Routledge
Taylor & Francis Group

Regional Studies

ISSN: 0034-3404 (Print) 1360-0591 (Online) Journal homepage: https://www.tandfonline.com/loi/cres20

Improved Estimation of Regional Input–Output Tables Using Cross-regional Methods

Xuemei Jiang , Erik Dietzenbacher & Bart Los

To cite this article: Xuemei Jiang , Erik Dietzenbacher & Bart Los (2012) Improved Estimation of Regional Input–Output Tables Using Cross-regional Methods, Regional Studies, 46:5, 621-637, DOI: 10.1080/00343404.2010.522566

To link to this article: https://doi.org/10.1080/00343404.2010.522566

Regional Studies, Vol. 46.5, pp. 621–637, May 2012

Improved Estimation of Regional Input–Output Tables Using Cross-regional Methods

XUEMEI JIANG*, ERIK DIETZENBACHER†‡ and BART LOS†

**Center for Forecasting Science, Academy of Mathematics and Systems Science, Chinese Academy of Sciences, Zhongguancun East Road, No. 55, 100190 Beijing, China. Email: jiangxuem@gmail.com*

†Faculty of Economics and Business, University of Groningen, PO Box 800, NL-9700 AV, the Netherlands. Emails: h.w.a.dietzenbacher@rug.nl and b.los@rug.nl

‡Graduate University, Chinese Academy of Sciences, Beijing, China

(Received June 2009: in revised form August 2010)

JIANG X., DIETZENBACHER E. and LOS B. Improved estimation of regional input–output tables using cross-regional methods, *Regional Studies*. Many regional input–output tables are estimated by means of non-survey methods. Often, information on the margins of the projected table is complemented by full information on intermediate inputs from tables for other regions. This paper compares the performance of four of such 'cross-regional' methods. Two of these were already proposed in the literature, whereas the other two are based on recent advances in regression analysis. The methods are tested not only against each other, but also against traditional methods that do not employ cross-regional information. To this end, twenty-seven regional input–output tables for China in 1997 and 2002 are used.

Non-survey methods   Cross-regional methods   Regional input–output tables   China

JIANG X., DIETZENBACHER E. and LOS B. 基于多地区集成的地区投入产出表非调查编制方法研究, *Regional Studies*. 基于已有统计数据进行非调查的地区投入产出表的编制一直是投入产出学界的关注焦点。利用其它多个地区的投入产出表以及目标地区的已知中间投入行和、列和向量，可以编制出目标地区的投入产出表。本文首先将这种方法定义为多地区集成编制方法，综述了文献中已有的两种多地区集成编制方法，并结合计量经济学模型的新进展，提出了两种结合计量经济学模型的非调查多地区集成编制方法。基于中国27个地区1997年和2002年的投入产出表，本文不仅验证了这四种方法的预测精度，还将其与传统非调查方法进行了比较。

非调查方法   多地区集成编制方法   地区投入产出表   中国

JIANG X., DIETZENBACHER E. et LOS B. Une meilleure estimation des tableaux d'échanges inter-industriels régionaux à partir des méthodes interrégionales, *Regional Studies*. Beaucoup des tableaux d'échanges inter-industriels régionaux sont estimés à partir des méthodes hors enquêtes. Souvent, les renseignements à la marge du tableau prévu sont complétés par des renseignements détaillés sur des facteurs de production intermédiaires qui proviennent des tableaux relatifs à d'autres régions. Cet article cherche à comparer la performance de quatre méthodes 'interrégionales' de ce type. Deux méthodes ont déjà été proposées dans la documentation, alors que les deux autres sont basées sur des développements récents dans le domaine de l'analyse de régressison. On teste ces méthodes non seulement l'une par rapport à l'autre, mais aussi par rapport aux méthodes traditionnelles qui n'emploient pas de renseignements interrégionales. A cette fin, on emploie vingt-sept tableaux d'échanges inter-industriels régionaux pour la Chine de 1997 à 2002.

Méthodes hors enquêtes   Méthodes interrégionales   Tableaux d'échanges inter-industriels régionaux   Chine

JIANG X., DIETZENBACHER E. und LOS B. Verbesserte Schätzung von regionalen Input-Output-Tabellen mit Hilfe überregionaler Methoden, *Regional Studies*. Viele regionale Input-Output-Tabellen werden mit Hilfe von anderen Methoden als Erhebungen geschätzt. Oft werden die Informationen über die Spannen in der prognostizierten Tabelle durch vollständige Informationen über die intermediären Inputs von den Tabellen für andere Regionen ergänzt. In diesem Beitrag wird die Leistungsfähigkeit von vier solchen 'überregionalen Methoden' miteinander verglichen. Zwei dieser Methoden wurden bereits in der Literatur vorgeschlagen, während die anderen beiden auf aktuellen Fortschritten bei der Regressionsanalyse beruhen. Die Methoden werden nicht nur im Vergleich zueinander überprüft, sondern auch im Vergleich zu herkömmlichen Methoden, bei denen keine überregionalen Informationen genutzt werden. Zu diesem Zweck kommen 27 regionale Input-Output-Tabellen für China in den Jahren 1997 und 2002 zum Einsatz.

Nicht-Erhebungsmethoden   Überregionale Methoden   Regionale Input-Output-Tabellen   China

0034-3404 print/1360-0591 online/12/050621-17 © 2012 Regional Studies Association   http://dx.doi.org/10.1080/00343404.2010.522566
http://www.regionalstudies.org

JIANG X., DIETZENBACHER E. y LOS B. Estimación mejorada de tablas de insumo-producto regional con ayuda de métodos transregionales, *Regional Studies*. Muchas tablas de insumo-producto regional se calculan mediante métodos indirectos. Con frecuencia, la información sobre los márgenes de la tabla proyectada se complementa con información exhaustiva sobre los insumos intermedios de las tablas para otras regiones. En este artículo comparamos el desempeño de cuatro de estos métodos 'transregionales'. Dos de estos métodos ya se han propuesto en la bibliografía mientras que los otros dos se basan en avances recientes del análisis de regresión. Los métodos se comprueban no solamente para compararlos entre sí sino también para compararlos con métodos tradicionales que no emplean información transregional. Para este propósito se utilizan veintisiete tablas de insumo-producto regional para China en 1997 y 2002.

Métodos indirectos Métodos transregionales Tablas de insumo-producto regional China

JEL classifications: D57, R11

INTRODUCTION

Fuelled by the policy relevance of regional input–output analysis, a vast literature on the construction of regional input–output tables has emerged. Hybrid methods, which combine non-survey approaches with superior survey-based data, have become especially popular (for example, JENSEN *et al.*, 1979; GREENSTREET, 1989; WEST, 1990; MIDMORE, 1991; JACKSON, 1998; MADSEN and JENSEN-BUTLER, 1999; LAHR, 2001). This does not mean, however, that non-survey methods are not currently being employed. On the contrary, non-survey techniques still receive considerable attention, if only because they are at the heart of the first step of hybrid methods (for example, LAHR, 1993, 2001; OKAMOTO and ZHANG, 2005; BONFIGLIO and CHELLI, 2008).

A number of non-survey techniques to estimate an 'object table' (or a table for the 'object year') have been developed over the past decades. What these techniques have in common, like all methods introduced and analysed in this study, is that row and column totals (such as sectoral gross output) are known, but the block of intermediate inputs has to be estimated.

Updating the latest available survey-based input–output table by iteratively rescaling rows and columns to known margin totals of the object table, that is, the so-called 'RAS' technique, is still a very popular method. In terms of estimation performance, it is hard to beat if no supplementary information is available (OOSTERHAVEN *et al.*, 1986; POLENSKE, 1997; JACKSON and MURRAY, 2004). Alternatively, regionalization using location quotients is an often-used method if a survey-based national table for the object year is available (for example, FLEGG *et al.*, 1995). In case survey-based tables for other regions are available for the object year, substituting input coefficients from a table for the region that is most similar according to some yardstick is also widely used (for example, RUEDA-CANTUCHE *et al.*, 2009, who used information for Belgium to construct import tables for Luxembourg). What these methods have in common is that estimated coefficients are based on information contained in a single survey-based table.[1] The present authors feel that much less experience has been gained with regional input–output table construction based on information contained in several other regional tables, although some methods have been proposed (for example, JENSEN *et al.*, 1988, 1991).

This study aims to provide information to practitioners about how to take full advantage of the information on intermediate inputs included in a cross-section of other regional tables in estimating a regional object table. Next to methods based on classical linear regression analysis as applied by JENSEN *et al.* (1988, 1991), methods grounded in more recent contributions to regression analysis, such as robust regression (ROUSSEEUW and VAN ZOMEREN, 1990) and threshold regression (HANSEN, 2000), are also studied. These advanced methods are applied after having shown that data contained in regional input–output tables can have distributional characteristics that render classical regression methods less appropriate. The methods analysed are empirically compared on the basis of a collection of survey-based input–output tables for Chinese provinces in 1997 and 2002, covering twenty-seven regions and thirty-one industries.[2] The choice for these Chinese tables is suggested by two considerations (for a brief description of the Chinese provincial tables and their compilation, see Appendix A). First, the Chinese set of regional input–output tables is unique in the sense that it is the largest available set of harmonized tables expressed in a single currency. Second, the well-known characteristic of large geographical disparities in China adds to the attraction of the analysis; the vast majority of regions are clearly not representative for the nation and heterogeneity abounds.

The paper is structured as follows. The second section briefly reviews 'traditional' approaches for constructing non-survey regional technical tables that do not rely on the identification of cross-regional patterns. The third section proposes the four cross-regional methods that will be employed. The fourth section presents a comparison of the estimation results obtained using the cross-regional approach with those generated by the traditional methods. The fifth section systematically tests the robustness of the comparison results if the available cross-regional sample were smaller and contained much fewer than twenty-six tables. These experiments provide guidelines on which method to use in a variety of situations regarding data availability. The sixth section summarizes the findings and concludes.

NON-SURVEY METHODS BASED ON THE COEFFICIENTS OF A SINGLE INPUT–OUTPUT TABLE

Before starting a review of the methods, one should first delve a little bit deeper into the nature of the Chinese regional input–output tables at hand. It should be emphasized that Chinese regional tables only provide information on intermediate deliveries including imports. This means that the intermediate delivery X_{ij} expresses the total input of products from industry *i* by industry *j* in region *r*, irrespective of the location of industry *i*. This means that some parts of the literature on the construction of regional input–output tables, which only focus on the estimation of intra-regional inputs, is not relevant for the situation at hand. Since the focus here is on what BOOMSMA and OOSTERHAVEN (1992) coined 'technical tables', one does not have to deal with the estimation of location quotients (alternatively called regional purchase coefficients).[3] Location coefficients (FLEGG *et al.*, 1995; FLEGG and WEBBER, 2000; TOHMO, 2004; RIDDINGTON *et al.*, 2006) indicate what share of a regional industry's inputs are sourced domestically. The sizes of regions and the transport costs of specific inputs are just two of the main variables that are often supposed to play an important role in the determination of location coefficients. One can abstain from these issues.

Inter-temporal updating

The RAS technique developed by STONE and BROWN (1962) has been acknowledged as one of the most widely used ways to update tables based on the input–output structure of an older survey-based table and information on the margins (such as total intermediate input use and total intermediate inputs supplied by industry) for the object table. Many variations of the original RAS updating techniques exist, however (for example, MORRISON and SMITH, 1974; SAWYER and MILLER, 1983; POLENSKE, 1997; JALILI, 2000; JACKSON and MURRAY, 2004). RAS can be seen as a method that tries to reconcile the old intermediate input structure as well as possible with the new column and row totals. Despite regular complaints about the poor performance of RAS, reviews of empirical results such as those by POLENSKE (1997) and JACKSON and MURRAY (2004) tend to conclude that RAS results are seldom outperformed by alternatives using the same type of information.

In the context of the present analysis, information on total inter-industry sales and total inter-industry purchases taken from a 2002 table and the input coefficients taken from the 1997 table for the same region allows one to apply the RAS method to update all twenty-seven regional tables to 2002. Next, the quality of these estimates by updating can be assessed by comparing the updated tables with the true 2002 tables by yardsticks that will be discussed below.

Regionalization of national tables

Updating techniques, however, cannot be used if input–output tables have not been constructed before for the object region. For regional analyses (as opposed to country-level studies), the literature recognizes many alternative approaches to produce non-survey input–output tables, but most of these focus on the domestic sourcing issue that is not relevant here, as explained above.

As far as technical tables are concerned (the cells of which contain both domestically produced and imported inputs), national tables are most often regionalized by RAS methods (BOOMSMA and OOSTERHAVEN, 1992). The national input coefficients are taken as a starting point and information on the row and column sums of the regional intermediate deliveries matrix is taken as constraints. Iterated rescaling of rows and columns then generates a table with estimated technical coefficients for the object region.

Exchanging coefficients

Instead of using a national table to reflect the economic characteristics of a particular region *r*, one might use information from an existing table for another region, *r*′. Especially if *r* and *r*′ are thought to be economically and technologically similar, the estimation error is likely to be small (MILLER and BLAIR, 1985). HEWINGS (1977) gave an example of coefficient exchange at the regional level, estimating a table for the state of Kansas 1965 borrowing input coefficients from the table of Washington State for 1963. Finally, RAS was used to balance the Kansas table obtained in this way.

A problem arises if several regional tables are available to choose from. Which of the regions is defined to be most similar to *r* (the object region), in particular in a situation in which the input coefficients of the object table are unknown? This issue has hardly been discussed in the literature. This paper proposes to use the vector of input coefficients for each sector in 1997 to represent the input technology of the corresponding region and sector.[4] The similarity index SI_j^{rk} for 1997 is then calculated for a pair of regions *r* and *k* for each and every sector *j*:

$$SI_j^{rk} = \frac{\sum_{i=1}^{n} a_{ij}(r) \cdot a_{ij}(k)}{\left[\sum_{i=1}^{n} a_{ij}(r)^2 \cdot \sum_{i=1}^{n} a_{ij}(k)^2\right]^{1/2}} \tag{1}$$

where a_{ij} denotes the input coefficients for a region. The expression in the right-hand side is the cosine between the two input coefficients vectors of r and k. JAFFE (1986) proposed such a measure (which is bounded by 0 and 1 given the non-negativity of input coefficients) based on shares of technology classes in the patent portfolios of firms.[5]

For each industry j, one considers the region k which has the highest SI_j^{rk} with the object region r as the most similar region. Consequently, its coefficients for 2002 have been inserted in the corresponding column of the object table. This experiment is repeated for all sectors, after which application of RAS ensured a balanced estimated table for 2002.

NON-SURVEY METHODS USING CROSS-REGIONAL INFORMATION

As opposed to the methods described in the previous section, methods using information from a multitude of regional tables have barely been evaluated. The availability of comparable regional input–output tables for as many as twenty-seven Chinese regions allows for a systematic analysis along these lines. Estimated tables will be compared against the survey-based tables, as well as with the more traditional estimates based on information from a single region. This section presents two commonly used cross-regional approaches. These are based on regression analysis. It is found, however, that assumptions essential to classical linear regression are violated in the data set. Hence, two novel methods that deal with these problems are also proposed.

The idea of using information from other available regional tables when constructing regional input–output tables is not entirely new. IMANSYAH (2000), for example, proposed the 'averaging' method, which computes the average input coefficients of the other regions, multiplies these with the industry's gross output level, and balances the resulting table using the RAS method to generate the objective table.

Another well-known way to produce a matrix of deliveries for the object region from a cross-regional perspective starts from the notion of the fundamental economic structure (FES), as proposed by JENSEN *et al.* (1988, 1991). By regressing the intermediate deliveries on an independent variable that represents the regional economic 'size', the concept of FES provides a cross-regional insight into the estimation of intermediate deliveries, as the following equation shows:

$$X_{ij}(r) = \alpha_{ij} + \beta_{ij} X(r) + \varepsilon_{ij}(r) \qquad (2)$$

where $X_{ij}(r)$ represents the intermediate deliveries for the rth region; $X(r)$ is an indicator of the economic size of the rth region; α_{ij} and β_{ij} are cell-specific parameters to be estimated; and ε_{ij} is considered to be random noise. Based on a series of input–output tables for ten regions of Queensland, Australia, JENSEN *et al.* (1988) found highly significant estimates for the parameters for many cells X_{ij}, though not for all. Jensen *et al.* considered the cells for which equation (2) has a high explanatory power to be part of the FES and indicated that such an FES could be used in a compilation of regional tables. VAN DER WESTHUIZEN (1992) and THAKUR (2004) actually tried to use the FES technique to compile regional input–output tables. They also estimated regression equations that related the intermediate delivery $X_{ij}(r)$ to alternative region-specific variables, such as total population, total value-added, gross output for sector I, and gross output for sector j in the region. Next, they estimated cells for the object table based on the parameters and corresponding independent variables, and applied RAS for balancing.

The present authors can show that IMANSYAH's (2000) averaging method represents a special case of the FES approach, if JENSEN *et al.*'s (1988) FES method is limited to regressions with regional sectoral gross output levels $X_j(r)$ as the independent variable. Denoting the input coefficients by a_{ij}, equation (2) can then be written as:

$$a_{ij}(r) = \frac{X_{ij}(r)}{X_j(r)} = \frac{\alpha_{ij}}{X_j(r)} + \beta_{ij} + u_{ij}(r)$$

If α_{ij} is set to zero, the averaging method produces identical estimates as this FES equation. The actual differences between the estimates depend on the extent to which returns to scale are non-constant. If regions with large sectors can use their inputs more efficiently, α_{ij} will be significantly positive. The following analyses will start from an equivalent regression equation that has the advantage of being linear in $X_j(r)$:

$$a_{ij}(r) = \kappa_{ij} + \lambda_{ij} X_j(r) + e_{ij}(r) \qquad (3)$$

All four cross-regional methods discussed below have equation (3) as their point of departure and can, therefore, be seen as originating from the FES approach.[6]

Averaging coefficients

The first cross-regional approach amounts to estimating equation (3) for all a_{ij}'s with the restriction that $\lambda_{ij} = 0$. The sample consists of all Chinese regional input–output tables for 2002 in the data set, with the exception of the object table. Next, the estimated input coefficients are multiplied by the values of X_j of the object region to arrive at estimated intermediate input flows for 2002. These are reconciled with the available margin totals for the object table by means of a simple RAS. The method is identical to that proposed by IMANSYAH (2000).

Ordinary least-squares (OLS) regression

Estimating equation (3) by means of OLS without any restrictions on the two parameters comes close to the procedures advocated by Jensen *et al.* (1988). The samples are identical to those used for the averaging method. After having obtained the estimates for the a_{ij}'s, the remaining steps in the procedure are identical to those used for the averaging method.

Fig. 1 depicts two situations. In the left panel (which relates to the inputs of 'textiles' per unit of gross output of the 'wearing apparel' industry), OLS regression yields an almost flat line that nearly coincides with the line produced by the averaging method. Apparently, the use of textiles in the wearing apparel manufacturing industry is not subject to economies of scale. The right panel shows an example of an input coefficient for which OLS regression and averaging yield completely different results. In this case, which refers to the inputs of 'electronic and telecommunications equipment' in the 'wearing apparel' industry, the OLS regression line is clearly upward sloping. Most probably, the input of such high-technology equipment (instead of labour or more traditional equipment) is only commercially attractive when high volumes are produced.

As is well known, linear regression by means of the method of least-squares leads to estimates with desirable properties if a number of assumptions are met. One of these assumptions is 'homogeneity of the data-generating process'. This assumption can be violated in several ways. An example is the occurrence of outliers, which are often generated by differences in parts of the data-generating process related to variables that are omitted from the regression equation. Another type of violation emerges if the true value of parameters included in the regression equation varies with ranges of values of the explanatory variables. Taking equation (3) as an example, one might think that increasing returns to scale do not play a role for relatively small values of X_j, but might set in for larger values (or vice versa). If so, the relationship between the variables cannot be represented by a single set of parameters and one should allow for parameter heterogeneity. So far, the limited body of literature proposing cross-regional methods has not addressed these potential problems.

The right panel of Fig. 1 suggests that violations of the homogeneity assumption may indeed play a role. The very high input coefficient of almost 0.006 in the upper-right corner of Fig. 1, for example, is either an outlier or points towards a relation between a_{ij} and X_j that is different between low and high values of X_j. Two advanced regression approaches that address these problems will be proposed below. The robust regression approach explicitly deals with the potentially disturbing effects of outliers, whereas the threshold regression approach allows for parameter heterogeneity.

Robust regression

Outliers can have substantial impacts on OLS estimates of parameters in a regression equation. If such estimates are not accurate, the estimates of the object tables will be inaccurate as well. The potential effects of outliers can

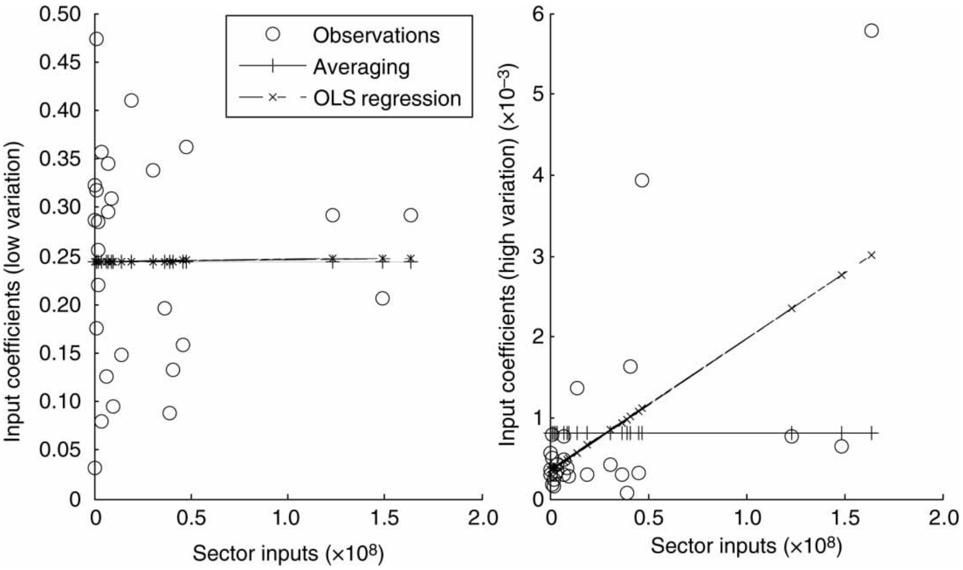

Fig. 1. The two cases studies: averaging coefficients versus ordinary least-squares (OLS) regression

Note: Both panels contain observations for all twenty-seven provinces for which input–output tables are available. In the empirical analyses, equation (3) is estimated on the basis of only twenty-six observations, since the object table is assumed to be unknown. The parameter estimates are used to estimate the input coefficients of the object table. Since each of the twenty-seven tables can be selected arbitrarily as the object table; this figure depicts observations for the entire population of tables be illustrated by means of Fig. 1 (right panel). The very high regional input coefficient of just below 0.006 associated with a sectoral total input of approximately RMB160 million is a clear outlier. Since this outlier is located at one of the extremes in the horizontal dimension, it tilts the OLS regression line anticlockwise. This single observation (which is called a 'bad leverage point' in the terminology of ROUSSEEUW and VAN ZOMEREN, 1990) has much more impact on the estimated coefficients than the observations that are closer to the centre of the cloud of observations. The second highest regional input coefficient of about 0.004 is located much closer to the centre of this cloud. Hence, this outlier does not have much of an impact on the estimated slope. Its effect largely remains limited to the estimated intercept.

In order to reduce the effects of outliers and bad leverage points, several robust regression techniques have been developed. In the robust regression approach to estimating equation (3), the procedure that underlies the *robustfit* algorithm in the Matlab programming language is used. This algorithm uses an iteratively reweighted least-squares sequence.[7] In this algorithm, observations that yield a large residual in the first iteration get a small weight in the weighted least-square estimation in the next iteration. Hence, the impact of outliers is severely reduced. In the application, weights are determined according to a bi-square weighting function (BEATON and TUKEY, 1974). After having obtained estimates for the parameters of equation (3) in this way, an a_{ij} for the object region is predicted based on the total sectoral inputs $X_j(r)$. If the sample for a specific a_{ij} does not contain outliers, the weights in the iteratively reweighted least-squares do not deviate much from each other and the estimates using robust regression will not be very different from those obtained using OLS. After all the input coefficients for the object table have been estimated using robust regression, the RAS algorithm is used to align the corresponding table of intermediate input flows to the marginal totals.

Threshold regression

If the relation between the dependent variable and the explanatory is characterized by strong parameter heterogeneity, estimating parameters as if they were identical for the entire sample is likely to lead to undesirable results. One of the simplest approaches to avoid such potential problems is threshold estimation, pioneered by HANSEN (2000).[8] In the context of the present paper, the point of departure is the following set of equations:

$$\begin{aligned} a_{ij}(r) &= \kappa_{ij}^{1} + \lambda_{ij}^{1} X_j(r) + u_{ij}(r) \quad \forall X_j(r) \leq \gamma_{ij} \\ a_{ij}(r) &= \kappa_{ij}^{2} + \lambda_{ij}^{2} X_j(r) + u_{ij}(r) \quad \forall X_j(r) > \gamma_{ij} \end{aligned} \tag{4}$$

where $r = 1, \ldots, m$; $i,j = 1, \ldots, n$. Equations (4) can be seen as a generalization of equation (3): for regions with large total inputs of sector j (X_j), the linear relationship between the intermediate input coefficient a_{ij} and X_j is characterized by different values of κ and λ than for regions with small total inputs. γ is the threshold between the two 'regimes'. It is endogenously estimated by taking the sample value for which the reduction in the sum-of-squared residuals attained by allowing for two sets of parameters is largest (HANSEN, 2000).[9] A likelihood ratio test, the outcome of which depends on the degree to which sum-of-squared residuals is reduced by allowing for two sets of parameters, leads to the decision about whether or not the split is significant.[10] If it is significant, the estimation of a coefficient of the object table depends on the size group to which the corresponding total inputs belong. If not, equation (3) is estimated for all the observations and the estimate for the input coefficient in the object table is based on the estimates for the coefficients in this equation. Fig. 2 describes the entire procedure underlying the threshold approach.

Fig. 3 gives two empirical examples of comparisons between the relationships between input coefficients and total sectoral inputs as found by applying three of the cross-regional estimation methods: OLS, robust regression and threshold regression. The two cases are identical to those depicted in Fig. 1, in which the results for the averaging coefficients method and OLS regression were compared. In the left panel, the results for each of the techniques are very much alike. The absence of outliers leads to results for OLS and robust regression that are virtually identical. The threshold regression approach yields two line segments that are slightly upward sloping, but do not show a clear threshold (it did not turn out to be significant at 10%). Following the procedure depicted in Fig. 2, OLS would be used in this case.

A completely different situation emerges from the right panel of Fig. 3. The importance of bad leverage points such as the one in the far north-east of Fig. 3 is reduced in the robust regression approach, which leads to a much flatter regression line than in the case of regular OLS regression. This implies that robust regression points towards much less pronounced decreasing returns to scale than OLS, since the required inputs per unit of gross output appear to depend much less on total output levels. The results for the threshold regression approach are also very different from the OLS results. For sectoral total inputs below the estimated threshold of RMB50 million, the regression results are much flatter than for OLS. The estimated intercepts are very different, however. For the subsample of four observations above the threshold size, the intercept is considerably higher than for the remaining observations associated with regions with small wearing apparel-manufacturing sectors.

The fact that the results across the three cross-regional methods are very different from each other

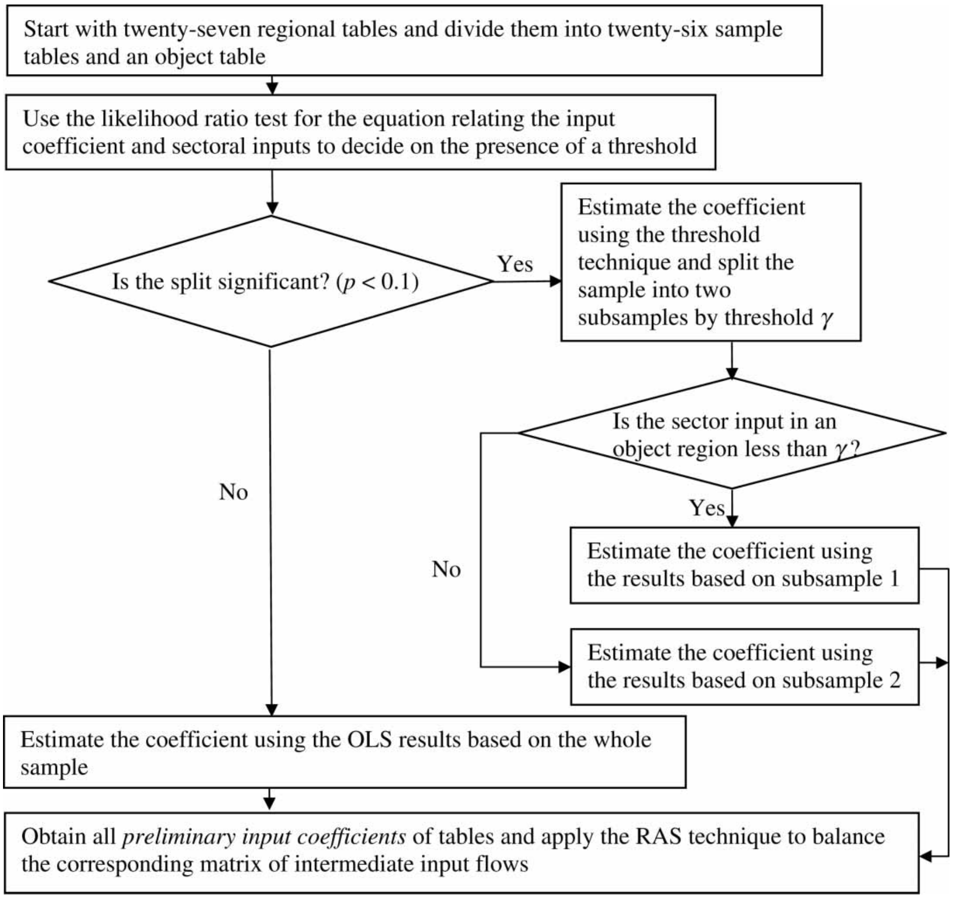
Start with twenty-seven regional tables and divide them into twenty-six sample tables and an object table
Use the likelihood ratio test for the equation relating the input coefficient and sectoral inputs to decide on the presence of a threshold
Is the split significant? ($p < 0.1$)
Yes
Estimate the coefficient using the threshold technique and split the sample into two subsamples by threshold γ
Is the sector input in an object region less than γ?
Yes
Estimate the coefficient using the results based on subsample 1
No
Estimate the coefficient using the results based on subsample 2
No
Estimate the coefficient using the OLS results based on the whole sample
Obtain all *preliminary input coefficients* of tables and apply the RAS technique to balance the corresponding matrix of intermediate input flows

Fig. 2. Threshold estimation procedure
Note: OLS, ordinary least-squares

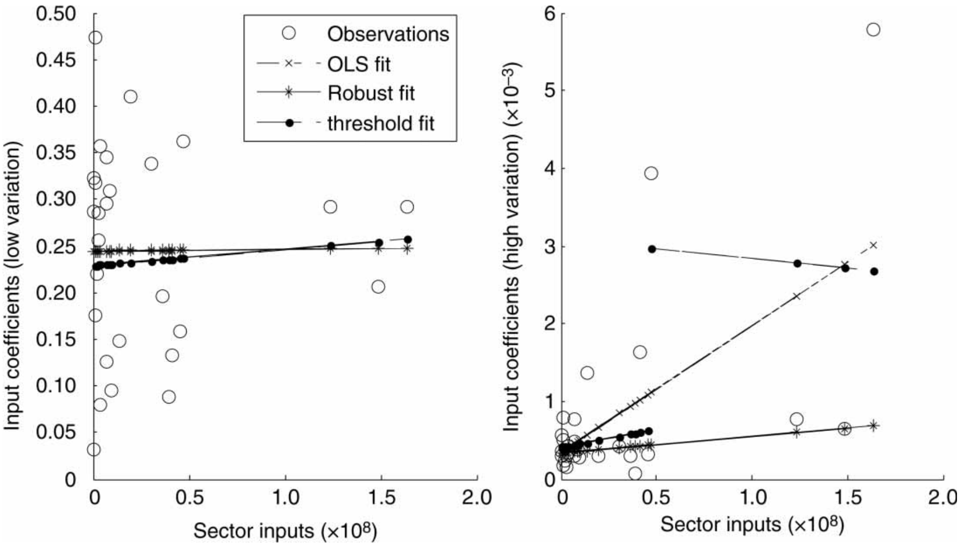

Fig. 3. The two cases revisited: ordinary least-squares (OLS), robust regression and threshold regression compared
Note: See the note to Fig. 1

does not offer proof that adopting more advanced methods is worthwhile. If samples like the one depicted in the right panel of Fig. 3 were very rare in regional input–output tables, not much could be won. Unfortunately, the robust regression analysis procedure does not make a dichotomous distinction between outliers and regular observations. As explained above, the algorithm re-computes weights for *all* observations.

For the threshold regression approach, more evidence can be provided. When considering observations for all twenty-seven regions, splits were found for 112 out of the 961 cells, which amounts to a share of 11.7%.[11] This share of cells seems sufficiently large to warrant further consideration.

The number of cells for which the estimated slopes (λ_{ij} in equation 3) are significant is small. For about 3% of the cells an R^2 of at least 0.25 for the univariate regressions is found, which indicates that deviations from constant returns to scale are generally not very strong. It should be noted, however, that statistical significance is not the main concern. Primary interest lies in the accuracy of the projections, for which a comparison of the estimated slopes is much more important. Table 1 provides a comparison of frequencies of classes of slopes as estimated by means of OLS regression and robust regression. It clearly shows to what extent corrections for the presence of outliers change the estimation results. The estimated slopes are generally closer to zero. The share of cells with an absolute value of $\lambda_{ij} > 0.005$ is 53% for OLS, and 43% for robust regression.

Table 2 compares the frequencies of estimated slopes for the subset of cells for which threshold regression yielded a split into subsamples corresponding to low and high values of sectoral output X_j (see equation 4) significant at a level of 10%. The results show that positive slopes larger than 0.005 are found slightly more often for the subsamples associated with large sectoral output levels. The differences are not very marked, however.

The next section will compare the estimating performance of the cross-regional methods introduced above not only with each other, but also with the more traditional methods based on single tables as discussed in the second section.

Table 1. Frequencies of estimated slopes for ordinary least-squares (OLS) and robust regression

Estimated slope	Frequency (OLS)	Frequency (robust regression
$\lambda < -0.005$	2	0
$-0.005 \leq \lambda < 0$	21	44
$0 \leq \lambda < 0.0025$	277	382
$0.0025 \leq \lambda < 0.005$	156	124
$0.005 \leq \lambda < 0.01$	133	114
$0.01 \leq \lambda < 0.025$	155	125
$0.025 \leq \lambda < 0.05$	114	90
$\lambda \geq 0.05$	103	82
Total	961	961

Table 2. Frequencies of estimated slopes for various regression approaches (the subset of cells with a threshold significant at the 10% level)

Estimated slope	Ordinary least-squares (OLS)	Robust regression	Threshold regression (small sectoral output)	Threshold regression (small sectoral output)
$\lambda < -0.005$	0	0	6	3
$-0.005 \leq \lambda < 0$	1	2	13	10
$0 \leq \lambda < 0.0025$	31	35	27	25
$0.0025 \leq \lambda < 0.005$	15	16	12	8
$0.005 \leq \lambda < 0.01$	8	13	10	11
$0.01 \leq \lambda < 0.025$	28	23	15	26
$\lambda \geq 0.025$	29	23	29	29
Total	112	112	112	112

COMPARISON OF THE ESTIMATION RESULTS

This section compares the deviations between the survey-based ('true') regional input–output tables for 2002 and the estimated tables obtained by applying the procedures outlined in the previous section. Throughout the empirical analysis, the weighted absolute percentage error (WAPE) will be employed as the measure of deviation:

$$\mathrm{WAPE} = \frac{\sum_i \sum_j b_{ij} \left| \frac{\hat{b}_{ij} - b_{ij}}{b_{ij}} \right|}{\sum_i \sum_j b_{ij}} = \frac{\sum_i \sum_j \left| \hat{b}_{ij} - b_{ij} \right|}{\sum_i \sum_j b_{ij}} \qquad (5)$$

where $\hat{b}_{ij}$ and b_{ij} denote the estimated and true values of the Leontief inverse $\mathbf{B} = (\mathbf{I} - \mathbf{A})^{-1}$, respectively.

The WAPE has been used in a large number of studies, since the weighted average of deviations is taken in such a way that large cells receive a larger weight than small cells (for example, OOSTERHAVEN *et al.*, 2008). It was decided to compare the deviations for individual cells of the Leontief inverse (instead of, for example, the values of intermediate input deliveries or input coefficients), because the cells of the Leontief inverse constitute the building blocks of multipliers used in traditional impact analyses.

Table 3 presents the WAPEs for each region and method. The last row ('count') indicates the number of regions for which the methods of the associated columns have the highest accuracy. In a similar vein, the row 'average' presents the unweighted averages of WAPEs over regions for the seven methods considered. The WAPEs appear to be high, but it is well known that applications of unmodified RAS generally lead to inaccurately estimated object tables (for example, LYNCH, 1986; POLENSKE, 1997). For the data set studied herein, most WAPEs would decline sharply to 0.1–0.2 when the 5% most important cells are replaced by the true, survey-based values (JIANG *et al.*, 2010). The actual construction of regional input–output tables is often done by means of such 'hybrid' methods.

Table 3. Accuracies of estimation methods by region (weighted absolute percentage errors (WAPEs) of cells in estimated regional Leontief inverse matrices)

	Single-table methods			Cross-regional methods			
Object region	Updating	Regionalization	Exchanging coefficients	Averaging	Ordinary least-squares (OLS) regression	Robust regression	Threshold regression
Anhui	0.347	0.281	0.324	0.240	0.246	**0.233**	0.251
Beijing	0.346	0.339	0.390	0.337	0.338	**0.324**	0.341
Chongqing	0.452	0.423	0.449	0.374	0.377	**0.366**	0.376
Fujian	0.444	0.370	0.382	**0.350**	0.353	0.362	0.357
Gansu	0.377	0.365	0.404	0.301	0.296	**0.286**	0.297
Guangdong	0.328	0.309	0.329	0.284	0.294	**0.284**	0.301
Guangxi	0.407	0.381	0.393	0.317	**0.311**	0.326	0.316
Guizhou	0.429	0.399	0.419	0.332	0.326	0.344	**0.321**
Hebei	0.264	0.228	0.351	**0.202**	0.210	0.205	0.213
Henan	0.385	0.335	0.408	0.306	0.323	**0.299**	0.330
Heilongjiang	0.297	0.263	0.284	0.214	0.220	**0.212**	0.223
Hubei	0.239	0.236	0.296	**0.207**	0.208	0.225	0.213
Hunan	0.364	0.290	0.335	**0.256**	0.260	0.256	0.258
Jilin	0.362	0.405	**0.374**	0.394	0.390	0.376	0.388
Jiangsu	0.337	0.306	0.314	0.272	**0.265**	0.269	0.268
Jiangxi	0.352	0.301	0.345	0.260	0.269	**0.243**	0.263
Liaoning	0.304	0.239	0.262	0.218	0.221	**0.214**	0.217
Neimeng	0.455	0.401	0.376	0.334	0.327	0.345	**0.325**
Ningxia	0.389	0.362	0.429	0.313	0.309	**0.308**	0.320
Shaanxi	0.335	0.313	0.390	0.283	0.288	**0.277**	0.292
Shandong	0.391	0.401	0.508	**0.348**	0.384	0.430	0.389
Shanxi	0.383	0.407	0.419	**0.373**	0.377	0.387	0.375
Shanghai	0.256	0.226	0.298	0.237	0.233	**0.214**	0.232
Sichuan	0.329	0.306	0.321	0.248	0.248	0.258	**0.247**
Tianjin	0.433	0.349	0.432	**0.330**	0.335	0.331	0.332
Yunnan	0.434	0.365	0.446	0.285	0.276	0.280	**0.265**
Zhejiang	0.320	0.275	0.348	**0.254**	0.258	0.286	0.254
Average	0.361	0.329	0.385	0.291	0.294	0.294	0.295
Count	0	0	1	8	2	12	4

Note: Emboldened values indicate the method with the highest accuracy for a region.

A first and very important finding is that cross-regional methods yield far better results than single-table methods. The estimations made with the cross-regional models produce overall average WAPEs between 0.291 and 0.295, while the corresponding range is 0.329–0.385 for traditional methods. At the level of individual regions, cross-regional methods also show a clear superiority over single-table methods, since only for Jilin the minimum WAPE is found for a single-table method. It is also observed that for most regions the WAPEs for cross-regional methods are very close to each other. In twenty-one out of twenty-seven regions, the worst cross-regional method still scores better than the best single-table method.

Second, it appears that regionalization based on the national table generates the best estimations among the class of single-table methods, followed by updating, while exchanging coefficients with the most similar region performs worst. This is a rather surprising result since updating a recent table is one of the most popular techniques used to compile regional input–output tables. It is also striking that the exchanging coefficients procedure is outperformed by regionalization, in spite of the fact that it uses information from all other regions in selecting the regional production structure that was most similar in 1997. A reasonable explanation for these results might be that input coefficients for regions undergoing rapid development are far less stable than ones for developed countries.[12] Dietzenbacher and Hoen (2006), for example, examined the stability of input coefficients based on a time series of annual input–output tables for the Netherlands, covering the period 1948–1984. They found that 80% of the cells had coefficients of variation below 0.3. For a set of Chinese survey-based national tables covering the period 1987–2002, it is found that not a single input coefficients features a coefficient of variation smaller than 0.5, and the proportion of input coefficients with a coefficient of variation below 0.8 is a mere 30%.

Third, turning attention to the cross-regional methods, it can be concluded that the four methods perform very close to each other on average, but that there are some marked differences at the level of individual regions. The robust regression method performs best for twelve regions, while the averaging coefficients method appears superior for eight regions. Although the WAPEs for OLS regression are similar to the WAPEs for robust regression if averaged over provinces (see the last row of Table 3), OLS and threshold regression score best in a substantially smaller numbers of cases. These relative performances are also reflected in the ranking of the accuracies (1 = most accurate; 4 = least accurate) of the four methods, averaged over the twenty-seven regions. These are 2.30, 2.72, 2.26 and 2.72 for averaging, OLS regression, robust regression and threshold regression, respectively. Apparently, OLS regression as advocated by the proponents of the FES suffers from problems caused by bad leverage points such as shown in Fig. 1 in this empirical application for China. Threshold regression emerges as an approach to this issue that should not be preferred. It yields substantially more accurate estimations for only two Western regions (Guizhou and, particularly, Yunnan). Instead, using both the averaging approach (which imposes constant returns to scale) and robust regression turns out to be a promising approach.

The overall average WAPE of the averaging method is slightly lower than the WAPE for the robust regression approach. Robust regression, however, is superior to averaging in the majority of cases (fifteen out of twenty-seven). This paradox is mainly due to two regions with ‘extreme’ results: Shandong and, to a somewhat lesser extent, Zhejiang. For these regions, the robust approach yields far worse accuracies than averaging. The results shown in Table 4 are based on robust regressions of equation (3) with all twenty-seven provinces included in the sample. The regression was run 961 times, that is, for each of the (i,j) pairs. The columns labelled ‘Number of outliers’ shows how often an observation for the corresponding region was found to be an outlier.[13] Shandong and Zhejiang are special indeed, in the sense that the numbers of cells considered as outliers are very high. About 12% of the 961 input coefficients in each of these two regions are located very far from the main cloud of observed input coefficients. In the robust regression approach, such observations get a very low weight, as a consequence of which the regression line is relatively often very far away from the observation. Hence, it is not surprising that predictions for regions with large numbers of outliers are relatively bad.

ROBUSTNESS TEST OF COMPARISON RESULTS

The most important conclusion so far is that cross-regional methods systematically generate better estimations than more traditional methods using information from just one table. It should of course be borne in mind that these results are obtained for a set of developing regions in China, of which some are undergoing rapid changes in production structure.

If one wants to judge the results in a more general context of practitioners in need of regional tables without the funds or time to construct survey-based material, it is a rather strong assumption that as many as twenty-six tables are available as inputs for cross-regional inputs. This section will investigate whether the superiority of cross-regional methods as reported in the previous section carries over to situations in which fewer tables can be used.

For reasons of space, this section focuses on the averaging coefficients and robust regression methods as representatives of the cross-regional methods. Further analyses of OLS and threshold regression will be omitted because these were most often outperformed. For similar reasons, the exchanging coefficients method is dropped from the set of approaches based on coefficients from a single input–output table. In this class of methods, the performance of inter-temporal updating and regionalization of national tables is scrutinized.

Experiments with sets of random samples

The relative performance of the estimation methods under consideration is likely to depend on the regional tables making up the sample. In the previous section, randomness did not play any role, because all twenty-

Table 4. Numbers of outliers and differences in accuracy between averaging and robust regression

Region	Number of outliers[a]	WAPEa - WAPEr[b]	Region	Number of outliers	WAPEa - WAPEr	Region	Number of outliers	WAPEa - WAPEr
Anhui	49	0.006	Heilongjiang	63	0.002	Ningxia	65	0.005
Beijing	62	0.014	Henan	62	0.007	Shaanxi	52	0.006
Chongqing	58	0.007	Hubei	91	−0.018	Shandong	116	−0.082
Fujian	97	−0.012	Hunan	61	0.000	Shanghai	59	0.023
Gansu	38	0.016	Jiangsu	62	0.003	Shanxi	90	−0.015
Guangdong	67	0.000	Jiangxi	46	0.016	Sichuan	70	−0.010
Guangxi	62	−0.009	Jilin	73	0.018	Tianjin	50	0.000
Guizhou	41	−0.012	Liaoning	59	0.004	Yunnan	57	0.005
Hebei	67	−0.003	Neimeng	48	−0.011	Zhejiang	108	−0.032

Notes: [a]Outliers are defined as observations receiving a weight smaller than 0.00005 in the final stage of the iteratively reweighted least-squares program as reported by Matlab’s *robustfit* routine.

[b]Positive values point at more accurate estimates by robust regression: WAPEa, weighted average percentage error for averaging; and WAPEr, weighted average percentage error for robust regression.

six tables (twenty-seven minus the object table) were automatically included in the sample. The intention now is to look closer at how the estimation methods perform if, for example, the averaging method is based on just ten observations. In principle, one could study results for all 26!/(10!·16!) = 5 311 735 possible distinct samples, but it was decided to use a different approach. In an experiment with strong similarities to bootstrapping, 1000 samples for each region and sample size studied were drawn randomly.[14] Next, WAPEs for each sample were computed. The empirical distribution of WAPEs as obtained in this fashion is summarized by means of the most straightforward statistic: the average WAPEs for the methods (as computed over 1000 WAPEs). Finally, to facilitate bilateral comparisons of methods, the percentage of random samples for which one method yielded lower WAPEs than for the other was computed.

Comparison between averaging and the robust method

First, the relative performance of the two cross-regional methods for situations with samples of ten, fifteen and twenty observations, respectively, is studied. The results are presented in Table 5. The average WAPEs for the averaging and robust regression methods are listed in the first two columns of Table 5 for each number of observations. The percentages in the rightmost columns denote the percentage of random samples for which averaging yielded a higher accuracy (lower WAPE) than robust regression.[15] For example, 34% in the first row and third column indicates that for the Anhui region, averaging coefficients outperformed robust regression for only 34% of the random samples.

First, observe that WAPEs increase when fewer observations are available, irrespective of the method adopted. This implies that as many tables as possible should be used when applying cross-regional methods.

Table 5. Comparison of the accuracy of the averaging coefficients and robust regression methods, with different numbers of observations[a]

	Number of observations								
	20			15			10		
Object region	Average WAPE of averaging coefficient	Average WAPE of robust regression	Percentage of WAPEa < WAPEr (%)	Average WAPE of averaging coefficient	Average WAPE of robust regression	Percentage of WAPEa < WAPEr (%)	Average WAPE of averaging coefficient	Average WAPE of robust regression	Percentage of WAPEa < WAPEr (%)
Anhui	0.242	**0.240**	34	0.246	**0.246**	49	**0.252**	0.256	68
Beijing	0.339	**0.336**	31	**0.341**	0.344	56	**0.345**	0.356	74
Chongqing	0.375	**0.367**	4	0.378	**0.370**	13	0.382	**0.377**	31
Fujian	**0.352**	0.363	99	**0.355**	0.366	94	**0.360**	0.371	86
Gansu	0.304	**0.290**	0	0.306	**0.294**	4	0.312	**0.304**	21
Guangdong	**0.285**	0.287	51	**0.288**	0.301	73	**0.291**	0.327	94
Guangxi	**0.319**	0.327	92	**0.322**	0.329	82	**0.329**	0.336	78
Guizhou	**0.335**	0.343	95	**0.338**	0.344	80	**0.344**	0.350	75
Hebei	**0.204**	0.207	62	**0.208**	0.216	73	**0.214**	0.231	81
Henan	0.308	**0.305**	31	**0.311**	0.312	50	**0.317**	0.327	70
Heilongjiang	0.217	**0.216**	33	0.222	**0.220**	42	**0.230**	0.231	56
Hubei	**0.210**	0.226	100	**0.215**	0.230	99	**0.223**	0.239	95
Hunan	**0.258**	0.260	76	**0.262**	0.265	74	**0.268**	0.273	78
Jilin	0.396	**0.382**	19	0.400	**0.392**	36	**0.405**	0.410	45
Jiangsu	**0.273**	0.279	71	**0.276**	0.290	82	**0.280**	0.308	95
Jiangxi	0.262	**0.248**	0	0.265	**0.254**	5	0.269	**0.266**	36
Liaoning	0.221	**0.217**	20	0.224	**0.222**	32	**0.230**	0.234	56
Neimeng	**0.337**	0.344	87	**0.341**	0.346	71	**0.347**	0.352	67
Ningxia	0.315	**0.313**	28	**0.318**	0.320	61	**0.324**	0.333	79
Shaanxi	0.285	**0.279**	9	0.287	**0.283**	20	0.292	**0.291**	44
Shandong	**0.350**	0.429	100	**0.353**	0.428	100	**0.358**	0.429	100
Shanxi	**0.374**	0.385	91	**0.376**	0.385	83	**0.380**	0.387	73
Shanghai	0.238	**0.223**	3	0.240	**0.234**	26	**0.245**	0.254	61
Sichuan	**0.250**	0.259	99	**0.254**	0.263	93	**0.261**	0.273	90
Tianjin	**0.331**	0.332	58	**0.332**	0.334	62	**0.335**	0.341	74
Yunnan	0.288	**0.283**	18	0.292	**0.287**	31	0.299	**0.296**	42
Zhejiang	**0.256**	0.290	100	**0.258**	0.298	100	**0.264**	0.308	100
Average[b]	0.293	0.297	52.3	0.297	0.303	58.9	0.302	0.313	69.2
Count	14	13	13[c]	17	10	10[c]	22	5	6[c]

Notes: [a]Emboldened values indicate the method with the highest accuracy for a region.

[b]Unweighted averages over regions.

[c]Number of regions with percentage of WAPEa < WAPEr smaller than 50%.

It is also found, however, that the WAPEs increase remarkably slowly when sample sizes are reduced, which is a reassuring result.

With respect to the comparison between the averaging coefficients and robust regression methods, it is found that the advantage of the latter over the first in terms of the number of regions for which it performs better (Table 3) switches to a disadvantage when the numbers of observations in the sample decline. For the case of twenty observations, the robust regression method performs better in thirteen regions according to average WAPE, while these numbers drop to only ten and five in the cases of fifteen and ten observations, respectively (see the bottom line of Table 5). In a similar vein, it is found that the advantage of the averaging coefficients method in terms of the unweighted average of average WAPEs as documented in Table 5 also grows if fewer observations are available (from 0.004 for twenty observations to 0.011 for ten observations). An analysis of the percentages of samples for which averaging coefficients performs better than robust regression tells a similar story. Only for Jilin with a sample size of ten is it found that the results for the majority of random samples favour robust regression, while the average WAPE is smaller for averaging. Apart from this case, the average WAPE appears to be a statistic that captures the entire empirical distribution well, at least for the purposes of the analysis.

The result that the performance of the robust regression method worsens with lower numbers of observations can be explained by the fact that robust regression is less capable of identifying outliers if the cloud of 'regular observations' is small (ROUSSEEUW and VAN ZOMEREN, 1990). Consequently, observations that are outliers for the entire set of twenty-seven provinces as counted in Table 4 are often treated as almost regular observations if sample sizes are small and the empirical differences between robust regression and OLS regression vanish. It was already found in Table 3 that OLS regression performs systematically worse than the averaging method. An important intermediate conclusion to be drawn is that if only a few regional tables are available, the use of the averaging coefficients method is recommended.

Comparison of averaging against traditional methods

This section compares the performance of the averaging coefficients method (a cross-regional method) with those of the inter-temporal updating and regionalization of national tables techniques. If only a few regional tables are available, it might be expected that the clear

Table 6. Comparison of averaging with different numbers of observations to single-table methods (1000 random samples)[a]

	Number of observations for averaging								
Object region	26[b]	20	15	10	8	5	3	Update	Regionalization
Anhui	**0.240**	**0.242**	**0.246**	**0.252**	**0.256**	**0.267**	0.286	0.347	0.281
Beijing	**0.337**	0.339	0.341	0.345	0.348	0.356	0.368	0.346	0.339
Chongqing	**0.374**	**0.375**	**0.378**	**0.382**	**0.385**	**0.394**	**0.408**	0.452	0.423
Fujian	**0.350**	**0.352**	**0.355**	**0.360**	**0.363**	0.372	0.384	0.444	0.370
Gansu	**0.301**	**0.304**	**0.306**	**0.312**	**0.317**	**0.327**	**0.345**	0.377	0.365
Guangdong	**0.284**	**0.285**	**0.288**	**0.291**	**0.295**	**0.302**	0.317	0.328	0.309
Guangxi	**0.317**	**0.319**	**0.322**	**0.329**	**0.333**	**0.345**	**0.364**	0.407	0.381
Guizhou	**0.332**	**0.335**	**0.338**	**0.344**	**0.348**	**0.360**	**0.379**	0.429	0.399
Hebei	**0.202**	**0.204**	**0.208**	**0.214**	**0.218**	**0.231**	0.251	0.264	0.228
Henan	**0.306**	**0.308**	**0.311**	**0.317**	**0.320**	**0.329**	0.345	0.385	0.335
Heilongjiang	**0.214**	**0.217**	**0.222**	**0.230**	**0.235**	**0.250**	0.271	0.297	0.263
Hubei	**0.207**	**0.210**	**0.215**	**0.223**	**0.228**	0.243	0.265	0.239	0.236
Hunan	**0.256**	**0.258**	**0.262**	**0.268**	**0.272**	**0.283**	0.301	0.364	0.290
Jilin	0.394	0.396	0.400	0.404	0.405	0.426	0.451	0.362	0.405
Jiangsu	**0.272**	**0.273**	**0.276**	**0.280**	**0.284**	**0.291**	**0.304**	0.337	0.306
Jiangxi	**0.260**	**0.262**	**0.265**	**0.269**	**0.274**	**0.284**	0.302	0.352	0.301
Liaoning	**0.218**	**0.221**	**0.224**	**0.230**	**0.235**	0.247	0.264	0.304	0.239
Neimeng	**0.334**	**0.337**	**0.341**	**0.347**	**0.352**	**0.363**	**0.381**	0.455	0.401
Ningxia	**0.313**	**0.315**	**0.318**	**0.324**	**0.328**	**0.337**	**0.353**	0.389	0.362
Shaanxi	**0.283**	**0.285**	**0.287**	**0.292**	**0.295**	**0.304**	0.318	0.335	0.313
Shandong	**0.348**	**0.350**	**0.353**	**0.358**	**0.362**	**0.371**	**0.387**	0.391	0.401
Shanxi	**0.373**	**0.374**	**0.376**	**0.380**	**0.383**	0.390	0.401	0.383	0.407
Shanghai	0.237	0.238	0.240	0.245	0.247	0.257	0.272	0.256	0.226
Sichuan	**0.248**	**0.250**	**0.254**	**0.261**	**0.265**	**0.278**	**0.299**	0.329	0.306
Tianjin	**0.330**	**0.331**	**0.332**	**0.335**	**0.336**	**0.344**	0.352	0.433	0.349
Yunnan	**0.285**	**0.288**	**0.292**	**0.299**	**0.303**	**0.314**	**0.333**	0.434	0.365
Zhejiang	**0.254**	**0.256**	**0.258**	**0.264**	**0.268**	0.279	0.295	0.320	0.275

Notes: [a]Emboldened values indicate that the averaging coefficients method outperforms both single table-based methods.

[b]For a sample size of twenty-six, only one sample can be constructed containing all regional tables except the object table. Thus, the reported weighted absolute percentage error (WAPE) is the same as shown in Table 1.

advantage of the cross-regional methods (as presented in Table 3) disappears and that the use of single table methods should be favoured. Like in the previous subsection, the accuracies based on average WAPEs over 1000 random samples will first be compared. The results are documented in Table 6.

For all regions except Jilin and the cities of Beijing and Shanghai, it is found that the cross-regional method beats both single-table methods as long as the number of available regional tables is eight or more. Apparently, small numbers of contemporaneous tables already yield sufficient information to compensate for the fact that the tables relate to regions different from the object region. Only if regions have very special structures, such as city-provinces, regionalization of national tables and (to a lesser extent) inter-temporal updating methods may prove superior also for larger samples.

Again, results are also presented for another statistic (the percentage of random samples for which the regionalization of national tables leads to higher accuracies than averaging), which provides more insight into the empirical distribution of relative WAPEs.[16] The results are presented in Table 7.

Table 7 by and large confirms the results obtained for the average WAPEs. For a sample size as small as seven, it is found that in as many as sixteen of twenty-seven regions regionalization is more accurate than averaging for fewer than 10% of the random samples. For smaller samples, the percentage of samples for which regionalization beats averaging coefficients increases. For a sample size of five, for example, it is found that this happens in eight regions for more than half of the randomly drawn samples.

Again, Beijing and Shanghai are the main exception to the rule of superiority of cross-regional methods like averaging. That is, regionalization performs better not only for moderately small samples, but also for large samples. The production structures of these metropolitan cities are apparently better reflected in national tables (which incorporate the structures of Shanghai and Beijing) than in regional tables for other regions. It is also found that some other coastal and central regions with a highly developed manufacturing sector, such as Fujian, Hebei, Hubei, Jilin, Liaoning and Zhejiang, tend to have lower accuracies of the averaging coefficients method in a relatively large fraction of the set of samples.

Table 7. Comparison of accuracies of averaging and regionalization methods for different numbers of observations[a]

	Number of observations							
Object region	20	15	10	8	7	6	5	3
Anhui	**0**	**0**	**0**	**0**	**1**	**5**	14	63
Beijing	53	64	70	75	78	80	84	91
Chongqing	**0**	**0**	**0**	**0**	**0**	**0**	**0**	14
Fujian	**0**	**0**	10	19	28	41	51	81
Gansu	**0**	**0**	**0**	**0**	**0**	**0**	**2**	16
Guangdong	**0**	**0**	**5**	13	19	25	38	62
Guangxi	**0**	**0**	**0**	**0**	**0**	**0**	**1**	15
Guizhou	**0**	**0**	**0**	**0**	**0**	**0**	**2**	16
Hebei	**0**	**0**	**8**	23	31	42	58	87
Henan	**0**	**0**	**5**	13	21	26	39	66
Heilongjiang	**0**	**0**	**0**	**0**	**2**	**5**	**13**	66
Hubei	**0**	**0**	**3**	17	30	51	69	96
Hunan	**0**	**0**	**0**	**0**	**3**	**8**	**26**	74
Jilin	25	35	44	47	48	50	52	60
Jiangsu	**0**	**0**	**0**	**2**	**4**	**9**	**16**	49
Jiangxi	**0**	**0**	**0**	**0**	**1**	**6**	**14**	44
Liaoning	**0**	**0**	16	33	46	56	68	89
Neimeng	**0**	**0**	**0**	**0**	**0**	**0**	**1**	17
Ningxia	**0**	**0**	**0**	**0**	**1**	**5**	**11**	38
Shaanxi	**0**	**0**	**1**	**4**	**8**	13	23	58
Shandong	**0**	**0**	**0**	**0**	**0**	**1**	**4**	22
Shanxi	**0**	**0**	**0**	**2**	**4**	**7**	14	36
Shanghai	99	96	95	94	93	96	96	100
Sichuan	**0**	**0**	**0**	**0**	**0**	**0**	**1**	35
Tianjin	**0**	**0**	**8**	16	18	27	33	53
Yunnan	**0**	**0**	**0**	**0**	**0**	**0**	**1**	13
Zhejiang	**0**	**0**	12	28	35	46	65	88

Note: [a]Values (percentages) indicate the share of random samples for which the regionalization method yielded a higher accuracy than averaging coefficients. Emboldened values represent shares less than 10%.

CONCLUSIONS

This paper has presented four cross-regional non-survey methods to estimate regional input–output tables (using as much data for other regions as possible) and tested these methods against three more traditional non-survey methods that rely on information contained in a single regional table: inter-temporal updating, regionalization of a national table and exchanging coefficients with a table for the most similar region in the previous period. The empirical analysis was performed on the basis of two series of Chinese survey-based regional input–output tables for 1997 and 2002. They cover twenty-seven regions and thirty-one industries.

It was first argued that IMANSYAH's (2000) averaging coefficients method can be seen as a special case of the ordinary least-squares (OLS) regression approach that JENSEN *et al.* (1988) advocated (inspired by the notion of the fundamental economic structure (FES)). Next, two alternative regression-based methods were introduced that deal with outliers and bad leverage points. In the present context, these are regions with a production structure that is very different from the production structures in many other regions (a situation that is frequently encountered in China). The robust regression method assumes that there is a single 'law' governing the size of input coefficients and gives a low weight to observations that do not appear to obey this relationship. Threshold regression, however, supposes that two 'laws' could prevail, one of which relates to small sectors and the other to regions in which the sector is large. If evidence for two laws is found, the sample is split into two and subsample-specific estimates are obtained.

It was found that cross-regional methods have systematically better performance than the traditional methods based on a single table. This result carries over to situations in which fewer regional tables are available. In most cases the availability of seven or eight regional tables is sufficient to render averaging coefficients more accurate than the regionalization of national tables and inter-temporal updating. Among the group of cross-regional methods, averaging coefficients and robust regression generally turn out to be slightly more accurate than OLS and threshold regression. The accuracy of the robust regression technique as compared with averaging is relatively weak if the number of available regional tables is rather small. In such cases, simple averaging of coefficients appears to be the preferred method.

The results obtained in this paper should be considered carefully because they cannot be generalized to all situations practitioners might face. The Chinese data used are attractive for the purpose of this study because sets of twenty-seven harmonized, survey-based regional input–output tables are very rare. This data set allowed the authors to compare the estimation performance of a number of techniques as if samples of different sizes were available. It should be taken into account, however, that this data set is also rather specific in at least two respects. First, the Chinese economy is both very heterogeneous and dynamic. Some regions are very backward, while other regions (especially those in the coastal zone) have been developing very rapidly. Regionalization of national tables might perform much better for regions that are part of a country without the differences in production structures associated with the Chinese regional inequality. A similar argument can be used for the bad estimation performance of inter-temporal updating in the study. If input–output tables are estimated for regions that do not develop as quickly as many of the coastal and central regions in China, production structures as reflected in input coefficients are likely to be much more stable over time. This would enhance the quality of estimates obtained by inter-temporal updating significantly.

Second, given the nature of the Chinese data, the study focuses on the estimation of technical coefficients, which are defined as intermediate inputs (both domestically produced and imported) divided by gross output. Often, however, practitioners are interested in estimating input coefficients, defined as domestically produced intermediate inputs divided by gross output levels. If cross-regional methods were used to estimate input coefficients, some additional steps seem necessary, including the estimation of location quotients to correct for differences in the economic size of regions: large regions will purchase relatively much from domestic sources, while small regions will import relatively much. This will be reflected in different sets of input coefficients, even if the production technologies were identical. An account of the relative qualities of the (adapted) cross-regional methods discussed in this study and more traditional methods based on information contained in a single table if input coefficients rather than technical coefficients are to be estimated is a subject for future work.

Acknowledgements – The authors thank two anonymous referees for their constructive comments.

APPENDIX A: CONSTRUCTION OF CHINESE PROVINCIAL INPUT–OUTPUT TABLES

The construction of survey-based provincial input–output tables became a regularly activity since 1987, at five-year intervals. During each survey year, the national statistical agency (National Bureau of Statistics (NBS)) establishes methods of conducting the survey and explains these to the provincial statistical bureaus. The guidelines include the survey forms, the tabulation method and the industry classifications.[17] In each region, provincial officials first train accountants of enterprises in the methods used to fill out the forms. Enterprises provide information of intermediate consumption for production and the generation of output by means of these forms. All large-scale enterprises are surveyed, while random sampling is done for medium- and small-scale enterprises. For 1997 and 2002, the proportions of sampled firms were set at 20% and 8% for the medium- and small-scale enterprises, respectively.[18]

Subsequently, the forms are submitted to provincial statistical offices, who forward the data to the NBS for its national tabulation and adjustments, whereas they also use the data to tabulate their own regional tables. The standardized method of data survey ensures the quality of data collection over space. For the purposes of this study, it is essential that provincial tables are not derived from a national table (which would imply that the production technologies of a province would be considered as similar to those of the country), but purposefully constructed from data at the provincial level.

It should be noted that the Chinese input–output survey defines intermediate inputs as including both domestically produced materials and materials that have been imported (either from another province or from abroad). This procedure results in a subtle but important difference between Chinese provincial input–output tables and the internationally more common regional tables. Input coefficients derived from Chinese provincial input–output tables could be considered as 'technical coefficients' that represent production technologies well. For studies of the impact of policy measures or changes in consumption or investment behaviour on provincial economies (for example, via multiplier analyses), Chinese provincial tables should not be used. In such cases, assumptions about the origin of inputs are needed to adapt the tables in a suitable way.

Table A1. *Industry classification*

Sector		Sector	
01	Agriculture	17	Electric equipment and machinery
02	Coal mining, crude petroleum and natural gas extraction	18	Electronic and telecommunication equipment
03	Metal ore mining	19	Instruments, meters, cultural and office machinery
04	Non-metal mineral mining	20	Other manufacturing products
05	Manufacture of food products and tobacco processing	21	Electricity, gas and water production and supply
06	Textile goods	22	Construction
07	Wearing apparel, leather, furs, down and related products	23	Transport and storage, post and telecommunication
08	Sawmills and furniture	24	Wholesale and retail trade, catering trade
09	Paper and products, printing and record medium reproduction	25	Finance and insurance
10	Petroleum processing and coking	26	Real estate
11	Chemicals	27	Social services
12	Non-metal mineral products	28	Health services, sports and social welfare
13	Metals smelting and pressing	29	Education, culture and arts, radio, film and television
14	Metal products	30	Scientific research and general technical services
15	Machinery and equipment	31	Public administration and other sectors
16	Transport equipment		

APPENDIX B: RELATIVE PERFORMANCE OF AVERAGING COEFFICIENTS AND INTER-TEMPORAL UPDATING

Table B1. *Comparison of accuracies of averaging and inter-temporal updating methods for different numbers of observations (1000 random samples)*[a]

	Number of observations							
Object region	20	15	10	8	7	6	5	3
Anhui	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**
Beijing	**8**	23	42	55	59	64	72	84
Chongqing	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**
Fujian	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**
Gansu	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**9**
Guangdong	**0**	**0**	**0**	**0**	**2**	**3**	**7**	30
Guangxi	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**1**
Guizhou	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**1**
Hebei	**0**	**0**	**0**	**0**	**0**	**0**	**2**	25
Henan	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**4**
Heilongjiang	**0**	**0**	**0**	**0**	**0**	**0**	**0**	10
Hubei	**0**	**0**	**1**	**7**	19	36	59	93
Hunan	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**
Jilin	100	96	92	89	87	88	89	92
Jiangsu	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**4**
Jiangxi	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**1**
Liaoning	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**3**
Neimeng	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**
Ningxia	**0**	**0**	**0**	**0**	**0**	**0**	**0**	13
Shaanxi	**0**	**0**	**0**	**0**	**0**	**0**	**1**	17
Shandong	**0**	**0**	**0**	**1**	**2**	**4**	11	38
Shanxi	**0**	11	39	48	52	61	65	84
Shanghai	**0**	**2**	18	28	36	41	49	71
Sichuan	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**5**
Tianjin	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**
Yunnan	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**
Zhejiang	**0**	**0**	**0**	**0**	**0**	**0**	**0**	10

Note: [a]Values (percentages) indicate the share of random samples for which the inter-temporal updating method yielded a higher accuracy than averaging coefficients. Emboldened values represent shares less than 10%.

NOTES

1. Purists would be right in arguing that exchanging or substituting coefficients first uses information from multiple regional tables to identify the most similar region. Next, however, it disregards all information contained in tables for regions that might have a high degree of similarity to the object region, but are not the most similar.
2. The mainland of China is administratively divided into thirty-one regions, including twenty-two provinces, five autonomous regions and four centrally administrative municipalities. The authors do not have data for Hainan province and the autonomous regions of Tibet, Qinghai and Xinjiang. In order to make the tables comparable for 1997 and 2002, the industries in the data set were aggregated into thirty-one industries. For the classification, see Table A1 in Appendix A.
3. For thorough overviews of these techniques, see ROUND (1983) and LAHR (1993, 2001).
4. This approach is inspired by LEONTIEF (1989), who viewed columns of input coefficients as lists of ingredients for sectoral ‘cooking recipes’.
5. For applications of the cosine measure as a similarity measure of two vectors of input coefficients, see OKSANEN and WILLIAMS (1992) and LOS (2000).
6. Many estimation experiments were conducted using other explanatory variables than regional sectoral gross output and non-linear forms (for example, using quadratic forms or allowing for parameter heterogeneity between ‘poor’ regions and ‘rich’ regions). Equation (3), however, consistently led to the estimated tables that most closely resembled the true object tables. Results obtained with other explanatory variables and other functional forms are not included in this paper, but are available from the authors upon request.
7. For an early overview of alternative robust regression techniques, see HOLLAND and WELCH (1977).
8. HANSEN (2001) presented a very accessible introduction to a strongly related approach used to identify structural breaks in time series. In an input–output context, YAMAKAWA and PETERS (2009) applied both robust

regression and (slightly different) sample-splitting techniques to study input coefficient stability over time.

9. In principle, more than two sets of parameters might govern the relationship between the input coefficients and the total sectoral inputs. This study focuses on a situation with two subsamples only. There are two reasons for this decision: first, the estimation theory for multiple sample splits was not developed thoroughly; and second, the numbers of observations in the samples were not very high, as a consequence of which many degrees of freedom would be lost when estimating multiple splits.
10. This study adopts a significance level of 10%. The threshold regression approach advocated by HANSEN (2000) requires the minimum size of both subsamples to be set exogenously ('trimming'). HANSEN's (2000, 2001) convention to set this value to 10–15% of the sample size was followed. This implies that the minimum size of each subsample is three observations.
11. This result obtained for Chinese regions does not necessarily generalize to other sets of national or regional input–output tables, particularly because the Chinese economy is characterized by a strong variation of regional specialization patterns.
12. Note that the similarity index (equation 1) is based on information for 1997.
13. Formally, the iteratively reweighted least-squares procedure does not yield a clear distinction between outliers and regular observations. However, if the algorithm leads to observations with a very small weight after the final iteration, this is a sign that the corresponding observation is located well above or below the robust regression line. Here, observations with a final weight smaller than 0.00005 are arbitrarily denoted as outliers.
14. In theory, it is possible that the sets of 1000 samples contained duplicates, since samples were drawn with replacement. Note that a single sample could not contain a regional table more than once since regions in each sample were drawn without replacement.
15. The percentages depend on the draw of the 1000 samples and are therefore random variables themselves.
16. For the large majority of Chinese regions, regionalization of national tables performs better than inter-temporal updating. Hence, averaging is benchmarked to regionalization. For a comparison of the averaging coefficients method and inter-temporal updating, see Table B1 in Appendix B. From a practitioner's point of view, the results in Table B1 might be very relevant because national tables are sometimes unavailable while an old regional table might exist.
17. The thirty-one-industry classification used in this study (Table A1) is slightly more aggregated than the input–output tables published for 1997 and 2002, which contain forty and forty-two industries, respectively. Aggregation was needed to have tables with an identical industry classification.
18. There might be minor adjustments in terms of the sample percentages made by local regional statistic bureaus. It might be the case, for example, that some regions do not have large-scale enterprises in a certain industry. In that case, the regional statistic bureau tends to increase the sample percentages for medium- and small-scale enterprises in the industries (QI, 2007).

REFERENCES

BEATON A. E. and TUKEY J. W. (1974) The fitting of power series, meaning polynomials, illustrated on band-spectroscopic data, *Technometrics* **16**, 147–185.

BONFIGLIO A. and CHELLI F. (2008) Assessing the behaviour of non-survey methods for constructing regional input–output tables through a Monte Carlo simulation, *Economic Systems Research* **20**, 243–258.

BOOMSMA P. and OOSTERHAVEN J. (1992) A double-entry method for the construction of bi-regional input–output tables, *Journal of Regional Science* **32**, 269–284.

DIETZENBACHER E. and HOEN A. R. (2006) Coefficient stability and predictability in input–output models: a comparative analysis for the Netherlands, *Construction Management and Economics* **24**, 671–680.

FLEGG A. T. and WEBBER C. D. (2000) Regional size, regional specialization and the FLQ formula, *Regional Studies* **34**, 563–569.

FLEGG A. T., WEBBER C. D. and ELLIOT M. V. (1995) On the appropriate use of location quotients in generating regional input–output tables, *Regional Studies* **29**, 547–561.

GREENSTREET D. (1989) A conceptual framework for constructing of hybrid regional input–output models, *Socio-economic Planning Sciences* **23**, 283–289.

HANSEN B. E. (2000) Sample splitting and threshold estimation, *Econometrica* **68**, 575–603.

HANSEN B. E. (2001) The new econometrics of structural change: dating breaks in U.S. labor productivity, *Journal of Economic Perspectives* **15**, 117–128.

HEWINGS G. J. D. (1977) Evaluating the possibilities for exchanging regional input–output coefficients, *Environment and Planning A* **9**, 924–944.

HOLLAND P. H. and WELCH R. E. (1977) Robust regression using iteratively reweighted least-squares, *Communications Statistics: Theory and Methods* **6**, 813–827.

IMANSYAH M. H. (2000) An efficient method for constructing regional input–output table: a horizontal approach in Indonesia. Paper presented at the 13th International Conference on Input–Output Techniques, Macerata, Italy.

JACKSON R. W. (1998) Regionalizing national commodity-by-industry accounts, *Economic Systems Research* **10**, 223–238.

JACKSON R. W. and MURRAY A. T. (2004) Alternative input–output matrix updating formulations, *Economic Systems Research* **16**, 135–148.

JAFFE A. B. (1986) Technological opportunity and spillovers of R&D: evidence from firms' patents, profits, and market value, *American Economic Review* **76**, 984–1001.

JALILI A. R. (2000) Comparison of two methods of identifying input–output coefficients for exogenous estimation, *Economic Systems Research* **12**, 113–129.

Jensen R. C., Dewhurst J. H. Ll, West G. R. and Hewings G. J. D. (1991) On the concept of fundamental economic structure, in Dewhurst J. H. Ll, Hewings G. J. D. and Jensen R. C. (Eds) *Regional Input–Output Modelling: New Developments and Interpretations*, pp. 228–249. Avebury, Aldershot.

Jensen R. C., Mandeville T. D. and Karunaratne N. D. (1979) *Regional Economic Planning: Generation of Regional Input–Output Analysis*. Croom Helm, London.

Jensen R. C., West G. R. and Hewings G. J. D. (1988) The study of regional economic structure using input–output tables, *Regional Studies* **22**, 209–220.

Jiang X., Dietzenbacher E. and Los B. (2010) Targeting the collection of superior data for the estimation of regional input–output tables, *Environment and Planning A* **42(10)**, 2508–2526.

Lahr M. L. (1993) A review of the literature supporting the hybrid approach to constructing regional input–output models, *Economic Systems Research* **5**, 277–293.

Lahr M. L. (2001) A strategy for producing hybrid regional input–output tables, in Lahr M. L. and Dietzenbacher E. (Eds) *Input–Output Analysis: Frontiers and Extensions*, pp. 211–242. Palgrave, London.

Leontief W. (1989) Input–output data base for analysis of technological change, *Economic Systems Research* **1**, 287–295.

Los B. (2000) The empirical performance of a new inter-industry technology spillover measure, in Saviotti P. P. and Nooteboom B. (Eds) *Technology and Knowledge; From the Firm to Innovation Systems*, pp. 118–151. Edward Elgar, Cheltenham.

Lynch R. G. (1986) An assessment of the RAS method for updating input–output tables, in Sohn I. (Ed.) *Readings in Input–Output Analysis; Theory and Applications*, pp. 271–284. Oxford University Press, New York, NY.

Madsen B. and Jensen-Butler C. (1999) Make and use approach to regional and interregional accounts and model, *Economic Systems Research* **11**, 277–299.

Midmore P. (1991) Input–output in agriculture: a review, in Midmore P. (Ed.) *Input–Output Models in the Agricultural Sector*, pp. 5–20. Avebury, Aldershot.

Miller R. E. and Blair P. D. (1985) *Input–Output Analysis: Foundations and Extensions*. Prentice-Hall, Englewood Cliffs, NJ.

Morrison W. I. and Smith P. (1974) Nonsurvey input–output techniques at the small area level: an evaluation, *Journal of Regional Science* **14**, 1–14.

Okamoto N. and Zhang Y. (2005) Non-survey methods for estimating regional and interregional input–output multipliers, in Okamoto N. and Ihara T. (Eds) *Spatial Structure and Regional Development in China: Interregional Input–Output Approach*, pp. 25–45. Development Perspective Series Number 5. Palgrave–Macmillan, New York, NY.

Oksanen E. H. and Williams J. R. (1992) An alternative factor-analytic approach to aggregation of input–output tables, *Economic Systems Research* **4**, 245–256.

Oosterhaven J., Piek G. and Stelder D. (1986) Theory and practice of updating regional versus interregional interindustry tables, *Papers of the Regional Science Association* **59**, 57–72.

Oosterhaven J., Stelder D. and Inomata S. (2008) Estimating international interindustry linkages: non-survey simulations of the Asia-Pacific economy, *Economic Systems Research* **20**, 395–414.

Polenske K. R. (1997) Current uses of the RAS technique: a critical review, in Simonovits A. and Steenge A. E. (Eds) *Prices Growth and Cycles*, pp. 58–88. Macmillan, London.

Qi S. C. (2007) Zhongguo Diqu Touru Chanchu Biao Bianzhi Qingkuang Jieshao [Introduction to the compiling system of the Chinese regional input–output tables]. Paper presented at the 7th Chinese Input–Output Conference, Nanjing, China, August 2007. [in Chinese].

Riddington G., Gibson H. and Anderson J. (2006) Comparison of gravity model, survey and location quotient-based local area tables and multipliers, *Regional Studies* **40**, 1069–1081.

Round J. I. (1983) Nonsurvey techniques: a critical review of the theory and the evidence, *International Regional Science Review* **8**, 189–212.

Rousseeuw P. J., and van Zomeren B. C. (1990) Unmasking multivariate outliers and leverage points, *Journal of the American Statistical Association* **85**, 633–639.

Rueda-Cantuche J. M., Beutel J., Neuwahl F., Mongelli I. and Loeschel A. (2009) A symmetric input–output table for EU27: latest progress, *Economic Systems Research* **21**, 59–79.

Sawyer C. and Miller R. E. (1983) Experiments in regionalization of a national input–output table, *Environment and Planning A* **15**, 1501–1520.

Stone R. and Brown A. (1962) *A Computable Model of Economic Growth*. Chapman & Hall, London.

Thakur S. K. (2004) Structure and structural changes in India: a fundamental economic structure approach. PhD dissertation, Ohio State University, Columbus, OH.

Tohmo T. (2004) New developments in the use of location quotients to estimate regional input–output coefficients and multipliers, *Regional Studies* **38**, 43–54.

Van der Westhuizen M. (1992) Towards developing a hybrid method for input–output table compilation and identifying a fundamental economic structure. PhD dissertation, University of Pennsylvania, Philadelphia, PA.

West G. R. (1990) Regional trade estimation: a hybrid approach, *International Regional Science Review* **13**, 103–118.

Yamakawa A. and Peters G. P. (2009) Environmental input–output analysis: using time-series to measure uncertainty, *Economic Systems Research* **21**, 337–362.