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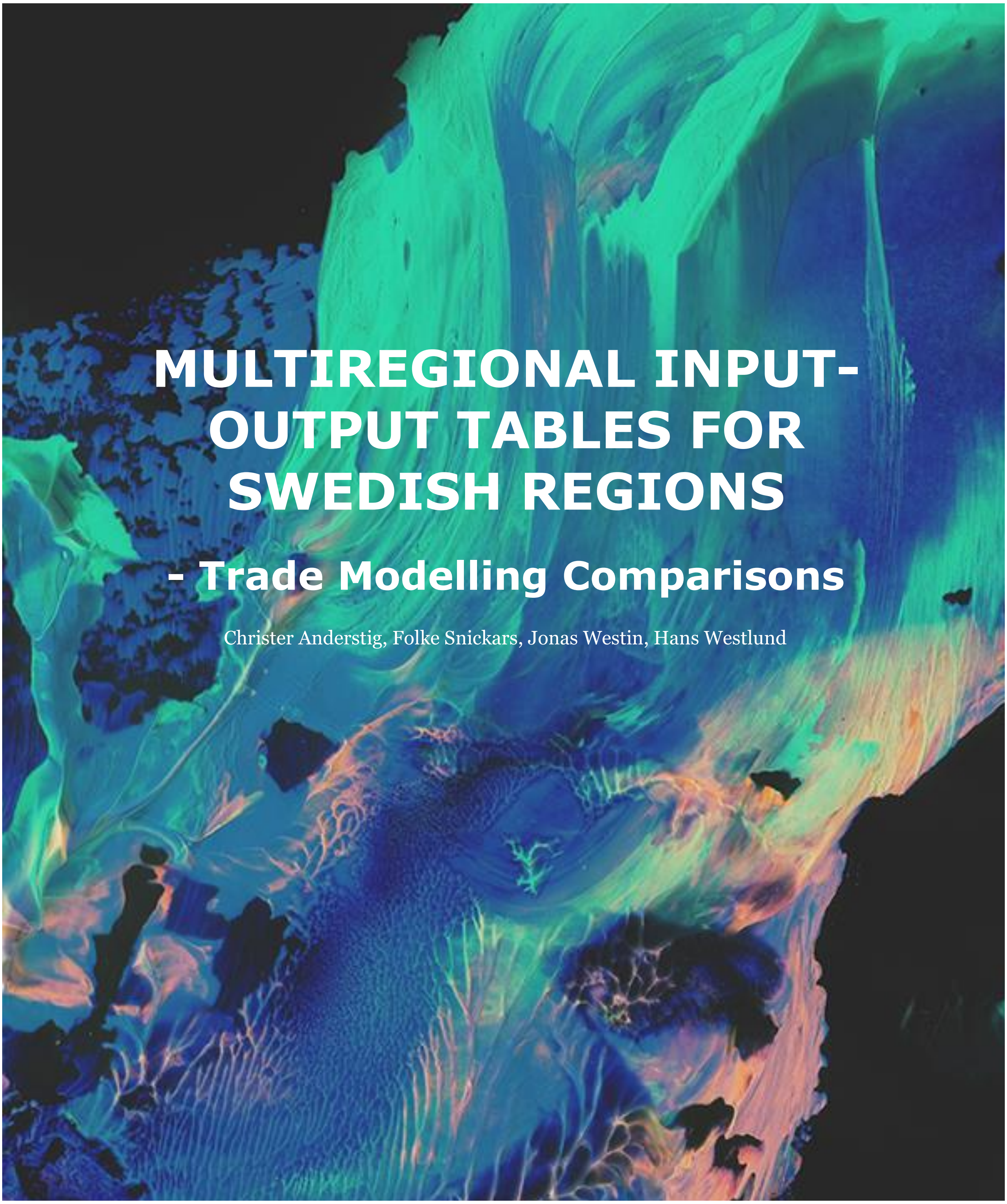

MULTIREGIONAL INPUT-OUTPUT TABLES FOR SWEDISH REGIONS

- Trade Modelling Comparisons

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Contents

1 Introduction

This report concerns the estimation and validation of interregional trade in the new multiregional input-output tables (MRIO-tables) of Statistics Sweden. It is a part of the quality assurance work to use interregional input-output tables for research, policy assessment, and planning. The report focusses on linkages among Swedish regional economies, and internationally, through trade in goods and services. A main result of the work reported in Anderstig et al. (2022) on MRIO-2 is that there is reason to continue and further develop the work on interregional input-output tables within Statistics Sweden. For this effort to be successful, it is necessary to add further resources for the collection of interregional trade statistics and the consistent modelling of interregional trade using a combination of survey and non-survey tools.

The purpose of this report is to discuss topics related to the further development of the new MRIO-tables for Sweden. The report stresses further cooperation between ongoing development work in the government agencies Growth Analysis and the Swedish Agency for Economic and Regional Growth as well as within Transport Analysis and the Swedish Transport Administration. This can consist of a coordination of collection of primary data for commodity trade and exports. These integration issues can be developed further in the third phase of the MRIO project. It is a main goal of this report to add to that component of future development work. This is more important than proceeding with add-on evaluation models. A model to build on already exists in the so-called Raps system for regional economic evaluations, see Anderstig (2017).

It was argued in Anderstig et al. (2022) that the next phase of the Statistics Sweden project will benefit from focusing on linking the Swedish regional and national accounts with the international work on consolidated input-output analysis for groups of countries. In this study we will focus on the recent development of the so-called EU EMS model for world and interregional trade where NUTS2 regions for the EU is used as a building block, see also Mandras et al. (2019), Thissen et al. (2019), and Ivanova et al. (2019). We will also summarize some work on trade statistics surveys done in the US by the Bureau of Transportation Statistics (2022).

2 Structure of Statistics Sweden’s MRIO tables

Statistics Sweden's multiregional input-output tables (MRIOT) of counties in Sweden have been developed in phase two of a project that includes three phases. The national IO tables in national accounts (NR) are produced from the supply and use tables in the annual GDP calculations. Production is estimated for about 400 products and 100 industries; household consumption is distributed for different purposes (COICOP); public consumption is distributed by sector, industry, and function (COFOG), as well as investments.

MRIOT for 21 counties is basically structured in the same way as the national accounts, see Figure 2.1. Detailed MRIOT refers to more than 400 products (*n= 446)*. In the illustration of MRIOT below, only product 1, 2 and *n* are highlighted; similarly, only three counties are marked, 1, 2 and 21; other counties are represented by dots. Shaded elements refer to deliveries within each county; other elements refer to deliveries to other counties and foreign exports (rows), respectively deliveries from other counties and foreign imports (columns).

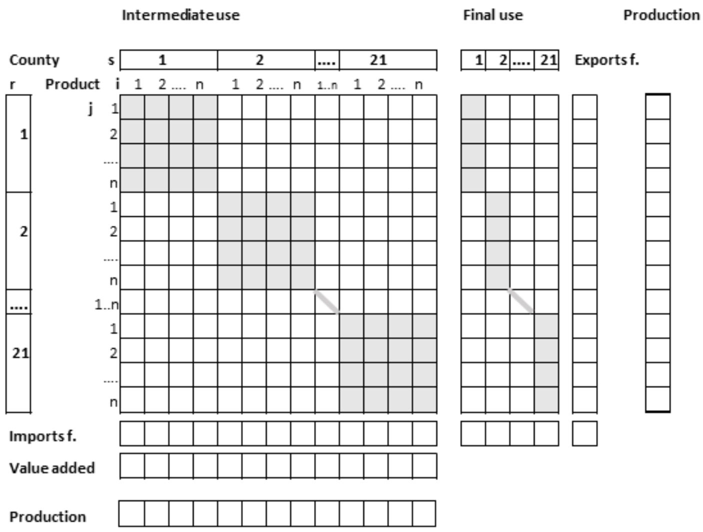

Figure 2.1: Illustration of MRIOT for 21 counties and n products.

In Figure 2.1 production by product and county can be read in two ways. A row sum shows how the product is used as input in production and final use in all counties, as well as exports abroad. The column sum for the same product and county shows production cost divided into inputs from all counties and abroad as well as value added. The complete structure of MRIOT as shown above can be described by the equations:

$$X_i^r = \sum_{s=1}^{21} \sum_{j=1}^{n} X_{ij}^{rs} + \sum_{s=1}^{21} \sum_{k=1}^{8} X_{ik}^{rs} + X_i^{rEx} \qquad (1)$$
$$X_j^r = \sum_{s=1}^{21} \sum_{i=1}^{n} X_{ij}^{sr} + X_j^{Imr} + VA_j^r \qquad (2)$$

where

X_i^r	production of product *i* in county *r* (use)
X_{ij}^{rs}	supply of product *i* from county *r* as input for producing product *j* in county *s*
X_{ik}^{rs}	supply of product *i* from county *r* for final use category *k* in county *s*
X_i^{rEx}	foreign exports of product *i* from county *r*
X_j^r	production of product *j* county *r* (production cost)
X_j^{Imr}	foreign imports to product *j* in county *r*, $X_j^{Imr} = \sum_{i=1}^{n} X_{ij}^{Imr}$
VA_j^r	value added product *j* county *r*

The construction of MRIOT takes place in two stages. The first involves estimating supply S_i^r and use D_i^r by product and county:

$$S_i^r = X_i^r - X_i^{rEx} \qquad (3)$$
$$D_i^r = \sum_{j=1}^{n} X_{ij}^r + \sum_{k=1}^{8} X_{ik}^r \qquad (4)$$

S_i^r	supply of product *i* in county r, i.e., production minus foreign exports
D_i^r	use of product *i* in county *r*, i.e., intermediate use plus final use.

When summing up to the national level supply equals use, $\sum_r S_i^r = \sum_r D_i^r$, but this balance does not apply at the county level.

In the second stage, interregional trade $\hat{X}_i^{rs}$ is estimated. The estimate of interregional trade is based on the assumption of the Chenery-Moses model, see also Oosterhaven & Hewings (2014), where trade flows for product i are specified with respect to sending county r and receiving county s, while use in county s is not specified. With this assumption, trade flows can be expressed with trade coefficients $\hat{X}_i^{rs}$ indicating the proportion of the use of product i in county s that comes from county r. Thus, equation (1) can be rewritten as

$$X_i^r = \sum_{s=1}^{21} \sum_{j=1}^{n} \hat{X}_i^{rs} \cdot X_{ij}^s + \sum_{s=1}^{21} \sum_{k=1}^{8} \hat{X}_i^{rs} \cdot X_{ik}^s + X_i^{rEx} \tag{5}$$

This model setup is used as a framework for the trade analysis in the report.

3 Estimating trade flows in MRIO

The section presents an overview of the system for estimating trade flows in Sweden, with particular emphasis on the estimation of commodity flows by using data from commodity flow surveys. Such survey data, coming from the Swedish Commodity Flow Survey (VFU), is produced at regular intervals since 2001.

VFU is carried out by the Swedish government agency Transport Analysis and is part of Sweden's official statistics in the field of transport and communications. The survey describes commodity flows to, from and within Sweden. The flow of goods is measured in both quantities (tons) and values (SEK). The two latest surveys were performed in 2016 and 2021. The data in the survey is collected from two sources: (1) A survey sent to a total of 12,000 workplaces about incoming and outgoing shipments during selected measurement weeks; (2) Register-based data collected from administrative materials and company registers (Trafikanalys, 2022).[1]

The Swedish Transport Administration uses VFU-data to estimate PWC matrices for the Swedish national model for freight transportation, Samgods. The PWC (Production-Warehouse-Consumption) matrices describe the demand for freight transport in tons per year for different aggregated commodity groups. Several data sources are used to estimate Samgods PWC matrices. These data sources include information on commodity flows from commodity flow surveys, foreign trade statistics, business statistics, national accounts and statistics on consumption and industrial production. In addition, information on properties of the transport system (ports, terminals, etc.) and distance matrices between different regions are used.

The estimation of PWC matrices uses a gravity-RAS approach where unobserved trade flows are estimated using a gravity model in combination with the RAS algorithm for fitting the estimated matrix to total production and consumption in each region (Cai, 2022; Fournier, 2020). The predicted matrices are then adjusted to take, among other things, transit traffic and singular flows into account.

[1] Among similar surveys in other countries, we could refer to the US counterpart. A Commodity Flow Survey (CFS), a component of the US Economic Census, is conducted every five years as a partnership between the Bureau of Transportation Statistics (BTS) and the US Census Bureau. The 2022 CFS is the seventh survey since the program started in 1993. The CFS is a shipper survey of approximately 100,000 establishments from the industries of mining, manufacturing, wholesale trade, auxiliaries (warehouses and distribution centres), and selected retail and service trade industries that ship commodities.

3.1 Comparative analysis of interregional trade in MRIO-2

In this section of the report, we update estimations of commodity flows from MRIO-2 in a systematic fashion. How have the flows developed from 2016 to 2021? To what extent can we forecast the flows for 2021 using the 2016 flows as priors and assuming that row and column totals are identical? In section 5 we continue the comparison with an analysis on how the impact multipliers change when new trade estimations are introduced in the Chenery-Moses framework.

In section 2 we have described how IO tables per product ($i = 1, \dots, n$) and county ($r = 1, \dots, 21$) have been developed. This data provides the constraints when estimating matrices for inter-regional trade flows by product, to get the multiregional tables, MRIOT. The sum of flows from county r shall be equal to production minus exports in county r; the sum of flows to county r shall be equal to the sum of use in county r, see equations (3) and (4). The matrix of interregional trade per product is estimated by balancing an à priori matrix against these margins.

An appropriate à priori matrix shows a trading pattern that we have knowledge of, à priori, based on observed (from surveys) and estimated trade flows. At a detailed level with n products there are no suitable à priori matrices. Interregional trade is therefore estimated stepwise:

1. Restrictions for all products i are summed up to aggregate I. At this level, à priori matrices are estimated based on survey data.
2. The matrices from step 1 are applied as à priori matrices in a RAS-balance procedure using restrictions for regional supply and use at the detailed level, $i \in I$.
3. Aggregation of the RAS-balanced matrices from the detailed $i \in I$ to the aggregate level I.

When the balanced matrices in step 2 are summed up to aggregate level, the resulting matrices will be better substantiated than the estimated matrices in step 1.

In MRIO-2, à priori matrices for commodity groups are initially based on estimated consignments of goods according to the commodity flow survey VFU 2016. For the same purpose, data from VFU 2016 has been used as input to the Swedish Transport Administration's modelling of freight transport. VFU is a sample survey, and the estimated consignments of goods are point estimates with often large confidence intervals. For now, we ignore this uncertainty and consider the point estimates as the best available à priori knowledge of trade flows. However, the trade flows from VFU do not provide a basis for complete à priori matrices. VFU does not report flows in all relationships where positive trade flows ($X_i^{rs} > 0$) may well be expected from restrictions on supply in county r ($S_i^r > 0$) and use in county s ($D_i^s > 0$).

Now, with available data from VFU 2021 it is of interest to examine how the first step can be improved, i.e., the estimation of à priori matrices. One question, raised above, is concerning the stability of trade patterns: To what extent can we forecast the flows for 2021 using the 2016 flows as priors assuming that row and column totals remain unchanged? Another related question is the following: To what extent will VFU 2021, or a combination of VFU 2016 and VFU 2021, lead to matrices with row and column totals closer to known margins, S_i^r and D_i^r, than VFU 2016 alone?

This question will be analyzed by using the following error indicator F:

$$F_s = \sum_s |D_i^s - \sum_r \hat{X}_i^{rs}|/V_i \qquad (6)$$
$$F_r = \sum_r |S_i^r - \sum_s \hat{X}_i^{rs}|/V_i$$
$$F = 0{,}5 \cdot F_s + 0{,}5 \cdot F_r$$

where

$D_i^s = \sum_r \boldsymbol{X}_i^{rs}$ sum of trade flows i from all r to s in the unknown final matrix,
$S_i^r = \sum_s \boldsymbol{X}_i^{rs}$ sum of trade flows i from r to all s in the unknown final matrix,
$V_i = \sum_r \sum_s \boldsymbol{X}_i^{rs}$ total volume, sum of trade flows i from all r to all s in the unknown final matrix,
$\hat{X}_i^{rs}$ estimated trade flow i from r to s according to VFU

The known margins D_i^s and S_i^r are processed data for 2016 from the Raps database. Whether the regional distribution of these margins also is applicable for 2021 cannot be controlled for. According to aggregate employment data for goods producing sectors there has been a redistribution of 1 - 2 percent of employment from 2016 to 2021 among the 21 counties. Let us for the moment assume that this matter is of minor importance. The fact that the total volume, i.e. $V_i = \sum_r \sum_s \boldsymbol{X}_i^{rs}$, has increased from 2016 to 2021 is of no importance since all values are normalized. An example of how the error indicator F is calculated is shown in Appendix A3. From Table 3.1 it can be observed that for most aggregates the error indicator has a lower value when combining the two surveys, compared with the value for separate surveys. This empirical observation may have various explanations. Anyhow it seems reasonable to use the two surveys in combination, to that extent the estimation of à priori matrices make use of survey data from VFU.

Table 3.1: Error indicator F for aggregates of commodity groups for VFU 2016, VFU 2021, and VFU 2016+2021.

Aggregate	**Label**	**SPIN**	**Error indicator F**		
			VFU 2016	VFU 2021	VFU 2016+2021
1	Agriculture, forestry, fishing	1+2+3	0.254	0.272	0.262
2	Coal, gas	05+06	--	--	--
3	Ore and minerals	07+08	0.783	0.826	0.780
4	Food, etc.	10+11+12	0.256	0.340	0.226
5	Textiles, etc.	13+14+15	0.668	0.630	0.539
6	Wood, pulp, paper	16+17+18	0.440	0.335	0.302
7	Refineries, petroleum	19	--	--	..
8	Chemicals, rubber, plastics	20+21+22	0.371	0.348	0.314
9	Non-metal minerals	23	0.245	0.318	0.215
10	Steel, metals	24+25	0.448	0.618	0.426
11	Machinery	26+27+28+325	0.364	0.393	0.351
12	Transport equipment	29+30	0.548	0.687	0.485
13	Other manufacturing	31+32 excluding 325	0.538	0.425	0.446

A further observation is that the error indicator has large values for many aggregate commodity groups. An unweighted average of the error indicators means an error of 40 percent, with respect to the deviation from the known margins. Obviously, the VFU estimates although important are only one piece in the puzzle to get satisfactory à priori matrices.

As often pointed out in the literature, see e.g. Sargento et al. (2012), transport statistics must be used cautiously as a proxy for interregional flows. Among several limitations pointed out in the literature, the following will also apply to VFU: (1) Regions with transport platforms show an over-estimation of trade flows; (2) Flows shipped by manufacturers are not distinguished from flows shipped by resellers, leading to problems of double-counting; (3) Low degree of confidence in the estimates of detailed origin-destination matrices.

3.2 Estimating à priori matrices in MRIO-2

The estimation of à priori matrices in Anderstig et al. (2022) can be shortly described as a combination of survey-based (VFU) and non-survey-based methods. The non-survey-based estimates were built on the core components of a traditional gravity model applied to the aggregate of all commodities, where the distance decay parameter α^{rs} was calculated given known supply S^r, demand D^s and a distance variable d^{rs} measured in kilometers between the regions:

$$\alpha^{rs} = \frac{\log\left(\frac{X^{rs}}{S^r D^s}\right)}{\log\left(d^{rs}\right)} \tag{7}$$

This parameter value is lowest within each county and tends to increase with the distance between counties. If we interpret the parameter as merely an expression of the distance sensitivity, the pattern is according to expectations. Intraregional trade often refers to goods with low commodity values (kSEK per ton) and high distance sensitivity, such as gravel and stone. Conversely, trade at longer distances often refers to goods with high commodity values and low distance sensitivity, such as machinery and pharmaceuticals.

But the α^{rs} parameter does not only reflect distance sensitivity, it rather expresses the influence of all factors that generate the trade flow X^{rs}, given S^r, D^s and d^{rs} . The parameter values can best be interpreted as "matching indicators", determining how well the supply of specific goods from region r matches the use in region s, conditioned the distance. We can note that the parameter value varies relatively clearly with the distance, see Figure 3.2. It illustrates what was mentioned above, that trade at longer distances tends to refer to goods with high commodity values and low distance sensitivity.

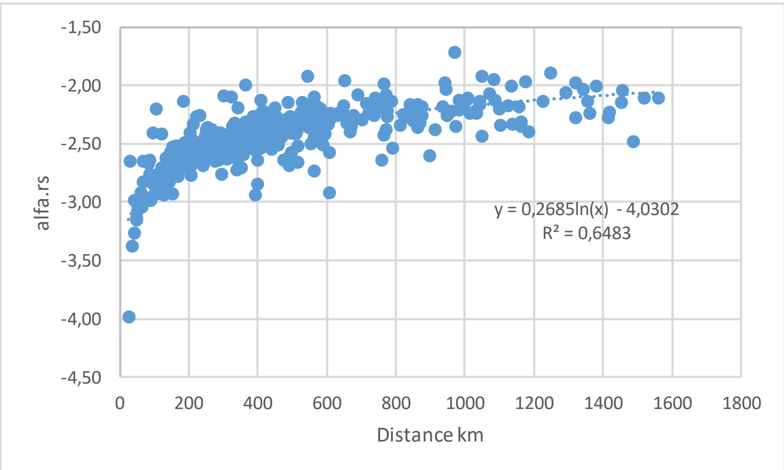

Figure 3.2: Parameter value α^{rs} and distance for all commodity flows aggregated.

The final à priori matrices in Anderstig et al. (2022) were weighted averages of survey-based (VFU) and non-survey-based estimates, where weights were calibrated to minimize the error indicator F. This resulted in an unweighted average error of 15 percent for all aggregates, and 11 percent when

excluding aggregate 3 “Ore, minerals”. Thus, the error is substantially lower than what was reported in Table 3.1.
It was mentioned above that VFU-data is being used to get trade matrices (PWC-matrices) as input to the Swedish Transport Administration's modelling of freight transport. These matrices refer to trade flows between municipalities for aggregated commodity groups very similar to aggregates in Table 3.1. The estimation of à priori matrices is based on gravity models, including the core variables (supply, use, and distance) as well as numerous additional variables. The models are estimated using stepwise regression using pseudo maximum-likelihood, see Silva & Tenreyro (2006). The core of the gravity model can be described as follows, suppressing index for commodity i:

$$X^{rs} = \alpha S^{r\beta_1} D^{s\beta_2} d^{rs\beta_3} \quad (8)$$

where

X^{rs}	trade flow from region r to region s
S^r	supply in region r
D^s	use in region s
d^{rs}	distance between r and s
α , β_1, β_2, β_3	parameters to be estimated

So far, the choice of model specifications to get appropriate à priori matrices has been guided by the result of a stepwise regression procedure, in terms of the resulting pseudo-R-square. In essence this means a minimization with respect to the deviation from the VFU-estimates, which according to the discussion above, implies an error of 40 percent with respect to the deviation from the known margins.

In this paper we use a gravity-RAS approach where the estimated trade matrices are used as à priori matrices in a RAS-balancing procedure to adjust the trade flows to restrictions in regional supply and use. An alternative approach would be to directly estimate region specific constants for origin and destination regions using a doubly constrained gravity model, see Cai (2021) for an example. A drawback of this approach is that we cannot use the error indicator to evaluate model fit.

Instead of direct use of the estimates from equation (8) as à priori matrices, it seems as a fruitful idea to use the estimates as a basis for further calibration, in order to minimize the error indicator. Such a calibration can take the following three notions as a point of departure.

First, the distance between r and s can only serve as a proxy for the transportation cost since there are economies of scale in trade, which will cause declining average costs, see, e.g., Rudolph (2009).

Second, the aggregates of commodity groups are very heterogenous, including commodities with varying commodity values. Since the relevant transportation cost is related to the commodity value it is expected that trade flows at longer distances more frequently refer to high commodity values. Trade flows of “Ore and minerals” exemplifies. An examination of grouped VFU-data gives support to this notion: For all aggregates the relation between commodity value and distance is strong and follows the same pattern as in Figure 3.2 above.

Third, the gravity model will have difficulties finding true zeroes, i.e. elements in the trade matrices with no reported trade. Given the specification of the gravity model, trade is always positive in the model.

3.3 A numerical comparison of methods for estimating à priori matrices for MRIOT for freight trade

Estimations of new trade matrices using the gravity-RAS approach requires survey data which can be expensive. A question is to what extent we can estimate gravity models without the need for new survey data? There are many techniques for updating or estimating multiregional input-output tables using non-survey methods. Lamonica et. al. (2020) classifies the methods into two groups: location quotient (LQ) methods and constrained matrix-balancing methods. Several studies have compared different approaches for estimating input-output tables, see Riddington, Gibson & Anderson (2006), Fournier (2020), and Pereira-López et al. (2021). The focus in this paper is on matrix-balancing methods where we present a novel approach using the error indicator function F to estimate a gravity model.

In this section we investigate the use of the error indicator in (6) to estimate à priori matrices by comparing three different methods to estimate the gravity model in (8).

1. Estimate the gravity model (α, β_1, β_2, β_3) using estimated trade flows in $\widehat{X_I^{rs}}$
2. Recalibrate the distance parameter (β_3) to minimize the error indicator F
3. Calibrate all full gravity model (α , β_1, β_2, β_3) to minimize the error indicator F

To estimate the initial gravity model we use the PPML-estimator used in Anderstig et al. (2015). The calibration in step 2 and 3 are based on numerical optimization using the Global Optimization Toolbox in Matlab 2022a. The methods are evaluated using RMSE of the predicted flows compared to the VFU-data and the error indicator based on the deviation to the margins.

Table 3.2 shows the estimated parameters for Aggregate 6 (Wood, pulp, paper) for year 2021 based on the three methods. As shown from the table, the parameter estimates for supply (β_1), demand (β_2) are similar both when they are estimated using the PPML-estimator and the VFU-data and by minimizing the error indicator F. The effect is stronger for the distance parameter where the error indicator is minimized for a value closer to zero.

Table 3.2: Estimated parameters for Aggregate 6 (Wood, pulp, paper) for year 2021 based on three methods.

Parameter	Method 1 - Gravity model	Method 2 - Recalibrate distance	Method 3 - Error calibration
α	0.136	0.136	-2.940
β_1	0.876	0.876	0.580
β_2	0.368	0.368	0.504
β_3	-0.910	-0.925	-0.154
RMSE	435.0	433.1	470.4
Error indicator F	0.419	0.411	0.380

The effect of this is shown in Figure 3.3 where the RAS-balanced MRIO flows for Aggregate 6 (Wood. pulp. paper) for year 2021 is shown both for the gravity-RAS model estimated using method 1 and the gravity-RAS model estimated using method 3. From the figure we see that the calibration method using the error indicator results in considerably smaller volumes of intracountry trade for this aggregated commodity group. Instead. the trade volumes are spread more evenly across the matrix. For other commodity groups. the same pattern is not shown.

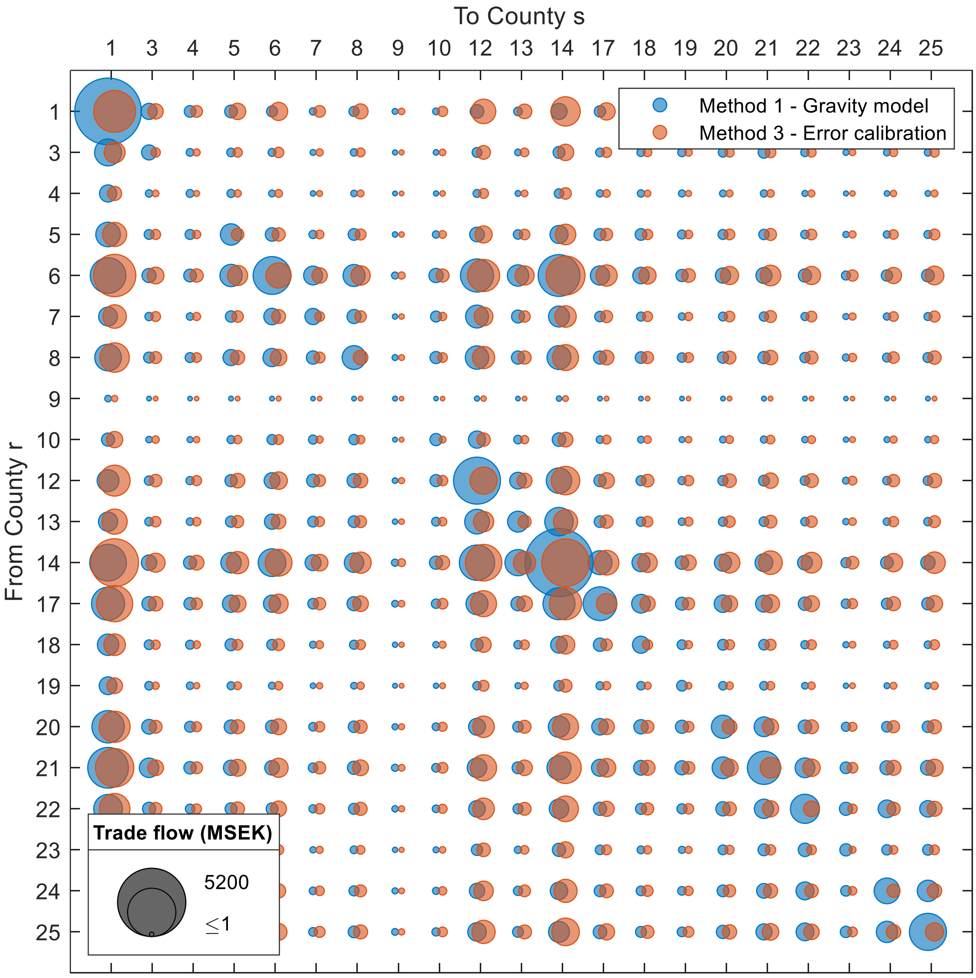

Figure 3.3: RAS-balanced MRIO matrices for Aggregate 6 (Agriculture. forestry. fishing) for year 2021. The blue circles correspond to the estimated flows using the gravity-RAS method with parameters estimated with the VFU-data (Method 1). The red circles correspond to the estimated flows using the gravity-RAS method with parameters calibrated to minimize the error indicator F (Method 3).

A summary of the estimated parameters using estimation method 1 and method 3 is shown in Figure 3.4. As shown in the figure. both methods result in similar parameter estimates. One exception is aggregate 3 (Ore and minerals) where the estimated distance parameter using method 3 differs greatly from the estimate given by method 1. A full comparison of the estimated parameters with the three methods for all aggregated commodity groups and years are shown in Appendix A2.

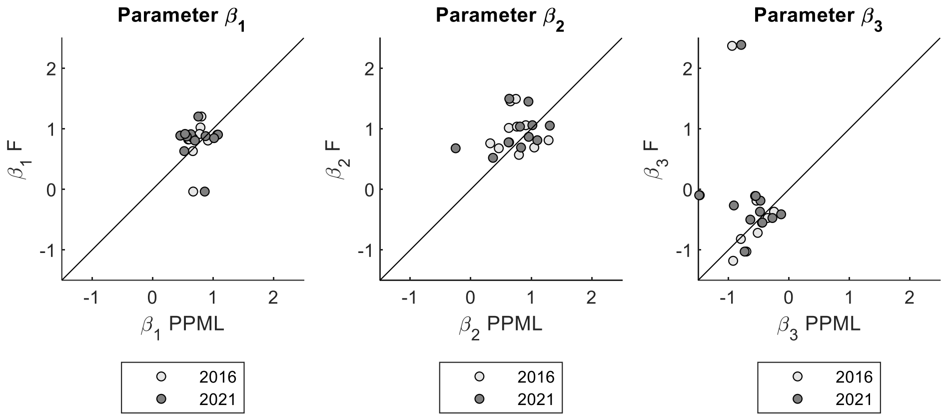

Figure 3.4: Parameter estimates for parameters β_1. β_2 and β_3 with method 1 (x-axis) and method 3 (y-axis) for the different aggregates and years.

A conclusion from the figure above is that the non-survey method 3 for most commodity groups produces parameter estimates that are similar to the standard survey-based method. One question that arises is to what extent these results can be generalized to other commodity and service flows. Further research is required to determine the validity of these results to other situations. In the method we used an error function with the absolute value of the error. A limitation of this function is that it is non-continuous. Other error functions. such as the root mean square error of row and column differences. may also be utilized to evaluate model fit and estimate parameters in the gravity model.

3.4 Aggregation bias in trade estimations

As mentioned in section 3.1. interregional trade in MRIO 2 was estimated by a stepwise procedure where à priori matrices are estimated at the aggregate level I is the first step. However, even if there are no suitable à priori matrices at the detailed level i, there is a strong reason to conduct estimations at a disaggregate level between i and I.

The reason is that the aggregates are composed of heterogenous commodities. with different values and properties. Estimating trade patterns on aggregates may therefore introduce bias in the estimations. The bias may be increased if the aggregate includes commodities with vastly dissimilar attributes, see Piñero et al. (2015), French (2017), Breinlich, Novy & Silva (2022), and Crown (1982).

The underlying idea is that by estimating gravity models for trade patterns and creating corresponding à priori matrices we can use more information in the estimation procedure compared to an approach where the gravity models are estimated on the aggregates. The RAS-balancing also uses more detailed information. A drawback of this disaggregated approach is that the estimates in the gravity models are based on less data which increases sample error.

In this section we provide an illustration on this approach using VFU data from 2016 and 2021 for the aggregate “Chemical products”. The aggregate comprises three different commodities (70 Chemical products, 102 Medical products, 103 Rubber and plastic). Table 3.3 shows estimated parameters for the combined aggregate and for each commodity in the aggregate. As seen in the table the estimated parameters vary between the different commodities. This is natural since the different commodity types themselves differ a lot. However, when comparing the estimates for the two different years, the smaller sample results in large variations in the estimated parameters.

Table 3.3: Estimated parameters for different commodities within the aggregate Chemical products for year 2016 and 2021.

	Commodity group 70		Commodity group 102		Commodity group 103		Aggregate (70+102+103)	
Parameter	2016	2021	2016	2021	2016	2021	2016	2021
α	-9.6275	-12.6356	-15.2054	-8.9202	-13.4682	-10.3530	-13.8969	-9.3824
β_1	0.7850	0.8315	0.8866	0.7149	0.8919	0.8052	0.8448	0.7046
β_2	0.8710	0.9739	0.9103	0.8071	0.9099	0.8897	0.9201	0.8513
β_3	-0.8017	-0.6948	-0.3605	-0.6194	-0.3551	-0.6700	-0.5629	-0.7001

Figure 3.5 shows the estimated trade flow matrix using data on an aggregated or a disaggregated level. The figure shows that the resulting trade flows from the two methods give different outcomes. By estimating trade patterns at a disaggregated level. more details are preserved. With more narrowly defined commodity groups. more detailed information on supply and use is preserved in the RAS-balancing.

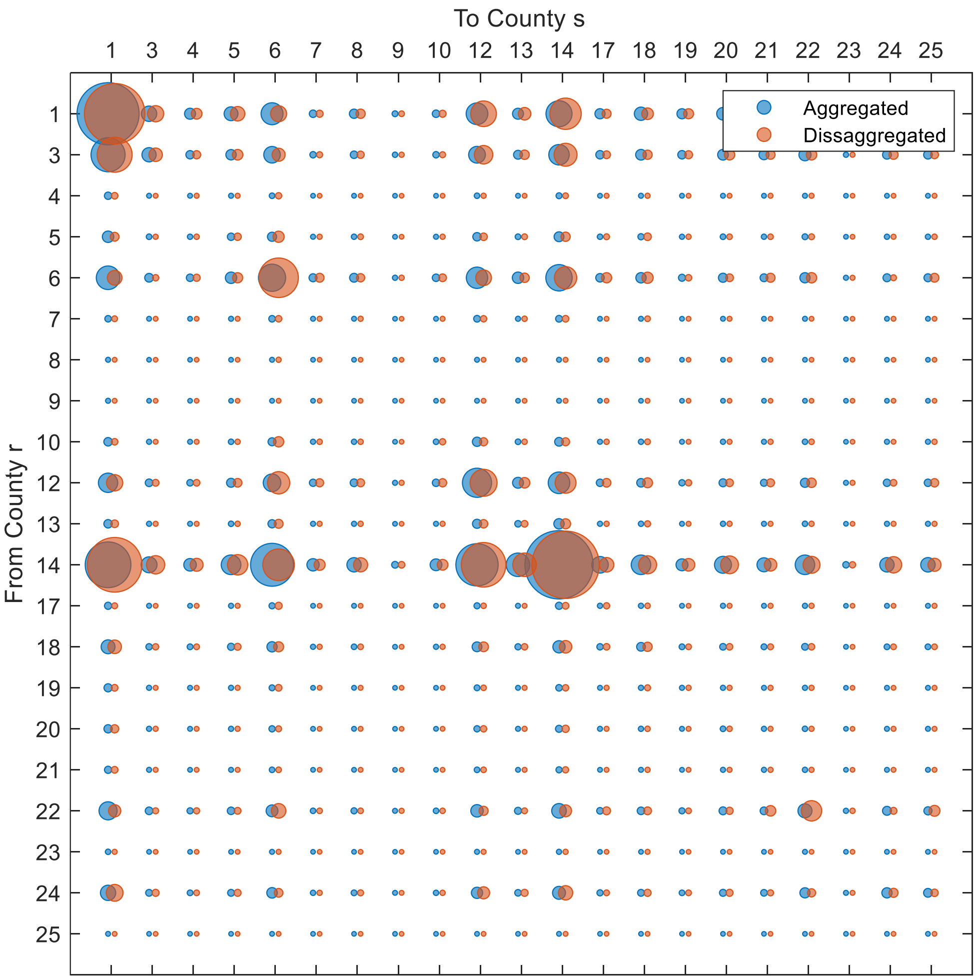

Figure 3.5: RAS-balanced MRIO matrices for Aggregate 8 (Chemical products) for year 2016. The blue circles correspond to the trade flows estimated on aggregated data. The red circles correspond to trade flows estimated on disaggregated commodity groups which are combined after RAS-balancing.

3.5 An application of error calibration method to trade in services

In the discussion above the question was raised to what extent we can estimate gravity models without survey data? At present this is the situation with respect to modelling trade in services. In Anderstig et al, (2022) provisional alternatives to survey data are applied.

As an alternative to survey data, method 3 may be of potential interest. Here we will apply this method for estimating interregional trade in two aggregate sectors, Business services and Hotel services. Using data on supply and use on county level, we estimate a simple gravity model based on minimization of the error indicator F described above. The results can then be compared to the trade flow estimations from MRIO-2 (Anderstig et al, 2022).

Table 3.4: Estimated parameters for Business services and Hotel services using the gravity-RAS approach based on numerical minimization of the Error indicator function F in method 3.

Parameter	Business services	Hotel services
α	-13.7743	-10.1356
β_1	0.8382	0.8158
β_2	1.1840	1.1107
β_3	-0.0080	-0.2003

Table 3.4 shows estimated parameters for Business services and Hotel services using the gravity-RAS approach based on numerical minimization of the error indicator F. The parameter estimates show a low distance sensitivity, especially for Business services. Figure 3.6 shows a comparison of the balanced matrices for Business services estimated based on minimization of the error indicator function F. Compared to the estimated service flows from MRIO-2, the share of local services is lower in the predicted trade matrices based on the error indicator function. This can be an indication that estimation of the gravity model using the error indicator function can have a risk of underestimating local service flows. A reason for this is that the input data for supply and use does not contain any direct information about the share of services that is local. More studies on the method are therefore needed.

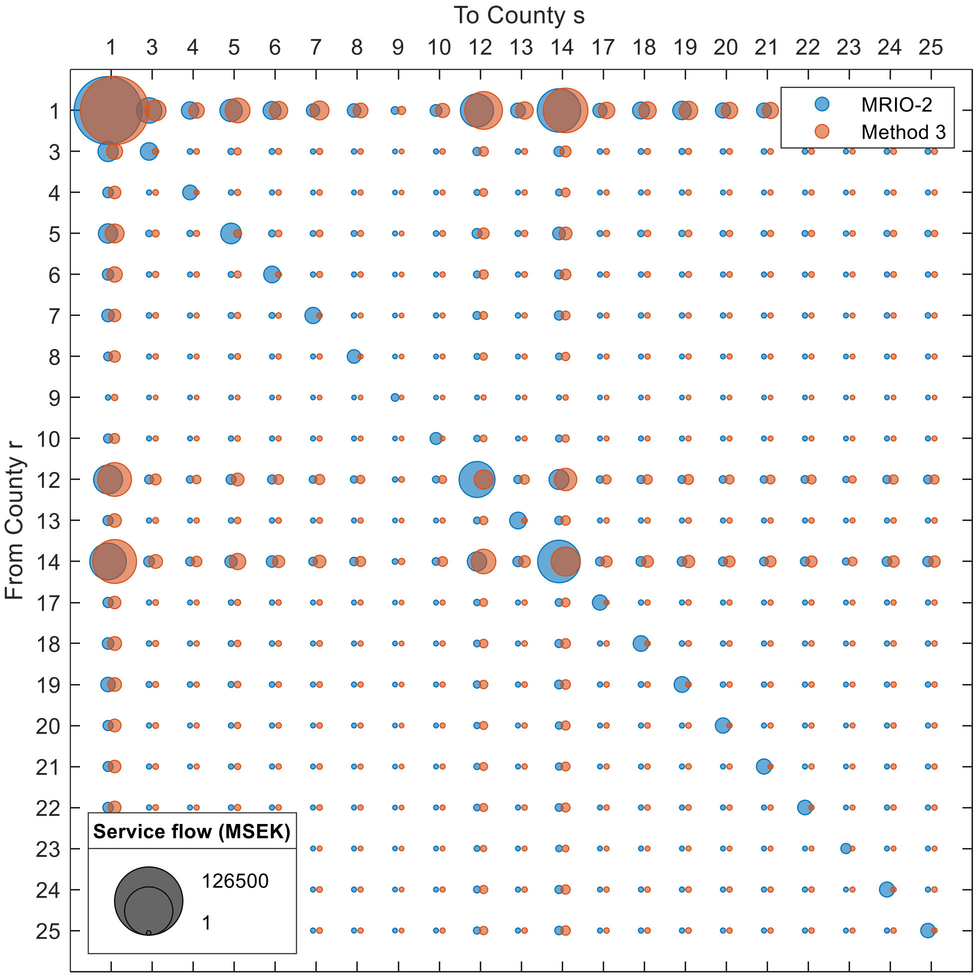

Figure 3.6: RAS-balanced MRIO matrices for Business services for year 2016. The blue circles correspond to service flows estimated in MRIO-2. The red circles correspond to service flows estimated using the gravity-RAS approach based on numerical minimization of the Error indicator function F in method 3.

4 Economic linkages and regional development work using MRIO-2

MRIO can be used to address issues in regional development work as scenario analysis and impact analysis. In MRIO-2 we used the county level as the fundamental building block. There is reason to believe that other regional subdivisions can be useful for both estimation and analysis. For instance, we have used data for municipalities to estimate distance matrices for counties. This method can also be used to compute other distance measures, for instance for NUTS2 regions. As the EU system mentioned below operates with this regional subdivision it becomes important to make comparisons easy. Also, questions of balances between town and countryside, or between support and non-support regions are highly policy relevant. MRIO results can be aggregated to these subdivisions.

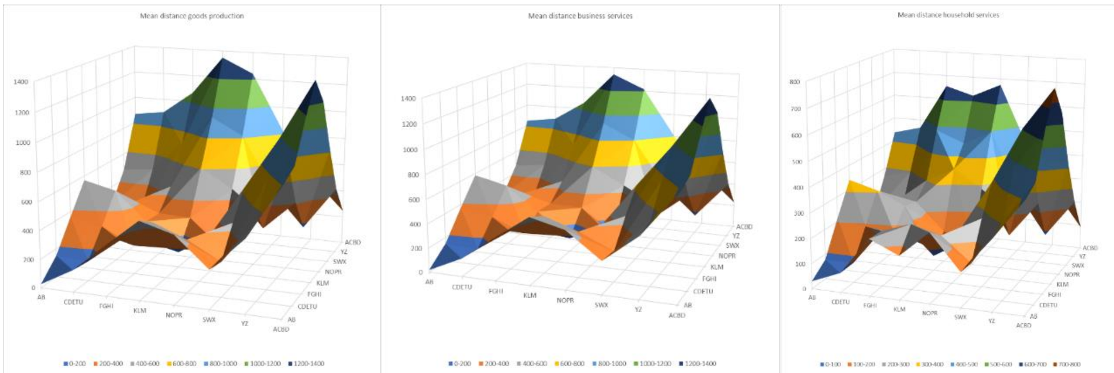

Figure 4.1: The Swedish transport cost landscape for NUTS2 regions.

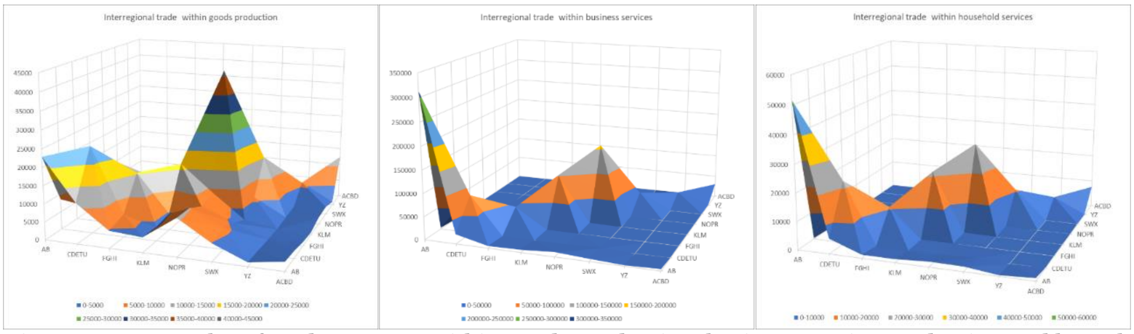

Figure 4.2: Examples of trade patterns within goods production, business service production and household service production.

The section will address the issues of using MRIOT with alternative regional subdivisions. Since the trade forecasting systems of Traffic Analysis and the Swedish Transport Administration use municipality data together with Raps it is warranted to have a section on policy-relevant regional subdivisions in the report.

As a starting point we have aggregated our county data on IO-linkages and average transport distances to the eight NUTS2 regions in Sweden, see Figure 4.1. There is a policy relevance in having multiregional input-output tables at the NUTS2 level because of the use of that level for international comparisons within the NUTS-system. In later years, a more direct importance must be attributed to that level because of the regional economic modelling work at the EU level which makes use of that subdivision, see for instance Thissen et al. (2019) and Tan (2016). Both papers have the ambition to make interregional trade forecasts for NUTS-regions in Europe disaggregated into NACE sectors.

The three separate figures refer to average transport distances between NUTS2-regions for a sectoral grouping comprising goods production, business services and household services. The distance measures have been constructed from corresponding distances between counties weighted by gross output for the sectoral aggregates for counties within the respective NUTS2-regions.

We see a landscape within which firms transport their intermediary and final products. The main impression is the considerable differences between foundations for production and trade introduced through the Swedish geography but also by the geographic distribution of production and consumption.

It should also be pointed out that there is a strong policy relevance in disaggregating the IO-tables to municipalities, at least as regards the trade component. There are several reasons for this:

- Transport costs used in MRIOT have themselves been constructed by aggregating data on distances between municipalities, so it is just a matter of returning to the basic data level;
- Production, consumption, and GNP data is available at the municipal level from the existing regional accounts produced by Statistics Sweden;
- The Raps system works partly at the municipal level;
- VFU-data which is being used to get trade matrices from PWC-matrices is collected at the municipal level.

The main difficulty for the disaggregation is that VFU trade data is sparse at the intermunicipal level which means that the survey component of the estimation work is less pronounced. Progress can be made using the estimation methods suggested in the current paper.

We also give some examples of interregional trade patterns for the sectoral aggregates between NUTS2-regions, see Figure 4.2. The examples represent excerpts from the full interregional and intersectoral IO table in which commodities are sent between all sectors in the economy. The first sub-figure shows how manufactured goods are traded among NUTS2-regions. We see the dominance of West Sweden as the source and sink for goods to be used in the value-added chain and being imported and exported. There is not a very marked tendency for intraregional trade to dominate interregional trade outside the own region.

Turning the attention to the second and third sub-figures we see a much clearer dominance of trade within NUTS2-regions than between them. The trade patterns between business service sectors, and household service sectors, show how the metropolitan regions have considerable internal networks among service firms. The pattern is most pronounced in this respect for household services.

It should be noted, however, than the figures must not be taken to represent a situation where services are not traded interregionally as inputs to goods producing sectors. The Swedish regional production system is to a large extent integrated via business services. This can be seen from, for instance, the Leontief multipliers presented in Anderstig et al. (2022).

5 Interregional trade in some international MRIO systems

Interregional trade and international trade can be estimated using similar approaches. The main difference is that international trade can to a larger degree be estimated using survey data. In Anderstig et al. (2022) we performed a brief overview of some international approaches to MRIO-estimation. In the current section we will further develop this comparison for the interregional trade component.

We have novel information from recent projects, for instance, within the EU where interregional trade analysis has been combined with interregional trade in the same analytic framework, see for instance Mandras et al. (2019). How have trade flows been modelled in this comprehensive framework? Since the EU system uses NUTS2 regions we have a possibility to compare estimation results for 14 NACE economic sectors and 8 NUTS2 regions in Sweden. The comparison is currently of relatively small practical significance for the quality assessment work around MRIOT, however, since the EU model for with the data base has been published comprises yearly data for the period 2000-2010.[2]

The study by Thissen et al. (2019) focuses on the construction of interregional trade in goods and services of the regions, within the same country as well as with regions in other EU member states. The estimation is based on a regionalization of supply and use tables. The production and consumption of goods and services in European NUTS2 regions were subsequently interlinked using data on both freight transport (5 modes) for goods and business travel (3 modes) for services. The estimated transshipment locations and the number of transshipments were specific for every good on every trade link.

The central principle in the methodology rest on inferring European regional trade flows from different sources of information thus increasing data reliability by imposing consistency with available statistics. Regional trade flows need to be consistent with statistics on production and consumption per region, which, in turn, must be in line with national data on production and consumption. These regional flows must also be consistent with international trade statistics, on a national level. The amount of goods traded between regions should also be consistent with the amount of goods transported. Furthermore, international trade statistics must also be consistent with national data on production, consumption, imports, and exports. Finally, trade statistics should be mutually consistent.

The result of the estimation work is a set of IO tables for a set of regions in Europe and the world, among which the Swedish NUTS2 regions are a subset. This means that international imports and exports to and from Swedish NUTS2 regions can be followed across the borders. In comparison to this the MRIOT IO-tables developed by Statistics Sweden make a distinction between interregional trade within Sweden and international trade.

Our intention with the current analysis is to compare the interregional trade patterns within Sweden between the MRIOT and the EU tables. For the moment we do not have full information about the methods used in the EU work but it seems that the methods have some similarity to our gravity model approach to merge survey and non-survey data. Since the EU framework is international the data sets are not quite compatible. The EU data we have used refer to 2010.

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[2] We will be receiving information about corresponding IO data for 2017 from the EU in due course of time.

However, data also exists for 2018 where it has been used as an element of the EU EMS computable general equilibrium model, see for instance Mandras et al. (2019).

The data base allows us to depict the Swedish interregional trade patterns in an international context. We provide Figure 5.1 as an example in which we have shown the networks for Sweden, Denmark, Finland and the Baltic countries. Norway is not shown since it is not an EU member.

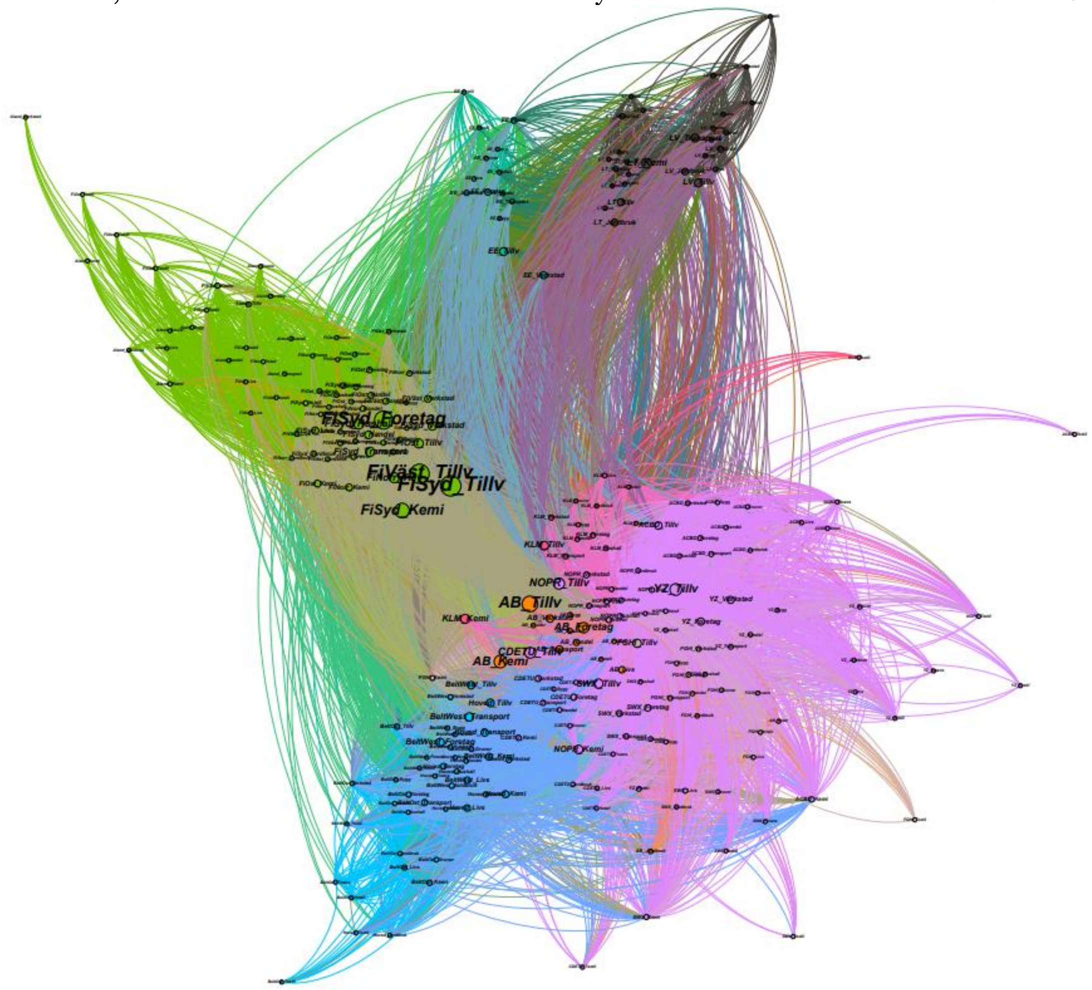

Figure 5.1: Trade among Nordic NUTS2 regions for fourteen NACE sectors 2010. Data from EU EMS data base.

The Baltic network is shown at the top. By using the so-called Gephi system for network analysis the regional economies have been split into eight groups shown in different colors depending on the values of the indicator betweenness centrality, which separates groups of economic sectors and regions according to their centrality, weighted by the trade flows. Sweden is split into several subgroupings depending on their trade orientation. There are fourteen sectors depicted of which most are manufacturing ones. They are, agriculture, mining, food, textiles, chemicals, manufacturing, other goods production, construction, trade, visitor services, transport, banking and finance, business services, and household services. We have aggregated these NACE sectors to the three sector groupings which we use for comparisons in the sequel.

The business service sector stands out as particularly well interregionally integrated. The sizes of the nodes reflect the weighted trade centrality. This reveals Stockholm's central role in the trade system but also the well-integrated production network of southern Finland within the Baltic context. The smaller role of the Danish regions is partly a reflection of the less important role of Nordic trade in comparison to trade with continental EU regions. These networks can also be shown in a more elaborated network analysis within the regionally separated EU system.

We can also compare the results of the multiplier analysis in Anderstig et al. (2022) with the EU-based multipliers. A comparison has been made for three sector-groupings and eight NUTS2 regions for Sweden, see Figure 5.2. Note that the multipliers refer to 2016 and 2010, respectively. The comparison shows that multipliers are of similar numerical values using the two data bases. The goods production multipliers are largest, and the household service ones are smallest. There are some differences especially for goods production sectors. Raps data shows higher multipliers for northern Sweden. One can observe somewhat larger differences for goods production, for instance, for West Sweden.

The general conclusion of this comparison is that the two statistical systems seem to produce similar Leontief multipliers. Of course, the EU statistical system comprises the whole world with a detailed NUTS2-region disaggregation of the EU. There is thus reason to take the comparison to a considerably more elaborate level in further analytic work in the future.

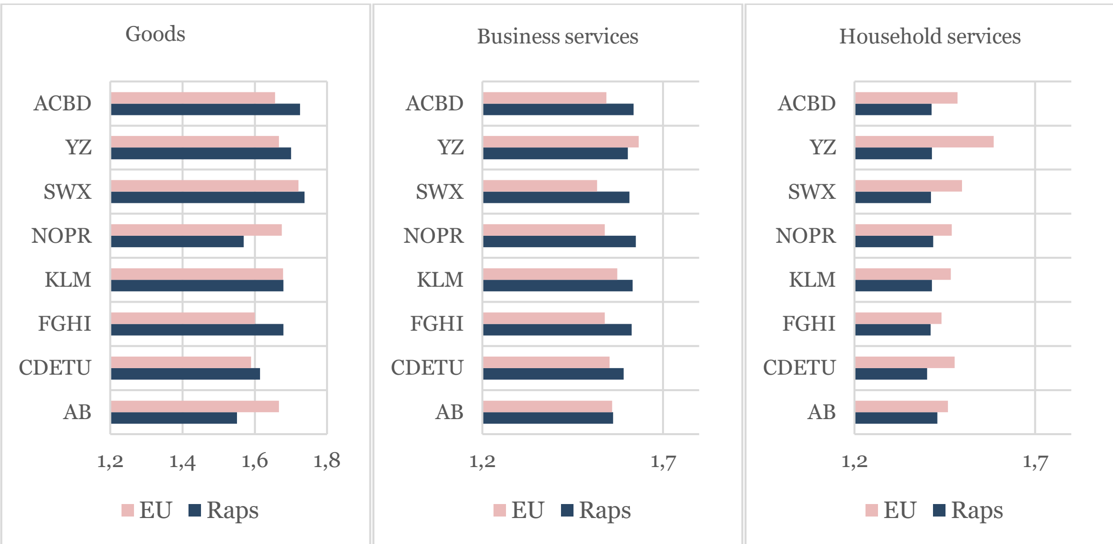

Figure 5.2: Interregional multipliers using Raps-based data and EU-based data.

As mentioned above the most interesting question in this analysis is whether the two methods for the trade forecasts produce significantly different results for Swedish NUTS2 regions.

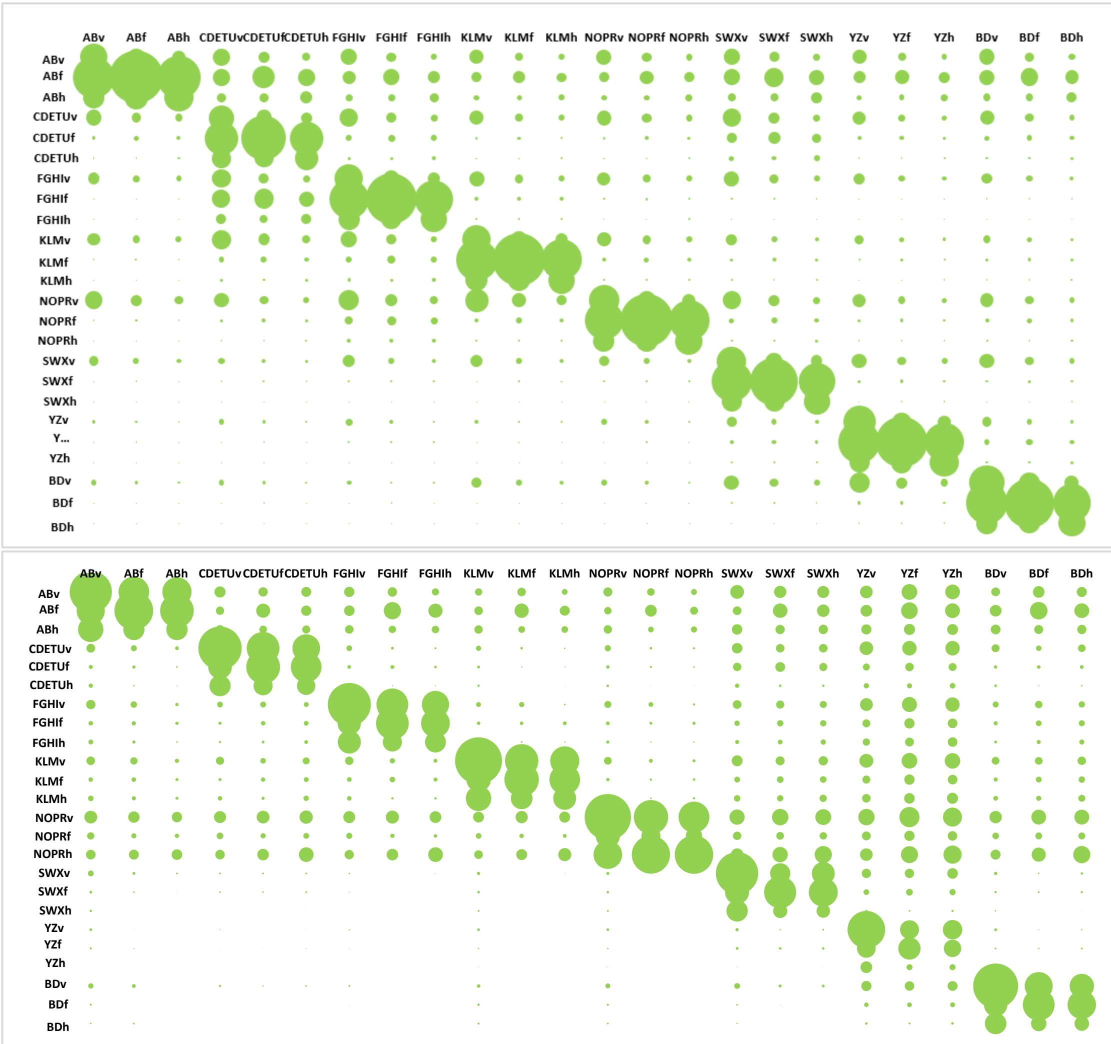

Figure 5.3: IO-coefficients for three sector groupings and eight regions according to Raps-data 2016 (upper) and according to EU data 2010 (lower). Goods are denoted by v, business services by f, and household services by h.

Figure 5.3 provides an example of such a comparison using our three-sector model (goods production, business services, household services) in combination with NUTS2 region data. We have performed analyses with the three-sector model for counties in earlier papers, Anderstig et al. (2022), and we have aggregated the EU data to the same three-sector level. Many methods can be used to make comparisons. Here, we have plotted IO coefficients pertaining to the two data sets in a similar matrix diagram.

The patterns are quite similar at a first glance. A difference is that the EU trade flows are more concentrated to the own region, and that links between southern and northern Sweden seem substantially weaker for the EU data set. Although this is the case the Leontief multipliers shown above do not seem to exhibit systematic differences. We will return to these comparisons when we have new data from Statistics Sweden from MRIO-2 and new data from the EU EMS on their work for 2018.

As a final comparison we zoom in on two detailed sectors in the EU data base among their set of 14 sectors in total. How do the trade patterns look? Can they be compared to the flows determined via our VFU and gravity approach? We have not performed an explicit comparison but simply wish to show that the EU data base seems to concentrate trade to the intraregional level to a rather large extent.

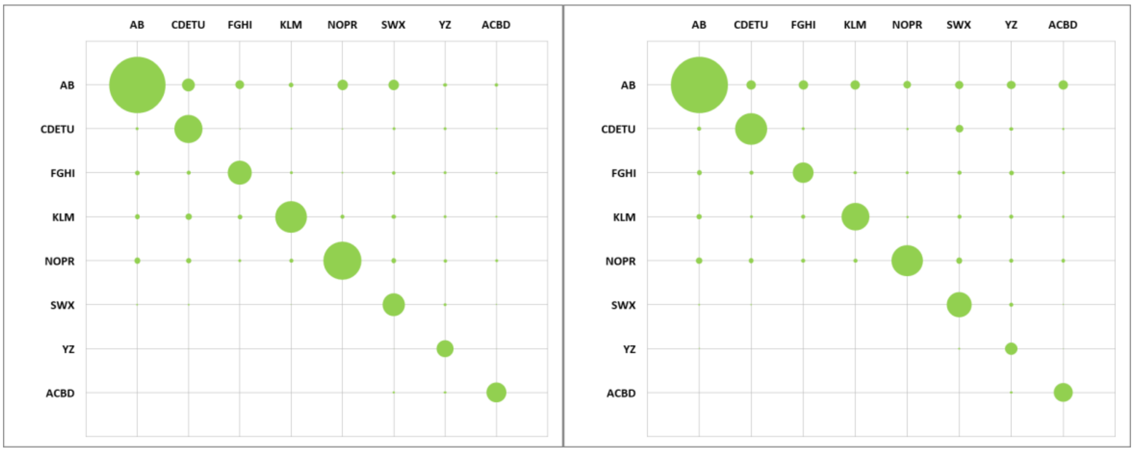

Figure 5.4: Interregional trade flows in Sweden for the manufacturing sector (left) and business services sector (right) according to the EU data base for 2010.

The review of international estimation approaches has stayed with the new EU system so far. However, we have also looked at some other approaches where trade patterns have been projected using theory-based backgrounds. Survey methods for setting up regional IO tables are nice, but costly (Jensen & Hewings, 1985).

A typical procedure distributes output and final demand by industry according to indicators such as employment and income. This yields region r's output in industry j, X_j^r, and region r's final demand D_i^r for goods from industry i. Furthermore, technical input coefficients a_{ij} (input per unit output from all sources) in the region are assumed to be the same as in the nation. The industry standard for solving the problem seems to be the cross-hauling adjusted regionalization method (CHARM), see Kronenberg (2009). However, we have found that this method is not of direct interest for our analytical work which mainly uses commodities as a basis. Instead, it seems warranted to look at methods where prices enter the analysis in a more direct way.

One of the best examples of such an analysis is the one by Bröcker & Burmeister (2015) and Burmeister (2019). That work is directly linked to the seminal work on computable general equilibrium models for analysis of EU TEN infrastructure projects developed by the late Johannes Bröcker. They provide a substantive contribution to trade analysis by formulating a theoretical gravity equation in the functional form of a doubly constrained gravity model for two regions, the region under study and the rest of the world. Solving for the region's internal flow, they derive an internal trade equation. This trade equation can be readily applied to scale down the national technical input coefficients to estimate the regional input coefficients for a single region. It depends on the economic size of the region as well as the region's ability to buy from and sell to the world market. They extend the approach to three regions to explicitly account for the geographical size of the region and the distance effect on trade. They call the method the gravity regionalization of trade approach (GRETA). GRETA does not tend to overestimate regional output multipliers, which is a common critique of existing techniques, and crucial for model applications. Their analysis leads to a simple equation for intraregional trade as shown below:

$$t_{rr} = \frac{(X_r+Y_r+Z_r)}{2} - \sqrt{\frac{(X_r+Y_r+Z_r)^2}{4} - X_rY_r} \qquad (9)$$

The internal trade equation above is the key to their non-survey gravity approach. Local output X_r and use Y_r are what we call supply and demand earlier in the current paper. But where to get Z_r from? The variable Z_r measures the size of the world market, scaled by trade freeness factors measuring its relevance for the region under study. It can be estimated using the optimization procedures presented in earlier chapters of the report.

In theoretical foundations of the gravity equation, trade costs usually enter as "iceberg-melting-costs". Rudolph (2009) offers an alternative approach to model trade costs. From a microeconomic point of view, trade costs should depend on trade input prices and the underlying trade volume. If trade costs are determined by the trade volume, and average trade costs are falling with the trade volume (due to economies of scale in the trade sector), empirical results from gravity equations are likely to be biased. This is in line with the empirical observations in earlier sections of the current paper.

The aim of the paper by Rudolph (2009) is to bring trade costs adequately into a theory-based gravity equation. Because iceberg-costs can be interpreted as fixed average costs, they are independent from the underlying trade volume. Since there are economies of scale in trade this assumption is inadequate: the higher the trade volume between two countries, the lower should be the cost of sending one (composite) unit of the export volume from the one to the other country since economies of scale cause declining average costs. This suggestion results from microeconomic theory. It leads to an endogeneity problem in empirical gravity equations and hence to a bias in the estimated parameters. Under certain circumstances, this bias can be a contribution to explain implausibly high estimates for border effects in gravity frameworks.

Rudolph (2009) takes his starting point in a CES utility function for consumers in a country j as shown below. Consider an importing country j. Recall that consumers over the world have identical preferences, so that preferences of the consumers in country j can be represented by the CES-utility-function U_j:

$$U_j = \left(\sum_i \beta_i c_{ij}^{\frac{(\sigma-1)}{\sigma}} \right)^{\frac{\sigma}{(\sigma-1)}} \qquad (10)$$

In equation (10), c_{ij} is the quantity of i's commodity imported by j (including country j's domestic consumption), β_i is a distribution parameter to weight the preference of the representative consumer for country i's composite good and σ is the elasticity of substitution between all goods of the world. In the paper, it is shown how one can derive a trade equation in which a central element is the elasticity of substitution which is assumed to be greater than 1.

If trade volume is seen as the output of a trade sector, microeconomic theory reveals that the according trade costs depend on input prices but also on the trade volume. Economies of scale in the trade sector, which is presumable according to several empirical studies, lead to decreasing average trade costs in trade volume. The paper brings these micro-founded trade costs into the theory-based gravity equation and extracts results that might influence empirical studies using the gravity equations, see also Tan (2016). The analysis bears substantial significance to the analysis of trade starting from formula (8) in our current paper in which we can also enter other functional forms such as CES functions. A difference is the focus on the two later examples on the distinction between intra- and interregional trade.

We have made a summary comparison between US trade survey data from the Bureau of Transportation Statistics and the VFU. What are the main characteristics of the US freight transportation data? In the US freight transport is dominated by trucks and parcel, UPS or courier shipments. For-hire trucks ship 38 percent of the commodity value in 2017, followed by company-owned trucks with 31 percent. Parcel shipments amount to 26 five percent, leaving other modes to share the remaining five percent of the value shipped. Rail carries a minute one percent of the value. The domination of truck carriers is further accentuated by rail, air and water transports being combined with access deliveries by truck. The parcel carrier market is generally larger for shorter and often within-state deliveries.

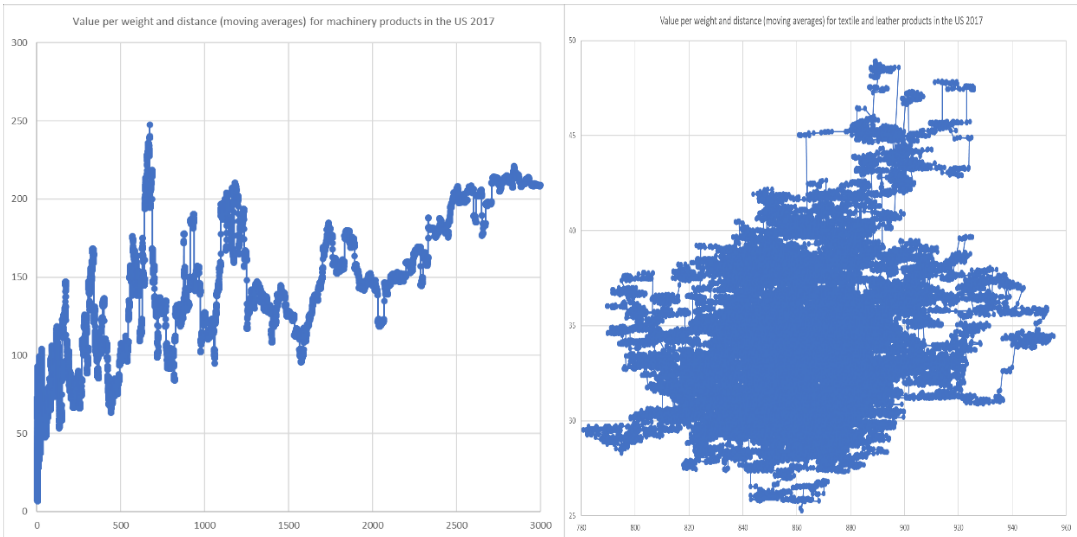

Figure 5.5: Value per weight of US shipments of machinery and textiles & leather products 2017 (moving averages).

The graphs in Figure 5.5 can be compared to the pattern in Figure 3.2. The machinery product group is a composite of commodities of heterogenous nature. This implies that the commodity can be shipped both locally and interregionally. The graph on the right side in the figure is much more dense implying that textile and leather products are found in a much more narrow value per weight span. It should be noted that the figures represent a very large number of shipments.

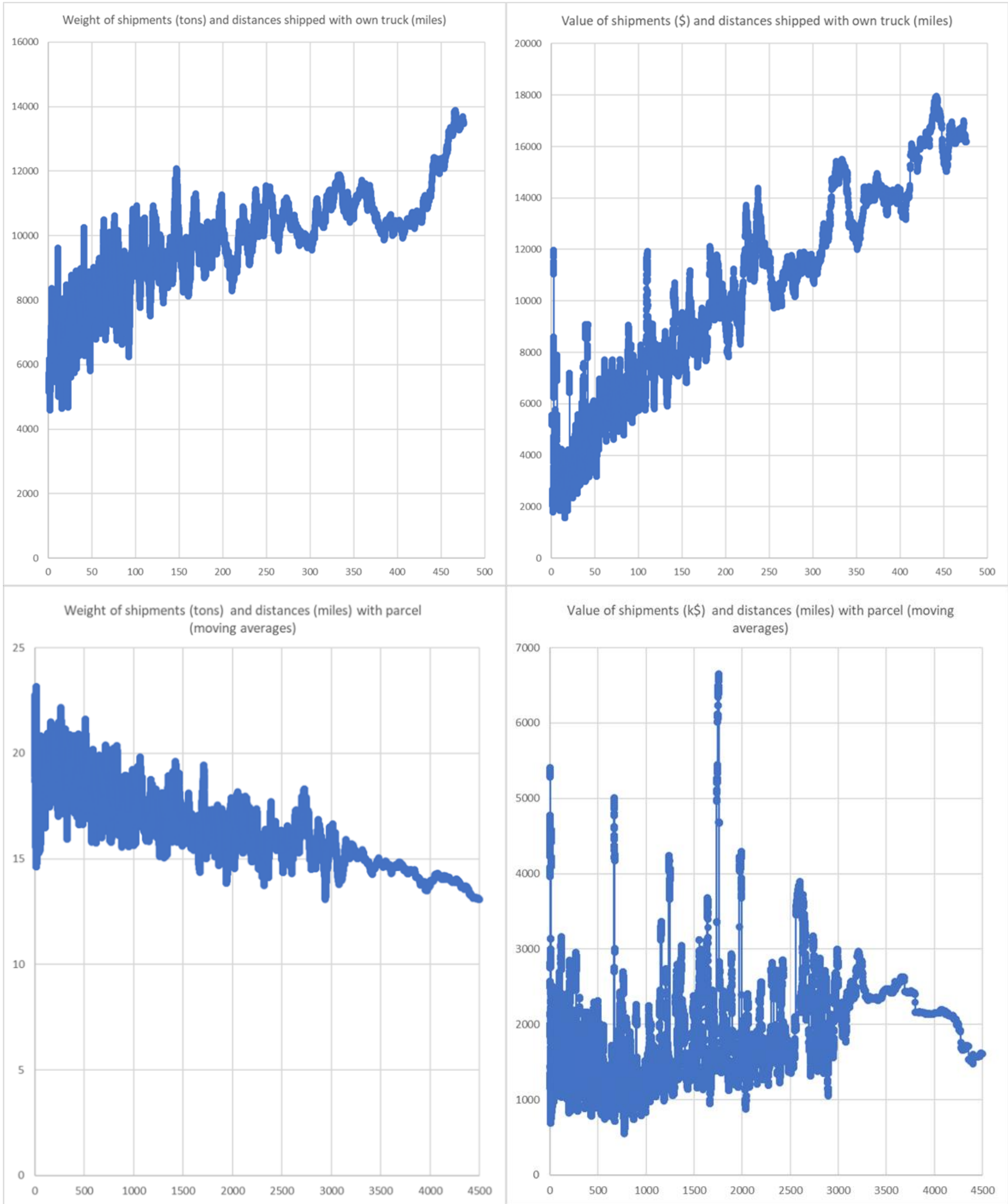

Figure 5.6: Value and weight of US shipments with company-owned trucks and parcels, UPS and courier 2017 (moving averages).

As a further example of the results of the US freight trade investigation we include four graphs on weight and value for shipments by company-owned trucks and parcel in 2017, see Figure 5.6. For owned trucks both value and weight increase with distance, faster for value. For parcel shipments the opposite patterns hold. Weight decreases markedly with distance and value is relatively independent of distance.

A new freight investigation has been carried out in 2021. The results are currently being collected and analyzed. There are considerable synergies to be achieved by establishing a contact between that work and the Swedish VFU investigations. This will also benefit phase three of the IO-project within Statistics Sweden.

Preliminary work has also been done on finding out information about ongoing work in other environments as concerns service trade. Two examples are reported below. The first example is from the work on establishing data bases for mobile phone calls at the Department of Human Geography under the leadership of Professor John Östh. The other example is the work on international trade in services performed by Professor Christinane Hellmanzik, University of Dortmund. The reason for this is that she has used similar specifications of service trade as we have in MRIO-2.

We have established contacts with Marina Toger, Uppsala University, who specializes in research on telecommunications and social interaction. One of her research questions is how to create interaction matrices using mobile phone data. The core of the Uppsala data is the location of mobile phones around cell masts around the clock. Through the localization of the masts, you can see which phones are connected to which masts, and then link the data to the geographical zone where the mast is located. In this way, 300 million observations per day have been collected for one operator. The operator's name is not public, but the company has around 15 percent of the market. Data applies to 2017-2022 and onwards.

If you connect the night-time location (it is assumed that this shows the phone's home address) to disaggregated data from the public LISA data base held at Uppsala University, you can get statistics on the socio-economic environment in the mast surroundings. Having knowledge of the hour of use, one can get an estimate of work- and home-related traffic by extracting data for times of the day.

If you know where in the geography a mast is located and which companies have workplaces in nearby work areas, you can get information about whether calls from a telephone's user may come from a certain industry. The result is a matrix with the number of movements between areas at a fine geographical level. Resulting data can be aggregated to the appropriate geographic level, for example municipality or county. This procedure is complicated but feasible and has been implemented in various applications.

Turning to service trade, Hellmanzik & Schmitz (2016) contains an analysis of international trade in services which is a useful entry into the question of the estimation of trade in services among Swedish counties. Such an analysis could, for instance, use Marina Toger's data as a measure of interaction. Hellmanzik uses suffixes, .se, .de, .com, .edu, etc. to create an interaction matrix.

Hellmanzik uses data on national indicators in her analysis for four types of trade in services as follows. The types are like the classification of service commodities in Anderstig et al. (2022).

A. Cross-border supply, where only the service crosses the border (for example financial, insurance and telecommunications services)
B. Consumption abroad, where non-residents consume services outside their country (for example travel)
C. Commercial presence abroad, where a branch or subsidiary is opened abroad to provide services there (for example a branch of a bank)
D. (Temporary) movement of (natural) persons to provide services (for example construction services)

Hellmanzik's data analysis then covers 11 explanatory variables of international trade in services. Each of the variables can be related to one of the groups A, B, C, D above.

1. Transportation (such as carriage of passengers)
2. Travel (such as goods and services by tourists or business travelers abroad)
3. Communication (such as telecommunication services)
4. Construction (such as construction works by an employee of a foreign company)
5. Insurance and pension services (such as provision of insurances)
6. Financial services (such as financial intermediation services)
7. Computer and information services (such as computer software)
8. Royalties and license fees (such as franchising)
9. Other business services (such as legal, research and development services)
10. Personal, cultural, and recreational services (such as audio-visual services)
11. Government goods and services (such as embassies and consulates)

Hellmanzik & Schmitz (2016) reports the following explanatory factors for analyzing international services trade (correlation in parentheses), see Table 5.1. Each factor relates to the characteristics of the countries used in the estimations. In addition, penetration of the Internet has been used as an indicator. The result of the analyzes is that bilateral hyperlinks remove some of the distance dependence in the service trade and transfer this to the hyperlinks. Considering the individual service categories, the largest decrease in the elasticity with respect to physical distance is found for financial services (coefficient decreases by .14), followed by insurance and audiovisual services (coefficients decline by .1) and communication and IT services (coefficient decreases by .08). The internet seems to matter less in terms of altering the negative impact of distance for other services, such as transportation and construction services.

Table 5.1: Explanatory factors in Hellmanzik's model of international service trade.

Factor	Correlation
Distance (log)	-0.062
Common border	0.206
Time zone difference	0.086
Common legal origin	0.104
Common religion	0.198
Common language Index	0.272
Migrants (log)	0.552
Bilateral hyperlinks	0.668
Cultural distance	-0.236

Further estimations have been made using the specifications given in the two equations below.

$$\ln(services)_{ij} = \alpha_i + \alpha_j + \delta \log\left(Z_{ij}\right) + e_{ij} \qquad (11)$$

$$Z_{ij} = virtualproximity_{ij}^{\phi_1} \cdot distance_{ij}^{\phi_2} \cdot migration_{ij}^{\phi_3} + \exp\left(\phi_4 contiguous_{ij} + \phi_5 time_{ij} + \phi_6 common\ law_{ij}\right)$$

Estimation results are presented in Table 5.2. We present the results only for a selection of the explanatory variables.

Table 5.2: Estimated parameter values in Hellmanzik's model of service trade.

Service	Distance (ln)	GDP/ capita	Migrants (ln)	Hyperlinks (ln)	Internet
Transport	-0.61	0.82	0.15	0.05	0.02
Travel	-0.49	0.95	0.18	0.20	-0.01
Communication	-0.78	0.81	0.19	0.36	0.00
Construction	-0.78	0.47	0.19	0.30	0.02
Insurance	-0.52	1.48	0.11	0.15	-0.01
Finance	-0.59	1.57	0.16	0.27	0.00
Computing	-0.45	0.84	0.17	0.35	0.03
Royalties	-0.69	1.58	0.16	0.27	0.04
Other business services	-0.45	0.87	0.16	0.03	0.02
Personal services	-0.63	1.05	0.14	0.33	0.01
Audiovisual services	-0.33	0.84	0.15	0.25	0.02
Government	0.02	1.06	0.21	0.19	0.01
All types	-0.41	0.94	0.19	-0.04	0.02

In our case with data for Swedish counties, most of the explanatory factors lose their influence since they will have the same value across the data set. In our case, migrants can be a measure of population composition. Cultural distance is measured as an index for different dimensions of the cultural environment. It hardly has any bearing here, but perhaps similar measures that capture whether you have friends and relatives or family elsewhere in the country. An important additional variable can be the ownership relationship in business and whether a firm will have establishments in several parts of the country. There is a lot of data in Sweden on the penetration of the Internet, but the variations geographically are not that great.

If you take the international trade in services as a point of departure and assume that the elasticities also apply within a country (Sweden is geographically large), you get the results in Table 5.2. The distance elasticity is largest for Communication and Construction. They are lowest for Audiovisual services and Government services. Countries with a large GDP/capita have more trade in services everything else given. The influence is largest for Insurane, Finance and Royalties. They are lowest for Construction. Migrants seem to have a relatively small impact on the level of trade and the impact varies little across countries. Hyperlinks have the largest influence for Communication and Computing. The influence is lowest for Government and Insurance. The influence of Internet penetration is generally small. These results can to some extent be compared to the analyses of service trade in report by Anderstig et al. (2022).

6 Conclusions

The focus in the current report has focused on freight trade. Trade in services is becoming increasingly important and will be further analyzed in our coming work. The brief analysis in this report indicates that the gravity model estimation based on the error indicator function may have problems detecting the share of local trade and service flows compared to interregional flows. The current study will be concluded with a suggested framework for the upcoming MRIO-3 project with special emphasis on the updating scheme for the interregional trade component. Recommendations will include proposals for further empirical studies on trade for both service and commodity shipments. The recent EU model system has implemented a trade component where the structure of the European and global logistics system seems to play as central role. How can we learn from that experience and from other ongoing work in other EU countries, and in the US? How can we better make use of surveys of service trade?

The MRIO project has used a database for 2018. It is important to produce tables for a time series. The difficulty will be making updates to VFU data and data for the service forecasts with historical and external survey data. Furthermore, it can be noted that going forward it should be appropriate to reduce the disaggregation in the core of the model and move from commodity groups to industries, for example at the 100 level. This is an important experience from phase 2.

One experience from the work with phase 2 is that it has been difficult to obtain supporting data from Statistics Sweden's various statistical areas. This applies to information on regionally distributed production values and information on consumption, investments, and foreign trade. Going forward, employment should not be used as a distribution key to such a high extent as in the earlier phase.

In the research report *Multiregional input-output analysis - today and tomorrow* there is a detailed account of proposals to improve the regionalization of the IO-statistics (Anderstig et al. 2022).

There is a need for better data for trade in services, for example through specially designed surveys, preferably together with other statistical authorities. Better data on freight transport from freight haulage companies is also needed. The continued MRIO project should not only focus on the publication of statistics and data bases. The need is also great when it comes to continuing to develop and apply different types of model estimates.

It is of great importance to bring about a continuation project without time delay. The focus of future work with the MRIO model should be to:

- Further develop the structure of the model;
- Ensure the development of a quality assurance model;
- Continue the work started with regionalization of supply and use statistics;
- Further develop the R programming of the model and document the model elements.

The MRIO model will have many important applications for national and regional stakeholders. It is therefore of great importance to continue the work as a development project with a circle of stakeholders in the coming years. In particular, some stakeholders will have to follow the project actively and continuously:

- Regions and County Boards;
- Authorities such as Growth Analysis, the Swedish Agency for Economic and Regional Growth, Transport Analysis and the Swedish Transport Administration, as well as the Environmental Protection Agency;
- Industry organizations such as the Swedish National Board of Trade;
- Researchers in social sciences and technology and knowledge-producing consulting companies.

Some areas will need special attention in MRIO-3 during a period of several years. We list these areas without defining their internal priorities. Some of them seem relatively straightforward to implement, whereas others will need larger research efforts.

1) Further development work around the regionalization of statistics for private and public investment, private and public consumption, foreign trade (import and export), and supply and use data. Investigate whether product or industry tables are most appropriate and what level of aggregation is reasonable;
2) Develop the methodology for producing a priori tables. Conduct an empirical investigation of flows of business services and business travel;
3) Further development of the programming of the model in R including presentation forms and documentation;
4) Validation and quality review of the results from the fully developed model through various national and international comparisons;
5) Investigate and make proposals for the organization, financing and operation of annually updated MRIO tables. Investigate how MRIO should be made available to various clients and applications in support of public policy, and research;
6) Create a network of Swedish and international stakeholders and build up training and competence development within MRIO-related issues.

One final proposal is to formally link the MRIO model to Raps. One idea could be that the Swedish Agency for Economic and Regional Growth gives Statistics Sweden an annual task to, in connection with the update of the statistics support in Raps, also produce updated MRIO tables.

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Appendix

Table A1: Commodity classification in Samgods 1.2.

Samgods classification	
1	Products of agriculture, hunting, and forestry; fish and other fishing products (excl. round wood)
2	Coal and lignite; crude petroleum and natural gas
3	Metal ores and other mining and quarrying products; peat; uranium and thorium.
4	Food products, beverages and tobacco
5	Textiles and textile products; leather and leather products
6	Wood and products of wood and cork (except furniture); articles of straw and plaiting materials; pulp, paper and paper products; printed matter and recorded media
7	Hard coal and refined petroleum products
8	Chemicals, chemical products, and man-made fibers; rubber and plastic products; nuclear fuel
9	Other non-metallic mineral products
10	Basic metals; fabricated metal products, except machinery and equipment
11	Machinery and equipment n.e.c.; office machinery and computers; electrical machinery and apparatus n.e.c.; radio, television and communication equipment and apparatus; medical, precision and optical instruments; watches and clocks
12	Transport equipment
13	Furniture; other manufactured goods n.e.c.
14	Secondary raw materials; municipal wastes and other wastes
15	Round wood

Table A2: Estimated parameters for all Aggregates and years (2016 and 2021) based on the three methods.

Method	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3
Aggregate	1	1	1	1	1	1	3	3	3	3	3	3	4	4	4	4	4	4
Year	2016	2016	2016	2021	2021	2021	2016	2016	2016	2021	2021	2021	2016	2016	2016	2021	2021	2021
α	-0.878	-0.878	-8.156	-0.878	-0.878	-8.172	0.354	0.354	-21.816	-4.025	-4.025	-21.905	-1.807	-1.807	-1.890	-4.518	-4.518	-6.983
β_1	1.067	1.067	0.902	1.082	1.082	0.904	0.672	0.672	-0.036	0.863	0.863	-0.036	0.589	0.589	0.825	0.634	0.634	0.911
β_2	0.634	0.634	0.777	0.625	0.625	0.777	0.657	0.657	1.454	0.954	0.954	1.451	0.797	0.797	0.570	0.959	0.959	0.868
β_3	-1.474	-1.489	-0.096	-1.483	-1.498	-0.096	-0.939	-1.029	2.370	-0.788	-0.907	2.387	-0.794	-0.791	-0.819	-0.638	-0.628	-0.500
RMSE	473.5	465.1	635.2	482.4	474.5	647.3	328.6	331.5	367.5	401.8	405.8	435.0	588.6	592.0	548.4	512.7	524.3	435.2
Error indicator F	0.333	0.326	0.205	0.334	0.327	0.205	0.733	0.662	0.526	0.794	0.665	0.527	0.316	0.315	0.271	0.298	0.294	0.253
Method	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3
Aggregate	5	5	5	5	5	5	6	6	6	6	6	6	8	8	8	8	8	8
Year	2016	2016	2016	2021	2021	2021	2016	2016	2016	2021	2021	2021	2016	2016	2016	2021	2021	2021
α	-1.015	-1.015	-1.125	-6.644	-6.644	-5.272	1.305	1.305	-3.148	0.136	0.136	-2.940	-2.785	-2.785	-9.187	-4.051	-4.051	-9.612
β_1	0.604	0.604	0.776	0.566	0.566	0.874	0.792	0.792	1.022	0.876	0.876	0.580	0.463	0.463	0.871	0.459	0.459	0.888
β_2	0.630	0.630	0.971	1.307	1.307	1.053	0.322	0.322	0.761	0.368	0.368	0.504	0.910	0.910	1.041	1.019	1.019	1.060
β_3	-0.516	-0.550	-1.012	-0.128	-0.164	-0.411	-0.922	-0.960	-1.179	-0.910	-0.925	-0.154	-0.537	-0.544	-0.206	-0.470	-0.495	-0.186
RMSE	24.2	24.3	30.0	16.4	16.9	17.6	510.1	509.5	817.7	435.0	433.1	470.4	340.3	339.1	325.9	261.3	261.7	260.4
Error indicator F	0.424	0.402	0.295	0.475	0.414	0.291	0.433	0.421	0.389	0.419	0.411	0.380	0.330	0.328	0.225	0.329	0.325	0.224
Method	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3
Aggregate	9	9	9	9	9	9	10	10	10	10	10	10	11	11	11	11	11	11
Year	2016	2016	2016	2021	2021	2021	2016	2016	2016	2021	2021	2021	2016	2016	2016	2021	2021	2021
α	-5.372	-5.372	-2.045	-1.565	-1.565	-2.049	-0.892	-0.892	-7.087	2.014	2.014	-7.085	-10.401	-10.401	-8.989	-8.702	-8.702	-8.988
β_1	0.777	0.777	0.916	0.537	0.537	0.916	0.668	0.668	0.847	1.017	1.017	0.847	0.808	0.808	1.203	0.756	0.756	1.203
β_2	1.051	1.051	0.691	0.832	0.832	0.691	0.464	0.464	0.679	-0.249	-0.249	0.679	1.287	1.287	0.815	1.101	1.101	0.814
β_3	-0.703	-0.707	-1.027	-0.732	-0.744	-1.027	-0.560	-0.579	-0.109	-0.549	-0.586	-0.109	-0.352	-0.381	-0.476	-0.273	-0.301	-0.476
RMSE	223.7	223.1	250.5	170.8	170.2	231.8	704.9	706.1	718.9	1067.0	1069.6	1109.7	476.2	494.6	473.9	393.3	400.0	405.6
Error indicator F	0.337	0.335	0.320	0.399	0.398	0.320	0.341	0.325	0.290	0.530	0.492	0.290	0.418	0.396	0.260	0.364	0.343	0.260
Method	1	2	3	1	2	3	1	2	3	1	2	3						
Aggregate	12	12	12	12	12	12	13	13	13	13	13	13						
Year	2016	2016	2016	2021	2021	2021	2016	2016	2016	2021	2021	2021						
α	-3.812	-3.812	-10.768	-1.495	-1.495	-10.440	-6.779	-6.779	-7.506	-4.145	-4.145	-7.487						
β_1	0.666	0.666	0.697	0.524	0.524	0.632	0.915	0.915	0.807	0.700	0.700	0.807						
β_2	0.746	0.746	1.361	0.637	0.637	1.496	0.764	0.764	1.038	0.814	0.814	1.037						
β_3	-0.445	-0.452	-0.347	-0.438	-0.454	-0.549	-0.246	-0.271	-0.366	-0.478	-0.495	-0.368						
RMSE	1595.2	1605.6	1443.5	1266.7	1268.3	1823.9	384.0	383.6	412.2	296.7	295.7	306.7						
Error indicator F	0.385	0.384	0.295	0.511	0.510	0.288	0.306	0.281	0.244	0.297	0.296	0.244						

Table A3: Calculation of Error indicator F for Aggregate 4 (Food, etc.) for year 2016. In the calculation, the error indicator for supply is $F_S = 0.325$ and for demand is $F_R = 0.186$. The Error indicator F value for the total matrix is $F = 0.256$.

	To County																							
From County	01	03	04	05	06	07	08	09	10	12	13	14	17	18	19	20	21	22	23	24	25	Sum	Supply	Absolute error
01 Stockholms län	11518	988	896	484	139	60	150	201	42	745	995	1264	343	553	895	733	287	335	195	222	205	21248	26577	5329
03 Uppsala län	427	621	33	0	6	0	99	5	0	4	2	4	0	30	17	5	3	17	0	5	0	1277	872	405
04 Södermanlands län	170	19	364	77	95	0	9	2	0	190	5	92	22	26	160	121	33	2	1	14	0	1401	2825	1424
05 Östergötlands län	1064	79	261	1963	148	43	136	46	10	637	118	709	92	173	556	91	66	37	9	41	24	6302	5029	1273
06 Jönköpings län	438	7	10	289	625	133	191	0	81	279	292	1394	3	133	156	113	1	1	7	10	11	4174	5013	839
07 Kronobergs län	1617	4	8	77	132	284	245	0	1	24	14	161	22	10	9	3	0	2	1	5	8	2627	1135	1493
08 Kalmar län	207	15	27	48	336	31	441	0	90	73	50	685	31	43	151	11	9	21	10	8	10	2296	4751	2455
09 Gotlands län	96	0	0	2	0	0	0	136	0	6	0	2	0	2	0	0	0	0	0	0	0	243	744	501
10 Blekinge län	106	54	1	46	6	44	21	5	24	601	92	174	25	15	14	12	6	0	0	5	3	1256	3323	2067
12 Skåne län	5285	627	170	1171	716	979	398	34	459	11058	2570	3905	178	473	2054	616	93	101	88	186	57	31219	26512	4707
13 Hallands län	253	5	114	63	162	87	57	0	50	856	1265	1116	26	12	145	151	4	10	3	3	1	4381	5332	951
14 Västra Götalands län	2517	188	59	876	603	197	181	16	159	2316	893	9131	732	386	698	497	28	87	35	98	60	19759	24037	4278
17 Värmlands län	113	1	7	18	2	1	0	0	0	65	26	189	1002	193	130	27	1	2	9	11	2	1800	2584	783
18 Örebro län	515	1372	211	116	75	55	6	5	7	305	157	440	153	1276	170	147	31	18	12	38	23	5130	5001	129
19 Västmanlands län	1712	726	484	244	0	90	47	8	0	572	1	553	56	300	553	589	61	32	14	87	29	6157	1060	5097
20 Dalarnas län	879	43	118	262	125	97	66	0	0	605	7	695	141	563	645	1278	799	629	413	977	438	8780	3315	5465
21 Gävleborgs län	432	34	7	64	22	0	1	0	0	253	8	5	14	73	414	142	509	45	36	1	0	2061	626	1434
22 Västernorrlands län	50	3	13	7	11	5	5	4	0	62	17	15	2	3	22	168	112	288	100	35	67	987	1032	45
23 Jämtlands län	38	1	1	0	0	0	0	0	0	0	2	39	1	2	46	27	0	0	45	0	0	202	722	520
24 Västerbottens län	66	0	7	8	6	0	0	0	0	84	6	58	1	3	57	61	1	235	65	919	409	1986	1777	209
25 Norrbottens län	82	13	1	13	4	4	4	1	2	33	5	41	7	20	27	5	13	52	36	222	371	956	1976	1020
Sum	27584	4800	2791	5830	3212	2111	2057	464	925	18768	6523	20672	2848	4287	6919	4798	2055	1915	1081	2886	1717	124242	124242	**Fs=0,325**
Demand	31634	3897	3136	5370	4092	2011	3163	836	2078	17544	4210	21032	3012	3547	2742	3160	2894	2589	1415	2930	2948	124242		
Absolute error	4050	903	345	460	880	100	1107	372	1153	1224	2313	361	164	741	4176	1638	839	674	334	44	1231	**Fr=0,186**		**F=0,256**