathbf{r})'[\mathbf{R}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{R}']^{-1}(\mathbf{R}\hat{\boldsymbol{\beta}} - \mathbf{r})/(m_s - 1)}{\mathrm{RSS}/(m_j - m_s)},$$

---

[4] This F-test is a modified version of the Chow test for structural change (Gujarati, 2003, pp. 275–279).

where $\mathbf{X}$ is a matrix of explanatory variables (industry j's output by product type in columns), RSS the sum of the (ordinary least squares) squared residuals, and $\mathbf{R}$, $\mathbf{r}$ and $\boldsymbol{\beta}$ as follows:

$$\mathbf{R} = \begin{pmatrix} 1 & -1 & 0 & \cdots & 0 \\ 0 & 1 & -1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 1 & -1 \end{pmatrix}_{(m_s-1)\mathrm{x}m_s}, \quad \mathbf{r} = \begin{pmatrix} 0 \\ \vdots \\ 0 \end{pmatrix} \quad \text{and} \quad \boldsymbol{\beta} = \begin{pmatrix} a_{ij}^{IT}(1) \\ \vdots \\ a_{ij}^{IT}(m_s) \end{pmatrix}.$$

By means of this F-test, the reader may test the equality of the regression coefficients and therefore, whether the input requirement of product i is independent of the commodity produced in industry j. For instance, if we have a p-value equal to 0.3, the imposition of the industry technology model pushes the error terms less in the tail with 30% mass. In general, a greater p-value indicates a better fit of the technology assumption to the data. The analysis can be extended to all the other inputs and as long as we accept H2 in most of them, we may accept eventually the industry technology model on the basis of a weighted ratio of the number of accepted inputs over the total number of inputs used. In this case, the weights correspond to the product input structures of the surveyed establishments of industry j.

2.2. Data Sources and Preparation

The Andalusian Input–Output Framework, MIOAN-95 (IEA, 1999) was one of the first Spanish regional input–output tables based on the new European System of Accounts (ESA-95) published by Eurostat (1996). The Institute of Statistics of Andalusia (IEA) provided the authors with the cross-section inputs and outputs establishment data used for the construction of the MIOAN-95. The data provided by the IEA had been completed and edited to obtain a full specification of inputs and outputs, e.g. including adjustments accounting for changes in inventories, computing trade outputs as a difference between sales and purchases of goods that are neither processed nor transformed; estimating net premiums in insurance services; financial intermediation services indirectly measured as intermediate consumption, etc. These adjustments led in some cases to consolidate input and output structures into single overall structures depending on the data availability. Evidently, those industries for which there was eventually one single input and output structure were not taken into account for the econometric analyses (e.g. public administration, finance, insurance services, agriculture, public hospital services, public social services, etc.). Redefinitions implemented in the course of the actual input–output compilation were not carried back to the establishment data used for our analysis. They were made at the aggregated level during the compilation process.

The conversion from purchasers' prices into basic prices is reported in ten Raa and Rueda-Cantuche (2007, pp. 332–334). We used the same trade, transport and net taxes on products' rates that were reported by the valuation matrices used in the compilation of the use table at basic prices in the IEA. We assumed equality of margins and net product taxes across establishments in industry j producing product k. Once trade and transport margins and net taxes on products were subtracted from the use flow data, we reallocate the subtracted total trade and domestic transport margins to trade and transport industries, respectively. We received the technical support of the IEA to carry out this task.

The surveys collected the information on inputs at the level of 89 products requiring a full specification of inputs used for the production process. At this point, there were also different *ad hoc* industry-specific designs for the surveys conveyed to wholesale trade, retail trade, construction, small and medium enterprises in the manufacturing industries, fisheries and services.

The sample used by IEA (1999) in the construction of the supply and use system covered nearly 45% of total domestic output and more than one-third of total employment. The IEA completed the initial survey-based data on industries' detailed turnovers and purchases with other statistical sources from the National Statistical Institute, the Central Balance Sheet Office and public institutions (health services, government budget data, education, agriculture, etc.) to achieve such large sample coverage. The final sample size eventually achieved 18,084 observations (ten Raa and Rueda-Cantuche, 2007), which were classified into 89 different industries (see the complete list in the appendix). The availability of establishments' data is not really very common outside statistical offices. Actually, this is the reason why we had to use data from a region and a less recent year. However, we recognize that it would be desirable to extend the analyses presented in this paper to other regions and countries to see their implications for the general applicability of the tests.

2.3. Discussion of the Empirical Results

Following the theoretical approach suggested in the previous section, we have tested the product technology and the industry technology hypotheses using establishments' data from Andalusia (Spain) for 43 products and 47 industries. The base year is 1995. The complete list comprises 89 products and 89 industries. The remaining products and industries were not analyzed for two reasons: (a) there was not enough surveyed information available to run the regressions and (b) there was insufficient and/or reliable information on the input structures of those establishments that produce secondarily one product that is produced almost exclusively by its own primary industry.

Tables 1 and 2 depict the parameters of estimation of the tests carried out for the product and industry technology assumptions. For instance, for the product technology test, we made the estimations for $c = 58$ non-zero inputs (number of estimated equations), with $n = 2$ different industry suppliers and a total amount of $r = 168$ establishments producing fish and fishing products; for the industry technology test, we included $m_s = 3$ different types of output (including its primary production) and estimated the regression with $m_j = 168$ establishments populating the fishing activities. Fifty-six regressions were estimated for $m_i = 56$ non-zero inputs. The same applies to other products and/or activities (see Tables 1 and 2 for details). In total, we run 2793 regressions for testing the product technology assumption and 2304 regressions for testing the industry technology assumption.

Table 3 summarizes the outcomes from the estimated regressions. For instance, 82.04% of the input requirements of the fish and fishing activities can be said to be used in the same proportion by other industries to produce fish and fishing products secondarily, but only 24.64% of the input structure might be considered specific from the industries that produce fish and fish products (primarily or secondarily). We might then interpret these two ratios as measurements of the likelihood of the respective technology assumptions. Accordingly, we may postulate that the input requirements used by secondary suppliers to produce fish and fishing products should be removed according to the input structure of the fishing activities

TABLE 1. Parameters of estimation for the product technology test.

Code	Products	c	n	r
6	Fish and fishing products	58	2	168
12	Meat and meat products	70	2	244
13	Canned and preserved fish, fruit and vegetables	67	6	424
14	Fats and oils	59	3	325
15	Milk and dairy products	58	4	123
16	Grain mills, bakery, sugar mills, etc.	61	4	626
17	Miscellaneous food products	65	9	601
18	Wines and alcoholic beverages	64	3	173
19	Beer and soft drinks	55	2	66
22	Clothing products	55	3	573
23	Leather tanning, leather products and footwear	50	2	144
24	Cork and wood products	52	2	4269
25	Paper and allied products	57	5	818
26	Printing, publishing and editing services	73	2	454
27	Petroleum refining products	56	3	64
28	Basic chemical products	60	5	117
29	Other chemical products	63	3	194
30	Rubber and plastic products	62	8	4227
31	Cement, lime and allied products	55	2	504
32	Ceramics, clay, bricks and other products for building	56	2	230
33	Stone and glass products	58	3	319
34	Primary metal products	53	3	128
35	Fabricated metal products	75	6	1496
38	Electrical and electronic machinery	56	4	2386
40	Professional and scientific instruments	71	2	109
41	Motor vehicles transportation equipment	54	2	52
42	Naval transportation and repairing services	52	2	78
43	Miscellaneous transportation equipment	52	2	66
44	Furniture	60	5	757
50	Construction work	78	4	1237
54	Wholesale trade services	80	24	9455
55	Retail trade and repair domestic and personal effects	71	7	8726
56	Hotels' services	76	2	51
57	Bars' and restaurants' services	80	5	596
62	Allied transportation services	79	3	164
63	Post and communications' services	76	4	251
68	Machinery and equipment rental	81	3	45
69	Computer services	69	2	94
71	Accounting and law activity services	76	3	276
73	Marketing services	74	4	63
79	Private education services	77	3	3618
84	Public drainage and sewerage services	70	2	35
87	Other amusement, cultural, sport and recreation services	79	3	588

Source: Own elaboration.

Note: c, number of non-zero inputs (estimated equations); n, number of industry suppliers of product i; r, number of establishments producing product i.

TABLE 2. Parameters of estimation for the industry technology test.

Code	Industries	m_i	m_s	m_j
6	Fishing	56	3	168
12	Meat manufacturing industry	53	11	239
13	Manufacture of canned and preserved fish, fruit and vegetables	56	12	148
14	Fats and oils manufacturing industry	53	11	252
15	Milk and dairy products industry	51	8	34
16	Grain mills, bakery, sugar mills, etc.	55	9	469
17	Miscellaneous manufactured food industry	56	14	139
18	Wines and alcoholic beverages fabrication	51	9	105
19	Beer and soft drinks industry	46	4	23
22	Clothing	49	6	483
23	Leather tanning, leather products and footwear industry	45	5	135
24	Cork and wood products industry	47	7	299
25	Paper manufacturing	45	6	51
26	Printing, publishing and editing	50	6	447
27	Petroleum refining	43	3	9
28	Basic chemicals industry	51	6	52
29	Other chemical products industry	50	7	96
30	Rubber and plastic industry	47	11	122
31	Cement, lime and allied products industry	50	10	200
32	Ceramics, clay, bricks and other products for building industry	51	3	126
33	Stone and glass manufacturing industry	50	5	282
34	Metallurgy	48	6	58
35	Fabricated metal products industry	51	14	1087
38	Electrical and electronic machinery industry	48	6	88
40	Professional and scientific instruments industry	47	3	60
41	Motor vehicles transportation equipment industry	44	9	45
42	Naval transportation and repairing	49	8	65
43	Miscellaneous transportation equipment industry	47	4	22
44	Manufacture of furniture	50	6	601
47	Electricity and irrigations' services industry	46	7	51
49	Water and sewerage services industry	45	6	67
50	Construction	55	7	1136
52	Petrol and motor vehicles trade	44	6	380
54	Wholesale trade	50	15	4535
55	Retail trade and repairing activities	56	12	4113
56	Hotels	60	12	20
57	Bars and restaurants	70	10	352
62	Allied transportation activities	50	7	142
63	Post and communications	42	4	205
69	Computer activities	30	4	84
71	Accounting and law activities	46	10	235
72	Engineering and architecture technical activities	38	4	31
73	Marketing services activities	28	4	8
74	Security services activities	41	4	48
79	Private education	56	5	150
84	Public drainage and sewerage services activities	40	6	15
87	Other amusement, cultural, sport and recreation activities	68	13	538

Source: Own elaboration.

Note: m_i, number of non-zero inputs (estimated equations); m_s, number of different products produced by establishments populating industry j; m_j, number of establishments populating industry j.

TABLE 3. Testing the assumptions. Weighted ratios of acceptance.

Code	Products/industries	PTM (%)	ITM (%)	Dec
6	Fish and fishing products	82.04	24.64	P
12	Meat and meat products	4.65	1.11	P
13	Canned and preserved fish, fruit and vegetables	19.00	69.09	I
14	Fats and oils	39.54	1.09	P
15	Milk and dairy products	38.28	1.85	P
16	Grain mills, bakery, sugar mills, etc.	43.70	0.75	P
17	Miscellaneous food products	40.03	41.41	I
18	Wines and alcoholic beverages	46.01	5.14	P
19	Beer and soft drinks	55.24	16.54	P
22	Clothing products	94.55	0.04	P
23	Leather tanning, leather products and footwear	100.00	10.28	P
24	Cork and wood products	6.30	1.39	P
25	Paper and allied products	36.81	37.11	I
26	Printing, publishing and editing services	3.36	1.05	P
27	Petroleum refining products	94.87	12.67	P
28	Basic chemical products	83.29	7.28	P
29	Other chemical products	98.37	23.59	P
30	Rubber and plastic products	1.43	21.01	I
31	Cement, lime and allied products	4.34	7.30	I
32	Ceramics, clay, bricks and other products for building	62.40	40.70	P
33	Stone and glass products	10.90	1.95	P
34	Primary metal products	99.64	50.89	P
35	Fabricated metal products	6.45	3.69	P
38	Electrical and electronic machinery	0.57	88.96	I
40	Professional and scientific instruments	98.83	3.58	P
41	Motor vehicles transportation equipment	87.39	60.52	P
42	Naval transportation and repairing services	92.68	7.13	P
43	Miscellaneous transportation equipment	67.51	45.36	P
44	Furniture	3.92	29.86	I
47	Electricity and irrigations services	–	0.11	P
49	Water and sewerage services	–	53.10	I
50	Constructions	28.92	0.43	P
52	Petrol and motor vehicles trade services	–	20.97	P
54	Wholesale trade	0.25	2.72	I
55	Retail trade and repair domestic and personal effects	0.22	1.03	I
56	Hotels' services	6.13	30.37	I
57	Bars' and restaurants' services	64.20	0.01	P
62	Allied transportation services	99.95	12.90	P
63	Post and communications' services	3.24	1.17	P
68	Machinery and equipment rental	5.21	–	I
69	Computer services	18.83	13.68	P
71	Accounting and law activity services	84.29	3.28	P
72	Engineering and architecture technical services	–	18.07	P
73	Marketing services	48.77	4.88	P
74	Security services	–	52.34	I
79	Private education services	0.59	0.02	P
84	Public drainage and sewerage services	0.06	38.47	I
87	Other amusement, cultural, sport and recreation services	96.43	0.02	P

Source: Own elaboration.

Notes: PTM, product technology model; ITM, industry technology model; 'Dec', decision adopted (P, PTM and I, ITM). Although labels correspond to the product dimension only, they can be interpreted as their equivalent industries for the interpretation of column ITM.

(product technology assumption). The tests might also be used to investigate if individual inputs (rather than entire input structures) are processed in product or industry style.

Our tests are not single tests of one technology against the other, but merely indicate which technology assumption is more likely. Due to the insufficient level of breakdown in the classification used, there are products and industries for which both ratios of acceptance are over 50% (or both under 50%). We simply select the technology assumption with the highest rate of acceptance. However, there were cases with only one available estimated ratio of acceptance; these cases we handled as follows. If the available product technology model ratio was below 50% (e.g. machinery and equipment rental), we opted for the industry technology model (and for the product technology model otherwise). If the available industry technology model ratio was below 50% (e.g. petrol and motor vehicles trade activities), we opted for the product technology model (and for the industry technology model otherwise). Last column of Table 3 lists our choices ‘P’ and ‘I’ (product and industry technology assumptions, respectively). Still the list of industries/products in Table 3 is not complete.[5] Therefore, we must simply assume either the product technology assumption or the industry technology assumption for those not covered by the econometric tests (see Table A.1 in the Appendix for a full list of all 89 products and their equivalent industries).

There are other examples, for which the choice in favor of the product technology assumption might even be clearer, i.e. weighted ratios of acceptance close to 100% for the product technology assumption while much $<$50% for the industry technology assumption, namely clothing; leather tanning, leather products and footwear; professional and scientific instruments; naval transportation; allied transportation services; and other amusement, cultural, sport and recreation services.

As regards the industry technology assumption, there are only two industries for which it is clearly more likely that the corresponding input structure might be of an industry-specific type, namely the manufacture of canned and preserved fruit, fish and vegetables and the fabrication of electrical and electronic machinery. The heterogeneity of the mix product classification in both cases definitely plays a relevant role in the results obtained, thus being unlikely to find a single input structure common to all industries. Therefore, the industry technology model is likely to be largely supported, as it is shown in Table 3. Nearly 70% of the inputs used in the canned and preserved fruit, fish and vegetables are industry-specific while this amounts to nearly 90% in the case of the fabrication of electrical and electronic machinery.

We believe that the results obtained from these tests might be helpful in the construction of symmetric input–output tables. For the very first time, a new approach uses establishment’s data not only for the compilation process but also for the testing of the assumptions in the construction of input–output tables. To illustrate it with an example, let us choose the fishing activities. Fish and fish products are produced almost exclusively by fisheries. Consequently, it can be said that the actual input structure of the fishing industry performs a single product (and industry) technology. But however, nearly a quarter of its total output corresponds to the production of canned and preserved fish, which makes the input structure be largely distorted. Hence, in order to achieve the pure product technology of fishing products, the

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[5] Recall that industries with one single representative input and output structure were excluded from the econometric analysis (e.g. public administration, finance, insurance services, agriculture and others mentioned in Section 2.2).

inputs used for its secondary production should be subtracted from its actual input structure according to its own specific technology (industry technology model). Indeed, Table 3 shows that there is not a likely common product technology for producing canned and preserved fish products throughout the industries. In other words, the industry technology model fitted better the data (69.09%) rather than the product technology model (19%). In the same line, the inputs used by the canned and preserved fish producers to produce fish and fishing products secondarily should be subtracted according to the input structure of the fishing activities (product technology model). However, hybrid technology-based product IO tables are compiled at the aggregate level, without individual transfers between industries.

As mentioned earlier, the heterogeneity of the mix product classification definitely plays a crucial role in the identification of a single product input structure common to all industries. As long as the classification is not largely broken down into detailed products, it seems that the empirical tests will favor the industry technology assumption against its counterpart. Nonetheless, we must be cautious in the conclusions. This does not mean at all that the product technology assumption might be false or unrealistic in some cases. All it means is that the heterogeneity of the mix product output of industries makes their input structures specific everywhere, thus making really difficult to single out almost any product technology. The power of the tests may be raised by increasing the number of observations and/or the detail breakdown of surveyed establishments' purchases and turnovers.

In the next section, we will go one step further and construct a set of hybrid technology input–output tables (only the intermediate use matrix) according to the choices made and depicted in Table 3. We will discuss their similarities with respect to the official product IO table. Pure product and industry technology-based product IO tables will also be constructed and compared against the official one. Complementarily, we will also discuss how close the official and the different product IO table estimates are to the use table at basic prices, which is basically the starting point of the IO compilation.

3. HYBRID TECHNOLOGY PRODUCT IO TABLES

Hybrid product and industry technology methods for the construction of product IO tables date back to the SNA-68 (UN, 1970). The hybrid technology method assumes that subsidiary production fits either the commodity technology or the industry technology assumptions. The hybrid methods require the supply table to be split into two matrices,[6] $\mathbf{V}_1$ and $\mathbf{V}_2$, where the former comprises the outputs for which the product technology assumption is made, and the latter, the outputs for which the industry technology assumption holds. One would expect that most commodities have the same input structure wherever they are produced, but that some secondary products are obtained as a result of industrial processes (i.e. by-products). Therefore, secondary outputs are most likely to be included in $\mathbf{V}_1$, and by-products in $\mathbf{V}_2$. We will use the notation and mathematical formulation of ten Raa and Rueda-Cantuche (2003).

Following the SNA-68 (UN, 1970), we assume that the secondary outputs included in $\mathbf{V}_1$ have product outputs ($\mathbf{q}_1$) proportional to the industry outputs ($\mathbf{g}_1$). Similarly, we assume

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[6] The interested reader can find numerical examples in ten Raa and Rueda-Cantuche (2003) and in Rueda-Cantuche (2010).

FIGURE 1. Hybrid IO constructs.

	Remainder	
	PTM	ITM
Z_H	Z_HP	Z_HI
Z_Y	Z_YP	Z_YI

that industries produce by-products ($\mathbf{g}_2$) proportional to their total commodity output ($\mathbf{q}$). This pair of assumptions together implies that the intermediate use matrix is $\mathbf{Z}_{\mathrm{H}}(\mathbf{U},\mathbf{V})$, specified below.

Alternatively, the secondary outputs may be assumed proportional to their commodity output (assuming fixed market shares) and the production of by-products proportional to their total industry output. Then the intermediate use matrix becomes $\mathbf{Z}_{\mathrm{Y}}(\mathbf{U},\mathbf{V})$, also specified below:

$$\mathbf{Z}_{\mathrm{H}}(\mathbf{U},\mathbf{V}) = \mathbf{U}\hat{\mathbf{g}}^{-1}(\hat{\mathbf{g}}_1\mathbf{V}_1^{-\mathrm{T}}(\mathbf{I} - \hat{\mathbf{q}}^{-1}\hat{\mathbf{q}}_2) + \mathbf{V}_2\hat{\mathbf{q}}^{-1})\hat{\mathbf{q}},$$

$$\mathbf{Z}_{\mathrm{Y}}(\mathbf{U},\mathbf{V}) = \mathbf{U}\hat{\mathbf{g}}^{-1}(\hat{\mathbf{g}}_1\mathbf{V}_1^{-\mathrm{T}}(\mathbf{I} - \mathbf{V}_2^{\mathrm{T}}\hat{\mathbf{g}}^{-1}\mathbf{H}) + \mathbf{V}_2\hat{\mathbf{q}}^{-1})\hat{\mathbf{q}},$$

with $\mathbf{H}$ such that $\mathbf{g} = \mathbf{H}\mathbf{q}$ or equivalently:

$$\mathbf{H} = (\hat{\mathbf{q}}_1\mathbf{V}_1^{-1}(\mathbf{I} - \hat{\mathbf{g}}^{-1}\hat{\mathbf{g}}_2) + \mathbf{V}_2^{\mathrm{T}}\hat{\mathbf{g}}^{-1})^{-1}.$$

As regards notation, $\mathbf{g} = \mathbf{V}\mathbf{e}$ and $\mathbf{q} = \mathbf{V}^{\mathrm{T}}\mathbf{e}$ stand for product and industry outputs, respectively, while $\mathbf{Z}$ corresponds to the intermediate part of the constructed product IO tables. The vector $\mathbf{e}$ denotes a column vector with all entries equal to 1. For each one of the hybrid technology variants, we will determine those products following either the product technology assumption or the industry technology assumption according to the results obtained from the econometric tests (Table 3). For the remainder up to 89 products/industries, we will assume either that all of them follow a product technology assumption or an industry technology assumption. Figure 1 summarizes the different hybrid technology-based variants that we have constructed.

As regards the choice between Z_H and Z_Y, there is not a clear statement in the literature to make a choice on this issue. Armstrong (1975) preferred Z_H for his application to the United Kingdom and ten Raa and Rueda-Cantuche (2003) proved that they both perform the same concerning the axiomatic framework proposed by Kop Jansen and ten Raa (1990). Therefore, we would just report on the results obtained from both hybrid technology variants.

In addition, pure product (Z_P) and industry (Z_I) technology-based IO tables were also constructed for the sake of comprehensiveness. For comparability purposes, we have used the mean average percentage error, the weighted average percentage error, the standardized weighted absolute difference and the coefficient of determination as in Temurshoev et al. (2011).

Our analysis of the methods of construction used in the compilation of the official product IO table is *ex post*. Ideally, the analysis would be done *ex ante*, guiding IO compilers in choosing between the two technology assumptions. Our analysis reveals which method agrees best with the official IO table, throwing some light on the implicit assumptions made

TABLE 4. Comparison between hybrid and pure technology models.

	MAPE	Rk.	WAPE	Rk.	SWAD	Rk.	R^2	Rk.	CmR.
	Comparison between different IO tables vs. official IO table								
PTM	36.30	1	6.14	1	0.0176	2	0.9944	3	1
ITM	73.08	6	6.33	3	0.0322	6	0.9973	1	5
Z_HP	50.27	3	6.39	4	0.0172	1	0.9939	5	2
Z_HI	58.53	5	6.28	2	0.0245	5	0.9945	2	3
Z_YP	45.63	2	6.79	5	0.0181	3	0.9940	4	4
Z_YI	56.29	4	7.03	6	0.0215	4	0.9934	6	6
	Comparison between use table at basic prices vs. official IO table and others								
Use vs. IOT	29.33	2	4.84	1	0.0202	1	0.9981	1	1
Use vs. PTM	61.85	6	7.87	5	0.0309	5	0.9933	5	5
Use vs. ITM	26.04	1	7.12	2	0.0300	4	0.9978	2	2
Use vs. Z_HP	56.01	4	7.19	3	0.0278	2	0.9940	4	4
Use vs. Z_HI	44.42	3	7.23	4	0.0294	3	0.9943	3	3
Use vs. Z_YP	59.12	5	9.56	6	0.0351	6	0.9922	6	6
Use vs. Z_YI	64.00	7	10.24	7	0.0394	7	0.9913	7	7

Source: Own elaboration.

Note: PTM, product technology model; ITM, industry technology model; IOT, actual input–output table; Z_HP, Z_HI, Z_YP and Z_YI, hybrid input–output constructs (see Figure 1); MAPE, mean average percentage error; WAPE, weighted average percentage error; SWAD, standardized weighted absolute difference; R^2, coefficient of determination; Rk., ranking; CmR., common ranking.

by input–output compilers in Andalusia. We had no access to the compilation method used by Andalusian IO compilers, the manual expert-based adjustments to balance supply and demand. The product technology assumption fits best into the transition from the use and make tables to the official IO table and this was confirmed by the IO compilers contacted at the Andalusian Statistical Office. However, the aim of this paper is not the difficult reconstruction of the methods used by IO compilers, but rather to use firms' data on inputs and outputs for splitting the make table and applying the hybrid technology model, to construct a product-by-product IO table.

Similarly, since it is very well-known that use tables at basic prices are the starting point for the construction of product IO tables, we will also discuss to what extent the former deviates or changes as a result of the compilation processes of the official and the different estimated product IO tables.

Table 4 summarizes the main results. The pure product technology assumption reports the least mean and weighted average errors with respect to the official product IO table. It amounts to 6.14% as a weighted average. In terms of absolute weighted differences, the hybrid Z_HP variant is closest to the official IO table (also mostly product technology-based). Conversely, the pure industry technology assumption gives the best fit in terms of linear correlations with respect to the official IO table, probably due to the fact that it is the only method that does not yield negatives and therefore, it might be the most highly correlated matrix with respect to a non-negative official product IO table. The common ranking shows that the product technology assumption (either in its pure or mixed forms) has played an important role in the compilation of the Andalusian official product IO table.

By definition, all the methods discussed for the construction of product IO tables modify the input structures of a use table at basic prices to accommodate column-wise industries into products. By using the same measures of error, we find that the official IO table is the one that changes the use table the least, followed by the industry technology assumption (where the absence of negatives might have played a role again; the negative values amounted on average 1% of the overall total) and the hybrid Z_HI variant (almost industry technology-based). The same applies in terms of correlations, being the official IO table the one with the highest coefficient of determination with respect to the use table.

4. LIMITATIONS OF APPLICABILITY

4.1. Detailed Data Requirements

The main problem of the applicability of our new approach is that it requires detailed commodity data on inputs and outputs at the level of individual establishments, (perfectly) classified according to the NACE Rev. 1.1 classification and valued in basic prices. These data are not readily available from surveys. Firms report data of goods and services with insufficient specification and mostly in purchasers' prices. Smaller firms are generally less accurate in the description of their inputs. There are many examples of partly specified inputs, e.g. single aggregates for a mixed bunch of goods (food and drinks in hotels and restaurants; consumed building materials in construction firms; office material in service firms, etc.) and the 'other costs' items, which may include a large variety of commodities. It is a common practice to complete the full specification of firms' data on inputs and outputs by using assumptions that come close to product or industry technology assumptions. In doing so, the adjustments are not made at the level of the reporting firms but rather at the level of industry groups, which might distort the final outcomes of the tests proposed in this paper.

Fortunately this shortcoming does not plague our study. The Institute of Statistics of Andalusia (IEA) specifies firms' data on inputs and outputs without filling incomplete responses with previously reported product or industry related input–output structures. Instead actual (real) structures of other firms/establishments (with the same economic activity and similar number of workers) are used. We believe that this procedure of filling the incomplete responses affects our test results little, because no prior product or industry input–output structure was imposed when filling the missing input–output data. Moreover, the IEA produces real input–output structures for all firms/establishments with more than 200–300 workers, which may well cover a substantial amount of the total output of each industry (IEA, 1999). This is another reason why we believe that the IEA procedure affects the results of our tests little.

A second limitation stems from the difference between the valuation at basic prices and at purchasers' prices, consisting of trade and transport margins plus taxes less subsidies on products. However, firms report the price paid including trade and transport margins and (if any) net taxes on products (purchasers' prices). In order to circumvent this problem, we have followed ten Raa and Rueda-Cantuche (2007) and have converted firms' input data from purchasers' prices into basic prices using the same procedure as the Andalusian Statistical Office did for the compilation of its Input–Output Framework (IEA, 1999).

We will briefly describe this procedure, which was carried out at the level of industry and product groups. Let u_{kj}^{b} and u_{kj}^{p} be the total domestic inputs of commodity k by industry j at basic and at purchasers' prices, respectively. We have

$$u^b_{kj} = u^p_{kj} - T^d_{kj} - T_{kj} - N_{kj} - H_{kj}.$$

Here, for each use of commodity k by industry j, T^d_{kj} and T_{kj} are the total amount of trade and transport margins, respectively, N_{kj} the total amount of taxes less subsidies on products (excluding not deductible value added tax, VAT) and H_{kj} the total amount of not deductible VAT. We assume that the trade margins are proportional to the use data at purchasers' prices

$$T^d_{kj} = t^d_{kj} u^p_{kj}, \quad 0 < t^d_{kj} < 1.$$

We also assume that taxes less subsidies on products (excluding not deductible VAT) and transport margins are proportional to the use data at basic prices

$$N_{kj} = n_{kj} u^b_{kj}, \quad 0 < n_{kj} < 1;$$
$$T_{kj} = t_{kj} u^b_{kj}, \quad 0 < t_{kj} < 1.$$

With respect to VAT, the assumption is as follows:

$$H_{kj} = h_{kj}\left(\frac{u^p_{kj}}{1 + h_{kj}}\right), \quad 0 < h_{kj} < 1.$$

Then, by substituting T^d_{kj}, T_{kj}, N_{kj} and H_{kj} into u^b_{kj}

$$u^b_{kj} = u^p_{kj}\left(\frac{1 - t^d_{kj} - (h_{kj}/(1 + h_{kj}))}{1 + t_{kj} + n_{kj}}\right),$$

which was used by the IEA to transform use data from purchasers' values to basic values provided some product ratios of trade and transport margins, not deductible VAT and remaining taxes less subsidies on products. Since, as stated before, the information on inputs and outputs is reported at the level of establishments and not at the level of industry groups, we must estimate the unknown u^b_{kji}, that is, the total use of commodity k by an establishment i from industry j at basic prices, with only information on data from industry and product groups. By assuming equality of margins and taxes less subsidies on products ratios across firms in industry j, which consume some commodity k, we use

$$u^b_{kji} = u^p_{kji}\left(\frac{1 - t^d_{kj} - (h_{kj}/(1 + h_{kj}))}{1 + t_{kj} + n_{kj}}\right)$$

for converting firms' input data from purchasers' prices into basic prices.

Once trade and transport margins and taxes less subsidies on products were subtracted from use flow data, the last step was to allocate the subtracted total trade and domestic transport margins to the trade and transport industries, respectively. This was done with the help and technical support of IEA.

4.2. Industry-By-Industry Input–Output Tables

Following Rueda-Cantuche and ten Raa (2009), input–output coefficients b_{ik} in industry IO tables measure the unitary supplies of industry i to industry k. Subsequently, the industry input–output coefficient is given by

$$b_{ik} = \frac{u_{ik} - \sum_{j \neq i} b_{jik} v_{ji} + \sum_{j \neq i} b_{ijk} v_{ij}}{\sum_j v_{ij}}.$$

The *fixed industry sales structure assumption* postulates that all industries have unique sales structures irrespective of the product market (removal of the second subscript). Consequently, fixed industry sales coefficients may be defined accordingly

$$b_{jik} = b_{jk}^{FI} \text{ for all } i. \tag{H3}$$

Under the hypothesis H3, inter-industry sales coefficients b_{jk} are the deliveries from industry j to industry k per unit of sales of industry j. As a consequence, if H3 holds then it is verified that

$$u_{ik} = \sum_j b_{jk} v_{ji}. \tag{6}$$

The *fixed product sales structure model* assumes that product i's unitary deliveries to industry k must be independent of the supplier industry (j). Therefore, all products have unique sales structures irrespective of the industry of fabrication (removal of the first subscript)

$$b_{jik} = b_{ik}^{FP} \text{ for all } j. \tag{H4}$$

If hypothesis H4 holds, then product-by-industry sales coefficients (market shares) b_{ik}^{FP} are the deliveries of product i to industry k per unit of output of product i. As a result, it is verified that

$$u_{ik} = \sum_j b_{ik}^{FP} v_{ji}. \tag{7}$$

With industry tables, we proceed as follows. Let $l = 1, \ldots, f\ (> n)$[7] be the number of firms producing a certain product i while being f_1 the number of those populating industry $1, f_2$ those populating industry 2, ..., so that $f = f_1 + f_2 + \ldots f_n$. Following Equation 6, we may regress industry k's firm consumption of products $i = 1, 2, \ldots, c$ on firm's output of commodity i by industries $j\ (= 1, 2, \ldots, n)$

$$u_{ikl} = \sum_{k=1}^{n} b_{jk}^{FI} v_{jil} + \varepsilon_{ikl} = b_{1k}^{FI} v_{1il} + b_{2k}^{FI} v_{2il} + \cdots + b_{nk}^{FI} v_{nil} + \varepsilon_{ikl}, \tag{8}$$

where u_{ikl} represents industry k's firm intermediate uses of inputs $i = 1, 2, \ldots, c$ and v_{jil} product i's firm output of industries $j = 1, 2, \ldots, n$.

But notice, however, that there is no easy way out in Equation 8 to find a proper econometric estimation of the parameters since the dependent and the independent variables do

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[7] Notice that f shall be greater than n (number of industries) to get positive degrees of freedom. Moreover, f might be regarded as well to be a more detailed breakdown of commodities, keeping the number of industries unchanged. We also assume that firms of the same industry have the same sales structure.

not correspond to the same units of observation. The unit (and number) of observations in the right-hand side (RHS) of Equation 8 might be different from that of the left-hand side. In other words, the RHS of Equation 8 depicts the number of firms producing product i, which does not need to correspond to the number of firms from industry k using product i. It might be that in the case of product tables, we have information of input uses and product outputs of the same unit of observation (establishment) but however, for industry tables, there is no explicit link between the supplier and the user industry for one certain product i. It seems that the necessary data for testing the market share assumptions in industry IO tables depend on the distribution of total output of establishments over the different user categories, which is very unlikely to ever become available. The same applies to the fixed product sales structure assumption (see Equation 7).

5. CONCLUSIONS

The main contribution of this paper refers to the choice of technology assumption for the construction of product IO tables. We provide input–output compilers with two new econometric tests that can be used in the compilation of a product IO table. These tests will enable statistical offices and researchers to apply more tailored hybrid technology assumptions, which can be complemented with expert judgments in order to improve the whole compilation process. Ideally, these tests should lead to statistically significant conclusions on the selection of the most appropriate technology assumption but the power of the tests can be largely affected by the heterogeneity in the product classification, the insufficient detailed breakdown of products and the errors of measurement at the establishment level. We are convinced, however, that as long as we were able to dispose of a high level of detail in the product classification, the tests presented in this paper can identify more clearly the correct assumption in all products and industries. In the meantime, we can experience sometimes inconclusive results due to the fact that the proposed tests are not single tests of one assumption against the other but rather independent tests, which provide likelihood ratios for each technology assumption separately.

These tests could be definitely used as a guide towards the selection of one of the two technology assumptions in the construction of a hybrid technology-based product IO tables. Unfortunately, similar econometric tests for industry IO tables are not allowed within this framework.

All in all, we must be cautious. The general applicability of the results obtained for Andalusia is very difficult to justify because each country and/or region may have their own specific economic structures and data availability. Nonetheless, we believe that the proposed tests and this methodology can be used by statistical offices provided that, in a previous stage, reporting firms' input and output data are fully specified and converted into basic prices.

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APPENDIX

TABLE A.1. NACE Rev.1.1 Classification.

Code	Description of products
1	Fruits and vegetables
2	Olive and vine
3	Other agriculture and related services
4	Livestock and hunting
5	Forestry and related services
6	Fish and fishing products
7	Coal mining
8	Extraction of crude petroleum and natural gas

(*Continued*)

TABLE A.1. Continued.

Code	Description of products
9	Mining of uranium and thorium ores
10	Metallic minerals
11	Non-metallic and non-energetic minerals
12	Meat and meat products
13	Canned and preserved fish, fruit and vegetables
14	Fats and oils
15	Milk and dairy products
16	Grain mills, bakery, sugar mills, etc.
17	Miscellaneous food products
18	Wines and alcoholic beverages
19	Beer and soft drinks
20	Tobacco products
21	Textile mill products
22	Clothing products
23	Leather tanning, leather products and footwear
24	Cork and wood products
25	Paper and allied products
26	Printing, publishing and editing services
27	Petroleum refining products
28	Basic chemical products
29	Other chemical products
30	Rubber and plastic products
31	Cement, lime and allied products
32	Ceramics, clay, bricks and other products for building
33	Stone and glass products
34	Primary metal products
35	Fabricated metal products
36	Machinery and mechanic equipment
37	Computers and office equipments
38	Electrical and electronic machinery
39	Electronic materials, radio and television equipments
40	Professional and scientific instruments
41	Motor vehicles transportation equipment
42	Naval transportation and repairing services
43	Miscellaneous transportation equipment
44	Furniture
45	Miscellaneous manufactured products
46	Recycling products
47	Electricity and irrigations' services
48	Gas and water steam and irrigation services
49	Water and sewerage services
50	Construction work
51	Preparing, installation and finishing construction services
52	Petrol and motor vehicles trade services
53	Repair motor vehicles' services
54	Wholesale trade activities
55	Retail trade and repair domestic and personal effects
56	Hotels' services
57	Bars' and restaurants' services
58	Railway transportation services

(*Continued*)

TABLE A.1. Continued.

Code	Description of products
59	Other earthbound transportation services
60	Sea and river transportation services
61	Air transportation services
62	Allied transportation services
63	Post and communications' services
64	Finances
65	Insurance
66	Allied financial services
67	Real estate
68	Machinery and equipment rental
69	Computer services
70	Research and development
71	Accounting and law activity services
72	Engineering and architecture technical services
73	Marketing services
74	Security services
75	Cleaning services
76	Other business services
77	Public administration
78	Public education services
79	Private education services
80	Public medical and hospitals' services
81	Private medical and hospitals' services
82	Public social services
83	Private social services
84	Public drainage and sewerage services
85	Social services
86	Cinema, video, radio and television services
87	Other amusement, cultural, sport and recreation services
88	Personal services
89	Household employers services

Source: NACE Rev.1.1