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On the accuracy of gravity-RAS approaches used for inter-regional trade estimation: evidence using the 2005 inter-regional input–output table of Japan

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ABSTRACT

In contrast to international trade, it is still difficult to find regional trade statistics within a nation. Given that the gravity model continues to be very popular, we test two gravity-RAS approaches used for interregional trade estimation: a standard one and an extended version, which additionally estimates intra-regional flows. We assess the accuracy with the help of two measures and for different sectoral aggregation levels. For that, we use the survey-based 2005 interregional input–output table of Japan as a benchmark. Results show high overall accuracy levels for the standard approach, better than when using international data, albeit with heterogeneous errors for sectors and regions. We further find that the results of a multiregional input-output model are highly sensitive to the trade estimation approach and that errors slightly increase for increasing sectoral disaggregation levels. Results from an experiment based on a random number generator show how RAS influences results.

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1. Introduction

Global value chains (GVCs), where the different stages of a production process happen across different countries, have gained importance over the years due to decreasing transportation costs, denser networks, improvements in communication, among other advances in technology.¹ As Jones and Kierzkowski (2005) note, this fragmentation process has resulted in a much more spatially distributed production system. Despite this, much of the world's trade still happens at the subnational level, as evidenced by strong home biases, meaning that interregional is much larger than international trade for many countries around the world (Anderson & Van Wincoop, 2003; Coughlin & Novy, 2016; Hillberry & Hummels, 2003; Okubo, 2004; Wolf, 2000).² Following the example of Timmer et al. (2014), where the authors slice up the GVC of German cars, it can be seen that although

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¹ GVC studies using the World Input-Output Database (WIOD) include Timmer et al. (2014) and Los et al. (2015) among many others; OECD ICIO examples are Rouzet and Miroudot (2013) and De Backer and Miroudot (2013).

² Subnational regions are typically more open to trade than are countries. Wolf (2000), using the 1993 U.S. Commodity Flow Survey, calculates the share of shipments within each U.S. state to total subnational shipments and finds that this ratio increases for increasing state's area.

foreign value added has been gaining relative relevance throughout the years, subnational (German) value added still represents about two-thirds of final output value. Similar figures arise for transport equipment in Germany or electrical machinery in the USA (Los et al., 2015).

Multiregional input-output (MRIO) tables usually need to be estimated due to the unavailability of subnational level data (Isard, 1951). The customary regionalization process comprises two steps: the estimation of intra-regional flows and interregional trade. These can be performed by survey, non-survey, or hybrid approaches. The second and third options, depending on the degree of superior information used, can be further categorized into different methods. These include column or row coefficient models (MRIO types) (Polenske, 1970), entropy and information theory (Canning & Wang, 2005; Fernandez Vazquez et al., 2015; Roy & Thill, 2004; Wilson, 1970), neural networks models (Nijkamp et al., 2004), or the gravity-RAS method (Oosterhaven, 1981), where gravity estimates are used as priors for RAS adjustment iterations, assuring that column and row totals conform to known values.^{3,4}

Studies trying to measure the accuracy of some of the above methods include Canning and Wang (2005), Sargento et al. (2012), Robinson and Liu (2006), Polenske (1970), and Lindall et al. (2006), among others. Unfortunately, previous studies suffer from several limitations. First, almost all use supranational instead of subnational data, for instance, trade flows between countries belonging to an economic bloc. None look at results at the regional level but only focus on total or sectoral accuracy. Further, all work with a very high degree of sectoral aggregation and hence do not assess the interplay between the methods and the sectoral aggregation level. Lahr and Stevens (2002) claim that applied models with high levels of aggregation tend to have inherent error, at least when produced by partial or non-survey methods. Sectoral aggregation increases the ubiquitous product-mix problem of input-output (IO) systems while simultaneously increasing empirical problems of measuring cross-hauling well. Note, however, that, after some extreme threshold, further sectoral aggregation appears to reduce the overall error of the system (Lahr & Stevens, 2002; Miller & Shao, 1990).

The first objective of this paper is to test the accuracy of two different gravity-RAS approaches popular in the literature: a 'standard' specification, only aiming at estimating interregional trade, and an 'extended' version, which additionally estimates intra-regional flows. Although the accuracy of 'standard' type gravity specifications is already tested in the literature, the novelty here is that we use subnational data to do so. In contrast, to the best of the author's knowledge, no scientific accuracy-test exists for the 'extended' gravity specification. Moreover, given that the data we use comes in three different sectoral aggregation levels, the second objective of this paper is to shed light on the interplay between the above approaches and the sectoral aggregation level.

Central questions to be answered along with expectations are:

- (1) Can the 'extended' type gravity-RAS approach achieve similar accuracy as the 'standard' gravity-RAS approach? We expect to find inferior accuracy levels for the

³ These can also be combined, as in RHOMOLO (Thissen et al., 2014).

⁴ RAS is a matrix balancing method used for achieving consistency between the entries of a matrix and known row and column totals.

‘extended’ gravity model. Although it estimates more variables (intra-regional flows) than the ‘standard’ model, it uses less information. Additionally, any errors in estimating intra-regional flows affect interregional flow estimates through a column constraint.

- (2) Given that both approaches include a RAS adjustment step, what is the contribution of this step in the accuracy levels? We expect to find a positive contribution depending on the accuracy measure considered.
- (3) How sensitive are the results of an IO model to the use of the different estimation methods? We expect a low sensitivity based on previous findings in the literature (Canning & Wang, 2005; Sargento et al., 2012).
- (4) Are accuracy levels homogeneous for all units of analysis? Since the parameters entering the models lack several unit-specific terms, we expect to find heterogeneous results for sectors and region pairs.
- (5) Do errors increase for increasing sectoral disaggregation levels? Given previous findings, such as those in Miller and Shao (1990), *a-priori* we cannot predict the direction or size of the aggregation effect.

For answering the above questions, we use data from the 2005 interregional input-output (IRIO) table published by the Ministry of Economy, Trade, and Industry (METI) of Japan. First, we transform the IRIO table, such that its trade component resembles the one that is usually estimated. We use the latter as the ‘true table’ for comparing estimates generated using the estimation approaches. Accuracy is assessed from a sectoral and regional perspectives by using a quasi-holistic measure, through a weighted mean absolute percentage error (MAPE), and a holistic one, based on the results from an MRIO model. The findings also include results from an experiment based on a random number generator (random approach), which gives a measure of the extent that bi-proportional adjustment methods, such as RAS, might influence results.

Findings show that accuracy heavily depends on the approach used as well as the accuracy measure considered. The standard gravity-RAS approach achieves the highest overall accuracy, albeit with heterogeneous results for sectors and region pairs. Although the random approach achieves almost the same holistic accuracy as the standard approach, we find that this is not the case for the extended approach. Finally, we find a low sensitivity to the sectoral aggregation level depending on the accuracy type. The paper is organized as follows: the next section gives an overview of the gravity approach, followed by the theoretical framework, the transformation process to reduce the IRIO table to a simpler one, the data, the models used to estimate trade flows, the accuracy measures, and the results. The last section concludes by summarizing the findings and giving advice on future work.

2. The gravity model

Since its first IO application by Leontief and Strout (1963), the gravity model has become ubiquitous in applied work for estimating interregional trade at both the supranational and subnational levels. Micro-foundations of the gravity equation can be derived from models such as the Heckscher-Ohlin (Deardorff, 1998) or monopolistic competition theories (Helpman, 1987; Helpman & Krugman, 1985). Recent studies included the idea of product differentiation by region and firm, following, among others, Armington’s (1969) principle.

Standard specifications of the gravity model resemble Equation 1, where d_i^{od} is the trade flow of commodity i from region o to region d , e is a constant of proportionality, GRP is a measure of economic size, $dist^{od}$ stands for distance between regions, and the betas are sector-specific parameters to be estimated. The mass terms, usually represented by economic or market size through gross regional products (GRP), reflect the idea that wealthier regions trade more than poorer ones (Coughlin & Novy, 2016; Frankel, 1997).⁵ On the other hand, the distance term reflects the idea that everything is related to everything else, but near things are more related than distant things (Tobler, 1970). For instance, Wolf (2000) finds a correlation coefficient of -.75 between distance and inter-state exports in the US.

$$d_i^{od} = e^{\beta_0} \frac{(GRP^o)^{\beta_1} (GRP^d)^{\beta_2}}{(dist^{od})^{\beta_3}} \quad (1)$$

A motivation for estimating the gravity equation with subnational level data was the so-called ‘home-effect’, which revealed that gravity equations underestimate intra-national trade (Wolf, 2000). For instance, Coughlin and Novy (2016) find that exports of U.S. states to foreign countries are about 71% lower than interregional trade in the US. McCallum (1995) and Anderson and Van Wincoop (2003) show similar figures for Canadian provinces and Okubo (2004) for Japanese regions.

Comparing analysis carried out at the international level with those at the subnational level reveals several differences. For instance, explanatory variables, such as common language or membership in a given trade agreement, are usually not needed at the subnational level. Further, international trade models usually estimate either imports, exports, or net trade, but without any sectoral detail. This motivates the inclusion of sectoral terms in gravity equations, such as self-sufficiency measures in Sargento et al. (2012) or even the derivation of sector-specific spatial models based on the gravity approach as in Liu et al. (2015).

3. Framework

Given that the benchmark data used in this article refers to a non-competitive inflow and competitive import type IRIO table, we begin by explaining how to reduce the latter, such that the resulting trade flows matrix resembles the typically estimated matrix. Letting a national economy be composed of $o, d = 1, \dots, G$ subnational regions, where o are origins and d destinations; of $i, j = 1, \dots, N$ sectors, where i denote rows and j columns; and of only one type of final demand and value added, the sector-by-sector IRIO system can be represented by Table 1, where $\mathbf{Z} = [z_{ij}^{od}]$, $\mathbf{Y} = [y_i^{od}]$, and $\mathbf{V} = [v_j^{od}]$ are arrays of regional intermediate, final demand, and value added, respectively, and $\mathbf{x}_i = [x_i^o]$, $\mathbf{e}_i = [e_i^{od}]$, $\mathbf{m}_i = [m_i^{od}]$ are vectors of total regional output, exports and imports of region o , respectively.⁶ Note that only each intersection of any region with itself has non-zero import and export accounts. The former results from the fact that the table is of competitive-import type, that

⁵ GRP as a mass variable can be problematic for explaining trade in intermediate inputs. However, Baldwin and Taglioni (2014) find that when pooling different regions and goods, the standard gravity equation performs well, since, for many trade flows, the pattern of trade in intermediates is quite proportional to trade in final goods.

⁶ Superscripts always represent regions whereas subscripts represent sectors, where a dot indicates summation across an index.

Table 1. Non-competitive inflow and competitive import IRIO table.

Full IRIO matrix															
O/D	1							...	G						Total
	Size	1	...	N	Y	E	M	...	1	...	N	Y	E	M	
1	1	z_{11}^{11}	...	z_{1N}^{11}	y_1^{11}	e_1^{11}	$-m_1^{11}$...	z_{11}^{1G}	...	z_{1N}^{1G}	y_1^{1G}	—	—	x_1^1
	⋮	⋮	⋮	⋮	⋮	⋮	⋮	...	⋮	⋮	⋮	⋮	⋮	⋮	⋮
	N	z_{N1}^{11}	...	z_{NN}^{11}	y_N^{11}	e_N^{11}	$-m_N^{11}$...	z_{N1}^{1G}	...	z_{NN}^{1G}	y_N^{1G}	—	—	x_N^1
	VA	v_1^{11}	...	v_N^{11}	—	—	—	...	v_1^{1G}	...	v_N^{1G}	—	—	—	v_1^1
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
	1	z_{11}^{G1}	...	z_{1N}^{G1}	y_1^{G1}	—	—	...	z_{11}^{GG}	...	z_{1N}^{GG}	y_1^{GG}	e_1^{GG}	$-m_1^{GG}$	x_1^G
	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
G	N	z_{N1}^{G1}	...	z_{NN}^{G1}	y_N^{G1}	—	—	...	z_{N1}^{GG}	...	z_{NN}^{GG}	y_N^{GG}	e_N^{GG}	$-m_N^{GG}$	x_N^G
	VA	v_1^{G1}	...	v_N^{G1}	—	—	—	...	v_1^{GG}	...	v_N^{GG}	—	—	—	v_1^G
Sum	—	x_1^1	...	x_N^1	y_1^1	e_1^1	m_1^1	...	x_1^G	...	x_N^G	y_1^G	e_1^G	m_1^G	—

is, imports for each sector are not divided into their actual ratios, but they are reported directly in the region demanding them.

Three additional vectors are also helpful in this paper: $\mathbf{TRD}_i = [\mathbf{TRD}_i^d] = [z_i^{\cdot d} + y_i^d - m_i^{dd}]$ standing for total regional demand of commodity i in region d ; $\mathbf{TRS}_i = [\mathbf{TRS}_i^o] = [x_i^o - e_i^{oo}]$ standing for total regional supply of commodity i in region o ; and $\mathbf{GRP} = [\mathbf{GRP}^o] = [v_i^o]$ standing for total value added (gross regional product) for each region o . Note that these three vectors can be obtained from available statistics, derived by some suitable method, or extracted from Table 1, if available, by summing over the respective elements and indexes.

To make trade tables resemble the usual tables estimated by the aforementioned approaches, sectoral destinations of each trade flow must be merged. This is analogous to an IRIO-to-MRIO reduction, which, as in Canning and Wang (2005), can be carried out by means of Equations 2 and 3, where d_i^{od} gives the flow value of domestic commodity i from region o to region d , whereas $z_{ij}^{\cdot d}$ refers to intermediate demand of commodity type i by sector j in region d .

$$\sum_{j=1}^N z_{ij}^{od} + y_i^{od} - m_i^{oo} = d_i^{od} \quad (2)$$

$$\sum_{o=1}^G z_{ij}^{od} = z_{ij}^{\cdot d} \quad (3)$$

Although both variables are required for an MRIO accounting system, here we are only interested in the d_i^{od} s. The estimation approaches presented below estimate either the interregional, that is, d_i^{od} for $o \neq d$, or the whole transactions of the $\mathbf{D} = [d_i^{od}]$ matrix, reproduced in Table 2 for illustrative purposes.

Table 2. Trade table (inc. intra-regional flows).

		Intra-regional D matrix				
O/D		1	2	...	G	Sum
	Size	All	All	...	All	
1	1	d_1^{11}	d_1^{12}	...	d_1^{1G}	$d_1^{1\cdot}$
	\vdots	\vdots	\vdots	\ddots	\vdots	\vdots
	N	d_N^{11}	d_N^{12}	...	d_N^{1G}	$d_N^{1\cdot}$
2	1	d_1^{21}	d_1^{22}	...	d_1^{2G}	$d_1^{2\cdot}$
	\vdots	\vdots	\vdots	\ddots	\vdots	\vdots
	N	d_N^{21}	d_N^{22}	...	d_N^{2G}	$d_N^{2\cdot}$
\vdots	\vdots	\vdots	\vdots	\ddots	\vdots	\vdots
G	1	d_1^{G1}	d_1^{G2}	...	d_1^{GG}	$d_1^{G\cdot}$
	\vdots	\vdots	\vdots	\ddots	\vdots	\vdots
	N	d_N^{G1}	d_N^{G2}	...	d_N^{GG}	$d_N^{G\cdot}$
Sum		$d_{\cdot}^{1\cdot}$	$d_{\cdot}^{2\cdot}$...	$d_{\cdot}^{G\cdot}$	–

4. Data and overview

The data used in this paper refers to the 2005 IRIO table published by the Ministry of Economy, Trade, and Industry (METI) of Japan, which we later use to get the benchmark **D**-matrix.⁷ This table began being compiled in 1960 and, since then, is updated every five years.⁸ The 2005 table includes nine regions and is disclosed in three sectoral disaggregation levels: 12, 29, and 53 sectors.⁹ This dataset is regarded as one of the most reliable (based on the amount of survey data used) in the literature (Miller & Blair, 2009).

The construction of the Japanese IRIO table is based on the combination of nine inter-regional competitive inflow and import type tables, one for each of the country's regions, that perfectly matches the nationwide IO table. According to the online available METI (2010) report, for estimating inflows and outflows, that is, interregional transactions between Japanese regions, METI uses several data depending on the sector under consideration. For industrial production, METI conducts a special survey (Commodity Distribution Survey) and combines it with interregional freight flow data from the Net Freight Flow Census (MLIT). The information available with survey content corresponds to outflows per sector and region to every geographic destination, but without specifying any sectoral destination, that is, not stating how inputs enter each destination sector. For this work, the missing information is not essential because we are only interested in the d_i^{od} – the trade flow type typically approximated by gravity models.

⁷ Note that the 'true' matrix might, in fact, not exist due to errors in data or table compilation methods, among others (Jensen, 1980).

⁸ The data is available online at: [<http://www.meti.go.jp/english/statistics/tyo/tiikiio/index.html>].

⁹ Although the sectoral scale has a rectangular form (519×406) in the regional tables under the basic sector classification (not available online), those are then accommodated to a square form and aggregated along the construction process up to $N = 53$.

Appendix Tables A1 and A3 (all appendices are available online only) show characteristics for each sector and region, while Table A6 gives a complete description of the sectoral classification with full names and correspondences. Distances between Japanese regions are calculated using the Google Map Distance Matrix API with driving travel mode. Since some regions contain many prefectures, distances are calculated between the most populated prefectures in each region, as indicated in the last column of Table A3.

5. Three approaches to estimate interregional trade

In this section, we present two popular gravity-RAS approaches along with one random-RAS approach, which serves as an indicator of the role of RAS in accuracy levels.¹⁰ Although they omit many relevant variables found to be significant in the empirical literature, the models are, as shown in the cited articles where they are employed, usually used in their original version. For this reason, we conduct our analysis on the baseline specifications. Appendix Fig. A1 gives a visual representation of the two approaches. From top to bottom, the figure begins by specifying data requirements and ends by comparing final estimates against the benchmark \mathbf{D}_i -matrix for Japan. There are a few key things worth highlighting: (1) Each approach has different direct data requirements, but, including the RAS step, the SG-RAS uses more data than the EG-RAS, even though the latter estimates more variables (intra-regional flows);¹¹ (2) The SG-RAS is directly linked to the \mathbf{D}_i matrix, whereas the EG-RAS needs additional steps to arrive to it; and (3) Given that the RAS method for the EG-RAS model adjusts total regional supply and demand, final row and column sums of $\bar{\mathbf{D}}_i$ are not equal to \mathbf{D}_i row and column sums (as in the case of the SG-RAS).

For estimating interregional trade flows, at least some basic information is needed. This typically refers to row and column totals of the \mathbf{D}_i -matrix, and sometimes the intra-regional part of it, that is, d_i^{oo} , which in our case we extract from the data presented above. Note that parameters entering the gravity equation, such as the betas in Equation 1, cannot be estimated beforehand since doing so would require interregional data, which is going to be estimated by the gravity equation. If this is the case, sector-specific parameters might be estimated in four different ways: (1) from another period for which observations are available (Boero et al., 2018); (2) from another geographical area (Nakano & Nishimura, 2013; Yamada, 2015); (3) by arbitrarily assuming parameter values or calculating them with help of known column and row totals (Sergento et al., 2012); or (4) by adapting estimates from other econometric analyses in the literature (Krebs, 2018).

5.1. Standard gravity RAS (SG-RAS) approach

The first approach we test is a standard gravity RAS (SG-RAS) approach, which is also tested by Sergento et al. (2012) and shown to be only slightly less accurate than the enhanced gravity model (sector-specific distance-decay parameters) but better than the

¹⁰ Further details of the formulas can be found in the respective cited papers.

¹¹ The complete SG-RAS process uses $5o + 2i$ whereas the EG-RAS uses only $4o + 2i$ elements, where the extra o elements of the former come from the GRP^o 's.

data-pooling model.¹² The main characteristics of this specification are that all traditional gravity parameters equal one, and it uses a degree of specialization (location quotient) measure.

The SG-RAS estimation process is represented by Equations 4 and 5. The estimation part is given by Equation 4, where \hat{d}_i^{od} stands for the estimates of off-diagonal elements of the \mathbf{D}_i -matrix, GRP^d stands for gross regional product of region d , $dist^{od}$ gives distance from each origin to each destination ($\mathbf{dist} = [dist^{od}]$). The second term in brackets is the degree of specialization, which is a locational quotient using regional outflow d_i^o , that is, the column sums of Table 2, and G_i^o is a constant of proportionality ensuring that $\sum_d \hat{d}_i^{od} = d_i^o$ holds.¹³

However, the $\hat{\mathbf{D}}_i$ generated using Equation 4 must be adjusted, such that $\sum_o \hat{d}_i^{od} = d_i^d$ also holds. This is achieved by means of the bi-proportional adjusting method RAS. Abusing notation, so that the RAS method is represented by a function $RAS(\cdot)$, Equation 5 gives the adjustment step, after which the hat is replaced with a bar over the variable.

$$\hat{d}_i^{od} = \left\{ \frac{GRP^o GRP^d}{dist^{od}} \right\} \cdot \left\{ \frac{d_i^o / \sum_i d_i^o}{\sum_o d_i^o / \sum_o \sum_i d_i^o} \right\} \cdot G_i^o, \quad \forall o, d, \quad (4)$$

s.t. $o \neq d$

$$\bar{\mathbf{D}}_i^{SGM} = RAS(\hat{\mathbf{D}}_i) \quad (5)$$

5.2. Extended gravity RAS (EG-RAS) approach

We call the second approach extended gravity RAS (EG-RAS), given that it also estimates intra-regional transactions, that is, the complete \mathbf{D}_i -matrix.¹⁴ Known as Horridge's formula, it refers to the method used for the 57 region TERM CGE model of Australia (Horridge et al., 2003; Horridge et al., 2005), which Dixon and Rimmer (2004) explain in some detail. Wittwer (2017) appears to be the sole researcher to attempt to measure the method's accuracy, using the 2012 U.S. Commodity Flow Survey (CFS) of the U.S. Census Bureau for comparison. But given that the CFS records movements to and from transport nodes, it over-concentrates on bulk commodities as well as upon wholesaling destinations, so the data were deemed unsuitable. Still, Wittwer (2017, p. 17) concludes that, 'the Census Bureau survey does not provide any evidence that the Horridge gravity formula is invalid'. We believe that before arriving at such a strong conclusion, the goodness of fit of the approach should be tested against a suitable interregional flow matrix, as we do here.

The process is given by Equations 6, 7, 8, and 9. The estimation part has two components: Equation 6 estimates diagonal, while Equation 7 estimates off-diagonal elements. $SHIN_i^{od}$ is sector's i trade share from region o to region d , TRS_i^o stands for total regional

¹² The SG-RAS approach resembles many other specifications in the literature. For instance, Lindall et al. (2006) and Boero et al. (2018) use a similar approach to estimate flows between regions in the U.S., Liu et al. (2015) do it for China, Nakano and Nishimura (2013) and Yamada (2015) for Japan, and Krebs (2018) for Germany.

¹³ G_i^o can be calculated as $G_i^o = d_i^o \times \left(\left\{ \frac{GRP^o GRP^d}{dist^{od}} \right\} \times \left\{ \frac{d_i^o / \sum_i d_i^o}{\sum_o d_i^o / \sum_o \sum_i d_i^o} \right\} \right)^{-1}$.

¹⁴ Applications include many regional studies, such as the U.S. (Dixon & Rimmer, 2004), the Azores (Haddad et al., 2015), Colombia (Haddad et al., 2016), Lebanon (Haddad, 2014), and Morocco (Haddad et al., 2017).

supply per sector and origin region o , TRD_i^d stands for total regional demand of commodity i in region d , the auxiliary indices g and v are aliases for o , and F_i is a scalar calculated from the data, giving a degree of sectoral ‘tradeability’ and lying between .5 and 1.0, where a higher value is attained if a sector’s output is not easily tradeable.¹⁵ Note that combined, both formulas satisfy the column condition $\sum_o SHIN_i^{od} = 1$. In Equation 8, the resulting shares are distributed over values of total regional demand. Finally, Equation 9 gives the RAS adjustment step and subtracts intra-regional elements.

$$SHIN_i^{dd} = \min \left\{ \frac{TRS_i^o}{TRD_i^d}, 1 \right\} \cdot F_i \quad (6)$$

$$SHIN_i^{od} = \left\{ \frac{1}{dist^{od}} \cdot \frac{TRS_i^o}{\sum_g TRS_i^g} \right\} \cdot \left\{ \frac{1 - SHIN_i^{dd}}{\sum_{v \neq d} \left[\frac{1}{dist^{vd}} \cdot \frac{TRS_i^v}{\sum_g TRS_i^g} \right]} \right\}, \quad \forall o, d, \quad s.t. \quad o \neq d \quad (7)$$

$$\widehat{FLOW}_i^{od} = SHIN_i^{od} \cdot TRD_i^d \quad (8)$$

$$\bar{D}_i^{EGM} = RAS(\widehat{FLOW}_i) - diag(RAS(\widehat{FLOW}_i)) \quad (9)$$

According to Equation 6, $SHIN_i^{dd}$ is smaller than 1.0 whenever demand exceeds supply for a given sector, implying a rather low degree of self-sufficiency. The leftmost term on the RHS of Equation 7 also implies a small share value for long distances between regions and for a small share of an origin region in the total regional supply of i . The rightmost term implies a small share for a higher self-sufficiency degree of the destination region and for a high value of the denominator, which is a regional aggregation of the leftmost term over an auxiliary index v excluding the destination region d being evaluated. Note that column condition $\sum_o SHIN_i^{od} = 1$ implies that any errors in estimating intra-regional flows (negatively) influence the estimation of interregional flows via altering the intra-to-inter trade proportions of each region.

5.3. A random-RAS (R-RAS) approach

Since both previous approaches include two stages, that is, the estimation itself followed by a RAS adjustment to make sure that totals coincide, it is interesting to look at the effect of the second stage alone. To do this, similar to Israilevich et al. (1996), random trade matrices are generated, \bar{D}_i^{RM} , ensuring that row totals equal $d_i^{o^*}$ for each i , but excluding intra-regional flows.¹⁶

¹⁵ The scalar F_i can be calculated in two steps: first calculate averaged regional supply-demand differences as $AGAP_i = \frac{1}{G} \cdot \sum_d \left| \frac{TRD_i^d - TRS_i^d}{[TRD_i^d + TRS_i^d]/2} \right|$; then calculate $F_i = \frac{1 + 0.5 \exp[5 \cdot (AGAP_i - 1)]}{1 + \exp[5 \cdot (AGAP_i - 1)]}$, where the functional form assures that the value lies between .5 and 1.

¹⁶ First, we generate evenly distributed random real numbers on the unit interval. Then, we divide each of the previous numbers by the sum of all random values for each row and multiply these by $d_i^{o^*}$, such that final row totals conform to $d_i^{o^*}$.

6. Accuracy measures

Building upon the work of Jensen (1980), accuracy in regional IO tables can be of different types. A-type accuracy refers to the degree to which an estimated table resembles the ‘true’ table, whereas B-type refers to the ability of a model to represent the functioning of the economy. On the other hand, partitive accuracy focuses on every cell of the table, treating them as individual and independent entities. In contrast, under the holistic counterpart, accuracy is measured for the most important components of the table, those representing the main features of the economy (usually in terms of size and structure).¹⁷ Both gravity-RAS approaches presented above are hybrid in that they are based on a gravity specification, which aims at partitive accuracy, and on an RAS adjustment step, which aims at holistic accuracy. On the other hand, the R-RAS approach only aims at the holistic accuracy of column/row sums. Although we believe that the empirical application should guide the decision on which accuracy type to use, we share the opinion of Jensen (1980) that pure partitive accuracy is not tenable in practice. Therefore, we focus on two alternative measures.

The first measure of accuracy is a mean absolute percentage error (MAPE) (Miller & Blair, 2009). We call it quasi-holistic to differentiate it from the second measure. Although the standard non-weighted version only measures partitive accuracy, we use a size-weighted version of it, as given in Equation 10. That is, for each trade flow, we weight the difference between the ‘true’ (METI benchmark **D**-matrix) and the estimated values by the weight of that trade flow in total trade.¹⁸ Note that, by alternating summations, different MAPE versions can be calculated and that, to compare results between each aggregation level, values from the 29 and 53 levels will be summed over correspondence sub-sets to arrive at the 12-sector level. In such a way, $MAPE_i$ is always kept at the 12-sector level.^{19,20}

$$MAPE = 100 \times \frac{\sum_{i=1}^N \sum_{o=1}^G \sum_{d=1}^G |d_i^{od} - \tilde{d}_i^{od}|}{\sum_{i=1}^N \sum_{o=1}^G \sum_{d=1}^G d_i^{od}} \quad (10)$$

An advantage of this measure is that not only does it not require a subjective selection of the relevant sectors and regions, but also that the accuracy level only focuses on the table. This is important since a matrix of estimated interregional trade flows does not only serve as input for an IO model. Additionally, it is the same as in Sargento et al. (2012), thus allowing us to compare results to theirs.

The second measure is holistic in that it focuses on the accuracy of the solution of an MRIO model, as defined in Miller and Blair (2009). Equation 11 reproduces it, where **f** and **x** are vectors of final demand and output for each region and sector, **I** is an identity matrix, and **C** and **A** are matrices of column and regional technical coefficients, respectively.²¹

$$\mathbf{x} = (\mathbf{I} - \mathbf{CA})^{-1} \mathbf{Cf} \quad (11)$$

¹⁷ Note that partitive implies holistic accuracy, but the opposite does not hold.

¹⁸ Here, we take the 2005 METI IRIO as being partitively accurate.

¹⁹ $MAPE_i$ ($MAPE^{od}$) is calculated by removing the summation over sectors (regions).

²⁰ For instance, at $N = 29$, calculation of $MAPE_{MET}$ needs a summation over origins, destinations, and the three subsectors of the MET sector at $N = 29$, specifically sectors 4, 5, and 6 in Table A1.

²¹ See details of the model in Miller and Blair (2009).

We proceed as follows: first, we calculate different versions of the $(\mathbf{I} - \mathbf{CA})^{-1}\mathbf{C}$ matrix, each time using a different interregional trade table calculated by one of the above approaches. We also include the ‘real’ METI table, which we use as the benchmark table. We then generate 20 random vectors of final demand \mathbf{f} , as in Miller and Shao (1990), which we use to calculate output vectors \mathbf{x} for each of the above matrices. Finally, we compare each of these calculated output vectors, \mathbf{x} , to the one that used the ‘real’ METI table. Given that we have 20 error measures for each random shock and trade matrix, we again use a size-weighted MAPE to derive the results.

Note that this accuracy approach, based on an IO model’s results, is suggested by Jensen (1980) and used in Polenske (1970) and Sargento et al. (2012). However, the approach in this paper is superior, given that multiple shocks are considered simultaneously and that results are calculated across all units, thus avoiding a subjective selection of relevant sectors and regions.

7. Results

The main results, by accuracy measure, estimation approach, and sectoral aggregation level, are presented in Table 3. The upper (lower) panel gives results using the quasi-holistic (holistic) accuracy measure, columns three, four, and five correspond to the SG-RAS, the next six to the EG-RAS, and the last three to the R-RAS experiments. Given that the EG-RAS approach also estimates intra-regional flows, we assess its accuracy for the whole estimated table (columns 6, 7, and 8) and for only its interregional part (columns 9, 10, and 11). Note that for assessing the holistic accuracy of the EG-RAS model excluding intra-regional flows, intra-regional flows, needed for the trade proportions of the MRIO system, are taken from the benchmark intra-regional tables. In the forthcoming analysis, MAPE values are in parenthesis, and CON and FIN sectors are left out the scope of discussion (although MAPE values still depicted) since both have a non-trading nature.²²

7.1. Quasi-holistic accuracy

The last row of the upper panel in Table 3 gives total MAPEs. Comparing these errors for the different approaches at the 12-sector aggregation level, the SG-RAS approach achieves the smallest total error (17.39). In contrast, the EG-RAS approach without intra-regional trade heavily distorts interregional trade flows (76.25). Despite this, the approach does a better job for intra-regional trade, as shown in column six, where total MAPE decreases (34.44).²³ Results for the R-RAS approach roughly lie in-between the previous two (43.94), giving evidence of the power of RAS to account for part of the accuracy achieved by the other approaches. Given the low accuracy achieved by the latter two approaches, in what follows, we only report results for the SG-RAS approach.

Note that total MAPEs from the SG-RAS approach are smaller than those in Sargento et al. (2012), where the authors use the same approach with supra-national data between

²² For CON and FIN, shares of sector’s trade in the same sector’s national supply are 0.18% and 1.10%, and sectoral weights in total trade are 0.06% and 0.59%, according to Table A1.

²³ CON (0.56) and FIN (0.71), which are nearly nontraded sectors, have only tiny error, meaning that intra-regional trade was very well approximated.

Table 3. MAPEs at the sectoral level.

		MAPE											
		Quasi-holistic accuracy											
Code	Sectoral agg./ Sectors	SG-RAS			EG-RAS						R-RAS		
		12-S	29-S	53-S	w/ intra-regional trade			w/o intra-regional trade			12-S	29-S	53-S
					12-S	29-S	53-S	12-S	29-S	53-S			
1	AGR	21.46	21.46	21.46	24.59	24.59	24.59	43.47	43.47	43.47	58.05	44.10	44.14
2	MIN	45.52	45.52	45.14	35.65	35.65	39.71	66.99	66.99	76.78	63.70	68.12	65.01
3	BEV	12.97	12.97	12.97	60.52	60.52	60.52	77.62	77.62	77.62	61.43	56.53	44.81
4	MET	18.72	19.23	19.23	60.63	50.03	50.02	84.48	70.16	70.15	35.50	51.09	47.37
5	MAC	20.74	20.92	24.11	86.20	78.50	66.56	80.35	73.36	63.94	34.06	52.89	37.68
6	MIS	15.12	23.99	24.36	75.01	65.25	59.69	82.26	73.28	67.58	48.30	55.13	51.07
7	CON	6.23	6.23	6.23	.56	.56	.56	157.22	157.22	157.80	54.50	29.65	39.49
8	PUB	49.42	49.42	43.64	7.58	7.58	6.39	54.62	54.62	52.00	65.67	77.75	42.77
9	COM	16.97	16.71	16.71	67.89	62.28	62.27	84.24	77.28	77.28	52.30	46.38	46.04
10	FIN	28.34	28.34	34.42	.71	.71	.73	43.29	43.29	47.68	34.14	37.87	37.84
11	INF	7.10	7.10	7.96	9.84	9.84	12.84	29.87	29.87	35.68	15.58	12.71	18.55
12	SER	15.89	16.95	18.00	5.74	6.29	6.13	52.19	56.10	54.72	37.21	47.41	46.76
–	All	17.39	19.18	20.10	34.44	31.51	29.85	76.25	70.22	67.05	43.94	49.46	43.70
		Holistic accuracy											
MRIO model		5.03	7.63	10.23	46.89	51.66	58.40	40.17	40.71	39.05	9.84	13.86	14.28

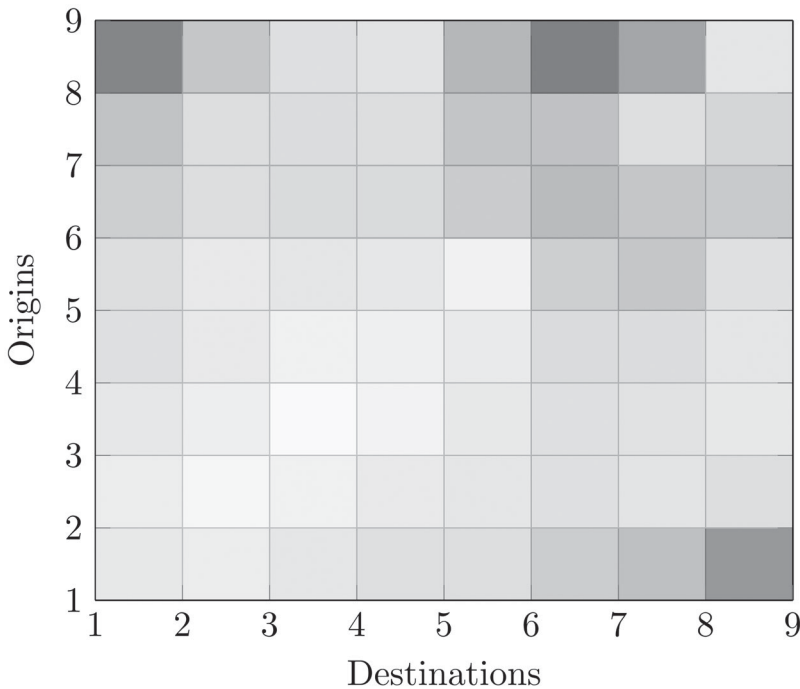
Notes: values can only change for different sectoral disaggregation levels if the sectors are in fact being disaggregated (except for the random experiment). Sectors are: AGR 'Agriculture, forestry and fishery', MIN 'Mining', BEV 'Beverages and Foods', MET 'Metal products', MAC 'Machinery', MIC 'Miscellaneous manufacturing products', CON 'Construction', PUB 'Public utilities', COM 'Commerce and transport', FIN 'Finance and insurance and real estate', INF 'Information and communications', and SER 'Service Industries'.

fourteen countries and four sectors, suggesting that the SG-RAS approach estimates interregional better than international trade.

At the sectoral level, SG-RAS does a better job for sectors like INF (7.10) or BEV (12.97), but a poorer one for PUB (49.42) or MIN (45.52). It is noteworthy that SER has a smaller error (15.89) than the average sector, giving evidence about the power of the approach to estimate trade-in-services at the subnational level.

Results for region pairs are in Table A4. Considering the 12-sector aggregation level only, the mean MAPE value is 44.20, the median 28.84, and the standard deviation 48.46, indicating a high variability of the results. The most accurate results are Kanto-Chubu (3.14) and Kinki-Kanto (6.30). In contrast, Okinawa-Hokkaido (240.77) and Okinawa-Shikoku (219.13) have the largest errors, giving evidence that bilateral trade estimates between the two more distant regions (islands) of Japan are very distorted.

To shed more light on this, Figure 1 gives a contour map for each origin-destination pair but excluding same region pairs. The darker the squares, the higher the MAPE value. The previous finding for Okinawa-Hokkaido can be found in the dark square at the top-left corner. It is also visible that the origin region with the largest errors is Okinawa. If we divide the whole table into four equally-sized quadrants, we see that the bottom-left quadrant achieves better results than the top-right. This means that trade between northern regions of Japan, which, according to Table A3, trade more, are the most populated, and are relatively larger in spatial size, achieve higher accuracy levels.

Figure 1. Origin-destination contour MAPE map (SG-RAS approach at $N = 12$).

Notes: Japanese regions are 1 (Hokkaido), 2 (Tohoku), 3 (Kanto), 4 (Chubu), 5 (Kinki), 6 (Chugoku), 7 (Shikoku), 8 (Kyushu), 9 (Okinawa).

7.2. Holistic accuracy

The lower panel of Table 3 contains results using the holistic accuracy measure. A comparison between approaches reveals that the SG-RAS approach again achieves the smallest error (5.03). As in the previous case, the EG-RAS approach generates a non-accurate result in both of its versions (46.89; 40.17), giving evidence that the generated trade matrices strongly distort the IO results. A striking finding is that the result of the R-RAS (9.84), although inaccurate according to the quasi-holistic measure, lies very close to that achieved by the SG-RAS approach.

The previous results contradict findings asserting that many regional IO models are not very sensitive to the insertion of different trade matrices (Miller & Shao, 1990; Sargento et al., 2012). Although sensitivity is small when comparing the SG-RAS and R-RAS approaches, the same cannot be said when comparing them to results from the EG-RAS approach.

7.3. Sensitivity to the sectoral aggregation level

We now analyze how the results change when we consider two different sectoral aggregation levels. Using the quasi-holistic accuracy measure, Table 3 shows that total MAPEs slightly increase for increasing sectoral disaggregation levels in the case of the SG-RAS approach. Note, however, that the difference in total MAPE between the 12-sector (5.03)

and the 29-sector (7.63) levels is larger than the one between the 29-sector (7.63) and the 53-sector (10.23) levels. This result is puzzling since the difference in the number of sectors for the former case is 17, while that for the latter is 24.

For sectors, we only report sectors with MAPE values larger or smaller than three compared to the same sector MAPE at the 12-sector aggregation level. Additionally, we report the number of a sector's sub-sectors in brackets (given in columns 3 and 4 of Table A1). For the SG-RAS approach, under the 29-sector level, there is only one sector with a larger (23.99) error: MIS[8]. This sector is in fact the most disaggregated sector at the 29-sector aggregation level. Under the 53-sector aggregation level, the errors of MIS[14] and MAC[13] increase (24.36;24.11), which are again the most disaggregated sectors. In contrast, the error of PUB[3] decreases (43.64). Apart from these, all other estimates remain stable. Thus, sectors with error increases correspond to those that were split into a larger number of sub-sectors. For the interested reader, Table A4 gives the region-pair values for each sectoral aggregation level.

Regarding the holistic accuracy measure (lower panel of Table 3), MAPE values also increase with increasing sectoral disaggregation level for both the SG-RAS and R-RAS approaches. But compared to results from the quasi-holistic accuracy case, the difference between the 12-sector and the 29-sector level MAPE is the same as that between the 12-sector and the 53-sector levels for the SG-RAS approach, with differences larger in magnitude.

7.4. Robustness checks

We test the robustness of our findings in three ways. First, we consider two alternatives to the weighted MAPE measure: Theil's U and SWAD (see Jackson and Murray (2004)), and recalculate Table 3. Results, in Table A5 for the former and Table A6 for the latter, show that the previous analytical findings remain the same. To better visualize the differences for the SG-RAS approach, columns 2 and 3 of Table 4 present differences in total error between different sectoral aggregation levels, with total MAPE values extracted from Tables 3, A5, and A6. The only remarkable change happens under the SWAD measure for the holistic accuracy case, where the difference in error between the 12-sector and the 29-sector level turns negative.

Second, we move the distance decay parameter of the SG-RAS approach to .5 and 1.5. Unfortunately, moving parameters of the EG-RAS approach is not possible due to the absence of parameters in the original specification. The selected d -values are in line with findings in Yamada (2015), where the parameter mean is close to one (1.29) and not very disperse (SD = .57) for the 2005 METI IRIIO table.²⁴ Full results are shown in columns 3 and 5 of Table A7, where values using $d = 1.0$ are also shown to facilitate comparison. For both accuracy measures, total MAPE decreases for $d = .5$ and increases for $d = 1.5$. The fact that the absolute difference between $d = 1.0$ and $d = 1.5$ is almost three times that between $d = .5$ and $d = 1.0$ gives evidence of the sensitivity of the SG-RAS approach to the distance parameter used. This general pattern does not change when using Theil's U or SWAD, as shown in Tables A8 and A9. Differences in total error are shown in columns

²⁴ The sector-averages of economic sizes are 0.99 (0.28) and 0.74 (0.23) at origins and destinations, respectively, where the number in brackets are the standard deviations (Yamada, 2015).

Table 4. Differences in total errors (SG-RAS approach).

Quasi-holistic accuracy					
Error measure	Sectoral aggregation level*		Difference btw. distance matrices (12-S)**	Distance decay parameter (12-S)**	
	Difference btw. 29-S and 12-S	Difference btw. 53-S and 29-S		Difference btw. $d = .5$ and $d = 1.0$	Difference btw. $d = 1.5$ and $d = 1.0$
MAPE	1.79	.92	−2.12	−3.63	10.95
Theil's U	.11	.16	−0.62	−4.5	10.78
SWAD	−.5	.03	.61	−2.58	7.07
Holistic accuracy					
MAPE	2.6	2.6	.95	−.82	2.8
Theil's U	2.76	5.19	−1.94	−1.94	4.97
SWAD	1.69	2.46	−.72	−.79	2.1

Notes: *Values are differences in total error for the SG-RAS model in Tables 3, A5, and A6. ** Values are differences in total error for the SG-RAS model in Tables A7, A8, and A9.

5 and 6 of Table 4. Interestingly, sensitivity is higher for the quasi-holistic measure, even higher than that found for the sectoral aggregation level. Still, we believe that the range of total MAPE values is still within an acceptable accuracy range, given that total MAPEs reported in Sargento et al. (2012) are close to those reported here for $d = 1.5$.

Finally, we use an alternative matrix of interregional distances. Although it would be possible to use a matrix of time instead of distances, we refrain from doing so, given that both matrices have a very high correlation coefficient (.95). Instead, we use the matrix of population-weighted distances in Nakano and Nishimura (2013), which has a slightly lower correlation coefficient (.88) with the matrix of standard distances. Results are given in Table A7, in column 6 for the SG-RAS approach, and column 8 for the EG-RAS approach. Differences for the SG-RAS approach are summarized in column 4 of Table 4. For both accuracy measures, the effect of using population-weighted distances is minimal, which is also confirmed by Theil's U and SWAD indicators in Tables A8 and A9, although with opposite sign for the latter.

8. Conclusions

While data on international trade abound, statistics on interregional trade within nations remain a rarity. Although several estimation methods exist, the gravity-RAS approach continues to be most popular. This work aimed to analyze the accuracy of two popular gravity-RAS approaches used for subnational interregional trade estimation. The first is standard, and the second is an extension, since it additionally estimates intra-regional flows. We assess accuracy by using regional trade statistics from Japan at different sectoral aggregation levels as a benchmark. For that, we use two accuracy measures: a quasi-holistic one, based on a weighted mean absolute percentage error (MAPE), and a holistic one, based on the results from a multiregional input-output (MRIO) model. We also derive results for an experiment based on a random number generator (random approach), which gives a measure of the extent that bi-proportional adjustment methods (RAS) influence results.

Quasi-holistic accuracy measures deem the standard approach satisfactorily accurate, albeit with heterogeneous results for sectors and regions, as well as better accuracy for trade flows between northern regions of Japan. Results further suggest that this approach

might be better suited to subnational, as opposed to international, data. The extended approach excluding intra-regional trade, on the other hand, appears quite unsatisfactory, insofar as goodness of fit is concerned. Practitioners should, therefore, prefer a two-step estimation process over the simultaneous estimation of intra-regional and interregional flows. Note, however, that the greater error generated by the EG-RAS approach might not only be related to its extension – that is, the estimation of intra-regional flows – but also due to the gravity model's specification and information requirements. The random approach obtains less error than its extended equivalent, which demonstrates RAS's power at improving quasi-holistic accuracy.

When using the measure of holistic accuracy, the standard approach is again more accurate. Interestingly, although the random approach is also quite accurate, the same cannot be said for the extended approach, which implies that the accuracy of MRIO accounts is quite sensitive to the choice of estimation approach.

With regard to aggregation, we find that sectors that are split into a large number of subsectors are subject to the largest increases in error and that total error increases slightly as we disaggregate. Note, however, that this effect might change when sectors are further disaggregated, for instance, above the 53-sector level. A further finding is that results using the quasi-holistic accuracy measure are more sensitive to the distance-decay parameter value than to aggregation by sector.

Note that tailoring parameters of the models, e.g. via a hybrid approach, is a possible alternative to what we have undertaken here: practitioners often apply their knowledge of regions by adding information from reliable sources. But the extent to which such information improves (or worsens) estimates with applications of algorithms like RAS remains largely unknown. Even in such cases, tests of the accuracy of baseline specifications remain important.

We believe that our findings of considerable differences in accuracy among alternative approaches provide strong evidence that certain types of estimation methods should be preferred. Our work is important, given that, to date, the applied IO literature has given little attention to the relative accuracy of trade estimation methods that are used. Besides the choice of *the* proper model, parameters of the gravity equation also affect results. As evidence, we provide differences in errors across various values of the distance-decay parameter. That we tend to find little sensitivity to the number of sectors included in the analysis suggests that sectoral aggregation may not be a problem for models in which sectors are already severely merged due to data constraints of one sort or another.

A limitation of this work is that we only work on data for a small number of Japanese regions of a single year. While we must have some confidence that our findings might be valid for the same set of Japanese regions in other years, it would be tough to extend such external validity to smaller regions in other years, let alone to other countries. Nonetheless, we contend that this work is an externally valid test of the estimation methods that we used.

Future work should cover alternative estimation methods, such as some of those suggested in the introduction of this paper. A further possibility could be to try to integrate additional components, such as sectoral or regional parameters, to the baseline specifications and see how these improve or worsen the 'baseline' accuracy. A good understanding of how accuracy levels vary among the table elements is particularly relevant for applied studies. This is because it often happens that many studies focus on one or more units of interest, for instance, specific regions or sectors of the economy. If these studies would use

an estimation method of which its accuracy is little known, those units of interest may receive wrong values. Consequently, conclusions could lose validity.

It would also be interesting to examine spatial aggregation effects by altering the number of regions in the analysis (e.g. in the U.S. by examining Census Divisions and states). Finally, although we tested via two different accuracy measures, it would be interesting to see how results change when using alternative measures, for instance, measures of holistic accuracy based on a general equilibrium model.

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