Chapter 6

Summary and Conclusion

6.1 Introduction

This final chapter is devoted to a summary of the major findings of the studies reported in this thesis. In Section 6.2, we offer suggestions for the compilation of regional input-output (IO) tables in a cost-efficient way. These suggestions are based on the findings from statistical analyses applied to Chinese regional IO tables. Although these suggestions are especially relevant for IO practitioners in China, we will also speculate about the extent to which the suggestions might be useful for the construction of IO tables in other countries. Section 6.3 discusses the most important findings from the applications of Chinese regional IO tables to describe and explain the huge differences in economic structures that are very prominent in China. Section 6.4 provides suggestions for future research.

6.2 Summary and Conclusions for the Compilation of Hybrid Input-Output Tables

The compilation of high-quality IO tables is the key to conduct regional IO analysis. Because non-survey estimates are generally too unreliable and construction methods based on surveys among companies are generally too costly, hybrid methods that combine non-survey approaches with ‘superior’ survey-based data have become the mainstream. A general finding in the literature is that additional superior data for certain coefficients of the target table may seriously improve the quality of the estimated IO tables. The collection of additional superior data, however, implies higher compilation costs. A crucial question that arises is: To what extent and for which intermediate deliveries should additional information be gathered? Another
question is: If (at least part of) an IO table has to be estimated by means of a non-survey approach, which one of the approaches is the most appropriate?

In the statistical studies of Chapters 2 and 3, we found answers to the above-mentioned questions, by acting as if the Chinese regional IO tables for 2002 had to be estimated. Systematic comparisons of the estimated tables and the actual tables provided insightful suggestions for practitioners involved in the construction of IO tables.

In Chapter 2, we studied and compared the estimation performance of various non-survey approaches, using provincial Chinese IO tables. We labeled the table to be constructed the ‘object table’, and the corresponding period and region were termed the ‘object year’ and ‘object region’, respectively. All methods assume that the row and column totals of intermediate deliveries and the sectoral gross outputs are available for the object table. Most often, these can be obtained from official regional statistical bureaus, which conduct Gross Regional Product (GRP) surveys. The accuracies of these row and column totals play a crucial role in the accuracy of estimates of the block of intermediate deliveries. In our experiments, we simply took the ‘true’ values of the totals as given.

Another important assumption is with respect to the availability of relevant survey-based IO tables. These tables provide quantitative descriptions of one or more intersectoral production structures that are supposed to be relatively similar to the structure in the object table. That is, one or more tables of the object region must be available for previous years in order to apply an intertemporal updating method. Similarly, a table—in the object year—of the nation to which the object region belongs is required to apply a regionalization method, and one or more tables—in the object year—of other regions are required to apply the method of the exchanging input coefficients. If tables are available for a set of other regions, a variety of
cross-regional methods can be applied. In real-world efforts to construct a regional IO table, the choice for a specific non-survey method is often driven by the availability of survey tables. In Chapter 2, we made use of the fact that the unique set of 27 regional IO tables for 1997 and 2002 allowed us to compare the empirical performance of all methods briefly described above in one integrated analysis.

The findings in this chapter can be summarized by some suggestions that might be relevant for practitioners who plan to compile a regional IO table. Firstly, the quality of cross-regional methods benefits from collecting as many tables of other regions as possible and taking full advantage of these. Accuracies increase when more observations are available, irrespective of the specific cross-regional method that is adopted. For the case of the Chinese provincial tables, cross-regional methods systematically outperformed the alternative estimation procedures if tables for at least eight other regions are available. It should be noted, however, that this conclusion appeared to be invalid for the two well-developed city-provinces Beijing and Shanghai. These two cities have very special economic structures and we found that regionalization of national tables led to better results than the application of any of the cross-regional methods. Hence, for regions that are known to be very different from most other regions, compilers (or practitioners) should consider adopting other approaches than cross-regional methods, if data availability permits.

Secondly, among the group of cross-regional methods, the averaging coefficients method and the robust regression method generally turn out to be slightly more accurate than the Ordinary Least Squares regression method and the threshold regression method. The relative accuracy of the robust regression method as compared to the averaging coefficients method is relatively weak if the number of available regional tables is small. In such cases, simple averaging method of input coefficients appears to be the preferred method.

It is not necessary that the object table corresponds to a region. For example, practitioners may want to compile an IO table for a city. In that case, they should try to collect tables of the city for previous years, or the table of the province to which the city belongs for the object year, or tables for similar cities for the object year. Similar suggestions apply to the case of compiling a table for a county, or a group of countries.
When only very few regional tables for the object year are available, the clear advantage of the cross-regional methods disappears. This suggests that one of the alternative, single-table methods should be chosen in this situation. Among the class of traditional single-table methods, exchanging coefficients from a similar region yields the worst estimates followed by intertemporal updating, while regionalization based on the national table performs the best in our systematic empirical comparisons. One should notice that the widely accepted intertemporal updating technique, which has been proved to work very well in developed countries, is not very suitable for the estimation of Chinese regional tables. Most probably, this result is due to the fact that many regional economies in China were very dynamic and underwent much more structural change than most regions in developed countries.

The analysis in Chapter 2 was based on the assumption that no survey-based information on the intermediate input part of the object table is available. When popular hybrid compilation methods are applied, such information is (made) available. Therefore, the collection of survey-based, superior data is another issue that deserves attention. In the literature, several methods have been proposed to select the cells of the object table for which superior data should be acquired. Some of these methods select a set of (unrelated) individual cells, while other methods select sets consisting of groups of cells, all of which are related to specific sectors (such as all cells in a specific row of the IO table, or in a specific column). In Chapter 3, we compared the performance of several methods of targeting cells for superior data collection.

The selection of cells with large input coefficients (LARGE) and so-called inverse important coefficients (INVIMP) were presented as two popular ‘individual cells’ methods. ‘Key sector’ methods have also been represented by two types of methods. One selects all cells in rows (ROWSUM) or columns (COLSUM) for which the respective Leontief multipliers are large, while the other selects all cells in rows or columns for which hypothetical extraction yields large effects on the region's gross output (ROWHYP and COLHYP, respectively). For the hypothetical extraction method, we also considered simultaneously selecting the entire row and column of the
sectors with the strongest effect (HYP). We evaluated these seven methods by simulating the updating of the regional intermediate deliveries matrices for each of 27 Chinese provinces in 2002, on the basis of the intermediate deliveries matrix for 1997 of the same region (i.e., we used the intertemporal updating method studied in Chapter 2, adding superior data). Data from the survey-based 2002 matrices have been used to mimic superior data, but the selection of cells was based on information contained in the 1997 tables. The gains in accuracy attained by inserting a given number of these “true” values are computed for each of the seven targeting methods, by comparing estimated matrices with the actual 2002 matrices. The findings in this chapter for the case of China yield two suggestions about superior data collection that might be relevant for practitioners in general.

First, higher budgets for superior data collection will always lead to better estimated tables, provided that the average costs of ‘revealing’ the true value of a cell are constant. The overall accuracies of estimated tables always improve, irrespective of which cells are inserted as additional information. It should be noted, however, that superior data can be collected from many sources, e.g. experts, a survey or publications on other studies. We did not consider differences in quality among such sources, since our superior data were perfect by construction.

Our second conclusion concerns the question which additional information on intermediate deliveries should be gathered once budgets have been determined. Among the group of “individual cells” approaches, the LARGE method invariably outperforms the more complicated INVIMP method, irrespective of whether accuracy is measured on the basis of the magnitude of intermediate deliveries, of input coefficients or of values of the Leontief inverse. This is somewhat surprising, since INVIMP targets the cells for which a small change in the cell value has the largest effect on the Leontief inverse. Among the class of ‘key sector’ approaches, the selection of the best method depends on the matrix that should be estimated with highest accuracy. For the estimation of the intermediate deliveries, the best estimation is obtained if superior data are collected for the columns that have been selected by
the hypothetical extraction method (COLHYP). In most applied IO work, in particular policy studies and impact analyses, the intermediate deliveries are of lesser interest. What matters most is the Leontief inverse, which is at the heart of any multiplier and impact analysis. In this case, adding superior data to cells in rows selected by the ROWSUM and ROWHYP methods (in this order) improves the accuracy more than any other method. For selecting entire rows, the simplest method (ROWSUM) thus performs best.

Our findings are based on the assumption that the number of cells (which are inserted as superior data) is identical, irrespective of the selection method. This does not imply that the associated costs of obtaining superior information are equal. Surveying a number of cells in the same sector is likely to be more cost-effective, when compared to surveying an identical number of individual cells belonging to different sectors. If we focus on the accuracy of the input coefficients matrix or the Leontief inverse, the reduction in the average error (computed as the weighted average percentage error) due to inserting superior data into \( p \) cells selected by means of LARGE is more or less the same as the reduction found with ROWSUM for \( 3p \) cells. Assuming that budgets for surveys are fixed, this implies that selecting the targeted cells by means of ROWSUM is preferred if LARGE is more than two times as expensive. Similar choices between costs vs. accuracy can be made between ROWSUM and HYP. Practitioners should make their own decisions by carefully considering the relative costs and accuracies of these methods.

When generalizing the conclusions towards estimation of IO tables for other countries, it should be borne in mind that our dataset of Chinese regional IO tables is rather specific in at least two respects. First, the intermediate inputs include both intraregionally produced and imported products. The associated input coefficients are thus technical coefficients rather than ‘regional input coefficients’, which are generally defined as intraregionally produced intermediate inputs divided by gross output levels. Therefore, our findings and suggestions for practitioners relating to the non-survey estimations in Chapter 2 should be restricted to estimating tables with
technical coefficients. If an IO table with regional input coefficients is to be estimated, cross-regional methods can still be used, but additional steps are necessary. Most importantly, the estimation of regional purchase coefficients is required in order to correct for regional differences in economic size. That is, large regions will purchase relatively much from domestic sources, while small regions will import relatively much.

Secondly, the Chinese economy as represented in the regional IO tables is very heterogeneous and dynamic. Some regions are very backward, while other regions (especially those in the coastal zone) are characterized by high levels of development. Regarding the relative performance of non-survey estimation methods, regionalization of national tables might perform much better for regions that are part of a country with less varied production structures. A similar argument holds for the bad estimation performance of intertemporal updating in Chapter 2. If IO tables are estimated for regions that do not develop as quickly as many Chinese regions, production structures as reflected in technical input coefficients are likely to be much more stable over time.

We feel that the results obtained in Chapter 3 are much less sensitive to the specificities of the Chinese database. Irrespective of the method to select cells for which superior data should be collected, intertemporal updating is the method used to estimate the cells for which superior data are not collected. The magnitude of the errors will generally be smaller for less dynamic regions than for dynamic regions, but we cannot think of reasons why the relative performance of targeting methods would systematically differ with the dynamism of the region considered.

2 Of course, other characteristics of regions can also play an important role in the determination of regional purchase coefficients. Examples of such characteristics are the presence or absence of natural resources and whether the region is an island or not.
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6.3 Summary of Economic Applications

The ultimate aim of compiling IO tables is to use them for analyzing the economy and/or its development. In the economic applications in this thesis, attention was paid to the disparities across China’s provinces. Regional labor productivity levels and their developments over time were studied in Chapter 4, while Chapter 5 dealt with specialization patterns for ICT production.

Chapter 4 analyzed the regional disparities in labor productivities and the changes therein from 1997 to 2002. The examination of the disparities in 1997 confirmed the observations in previous research (based on different data sources) that the regional labor productivity levels were well above the national average for provinces and cities in what we termed the “East Rim” of China (i.e. the provinces on the East coast, the three provinces in the North-east, and the cities Beijing, Shanghai and Tianjin). For the rest of China, labor productivities were essentially below the national average. The most important proximate causes of these regional differences turned out to be that regions with high (low) labor productivity levels were characterized by large (small) output per worker ratios and by large (small) employment shares in high-productivity sectors. The examination of the evolution of the regional disparities between 1997 and 2002 indicated that the “East Rim” showed a substantially higher labor productivity growth than the rest of China. The changes in sectoral employment shares were found to be the most important determinant. In all but one region, production has shifted towards sectors with higher productivity levels. We also observed that the effect of changing output per worker ratios was negative (i.e. lowered the labor productivity) for regions with a large effect of changing employment shares. A (somewhat speculative) explanation was sought in the massive migration from the Midwest to the Southern part of the “East Rim” plus Beijing. The inflow of many low-skilled workers into sectors with relatively high productivity levels tends to lower the average output per worker in the region but to substantially increase the employment share of high-productivity sectors.
Chapter 5 analyzes the proximate causes behind the strong geographical concentration of China’s ICT sector. The rapid growth of the ICT-producing sector in China has been accompanied by an uneven distribution of its production activities across the country. We found that the home market effect (producing close to customers) is not the main reason why the coastal provinces host relatively much ICT activity in comparison to Central and Western regions (although the home market effect is not negligible). Differences in exports of ICT products turn out to be the main determinant of the clustering. Apparently, transport costs do not play a major role, and firms seem to locate their activities in regions that offer advantages in terms of supply-side aspects (examples of which would be a large supply of high-skilled labor, geographically bounded knowledge spillovers or the proximity of seaports).

The findings in Chapters 4 and 5 are of potential interest to designers of regional policy with the aim to increase economic development, especially in the more backward regions. The message that we take from Chapter 4 is that for a backward region to improve labor productivity, it is of utmost importance to increase its output per worker levels. Policies that might achieve this involve investments in productive environments and infrastructure, and a stimulation of innovation and technology diffusion. As an additional effect, it would be helpful to promote that labor flows (especially within the own region) from low-productivity sectors like agriculture to high(er)-productivity industries in manufacturing and services.

The results in Chapter 5 provided a measurement of the proximate causes for spatial concentration of ICT activities in China. We argue that policy implications can be generated if the quantified proximate causes are coupled with studies of the ultimate causes that shape them. For example, the poor, Western province of Shaanxi exports remarkable amounts of ICT services (to other Chinese provinces and/or abroad). The ultimate causes can be of a different nature as has been extensively discussed in the economic geography literature. In the case of Shaanxi, the large pool of highly educated workers from its high-quality research centers and specialized
universities has been mentioned explicitly. If this is indeed the main cause of the success, Shaanxi is an example that might be copied by other underdeveloped regions.

The work on these economic applications also led to two methodological contributions. First, in order to arrive at the results described above, we adapted the shift-share model (in Chapter 4) and the structural decomposition model (in Chapter 5). Although the models that we used were different, our adaptations shared one common aspect. That is, both chapters contain new methodologies to conduct multilateral comparisons with more than two determinants. In general, for a set of \( K \) regions, \( K(K-1) \) bilateral comparisons are needed to compare any pair of regions. If a transitive methodology can be applied, only \( K-1 \) bilateral comparisons suffice to provide full information for the entire set of \( K \) regions. Neither the traditional shift-share model nor the structural decomposition model maintains this property. To produce transitive multilateral indexes from linking together intransitive bilateral indexes, it has been argued that all methods have an underlying ‘spanning tree’. In general, there are \( K^{K-2} \) different spanning trees, each with \( K-1 \) bilateral edges that link the full set of \( K \) regions and produce transitive multilateral comparisons. Chapter 4 employs a specific form (the so-called star spanning tree) in which the national average is treated as the center to produce transitive multilateral comparisons. The idea is to take the national average as the fixed point of reference and perform \( K \) bilateral comparisons between each region’s labor productivity level and the national average. Comparing the comparison of region \( A \) with the national average to the comparison of region \( B \) with the national average then gives to comparison of regions \( A \) and \( B \). Chapter 5 employs another form (the so-called Minimum Spanning Tree) to chain the regions. It is well-known that the decompositions in Chapter 5 are not unique. An ‘overall decomposition spread’ is defined that measures the variability of the outcomes for each bilateral comparison. Next the chain of \( K \) regions is selected that minimizes the sum of spreads. The problem due to the non-uniqueness of the decompositions is minimized and the results are transitive.
The second methodological contribution was with respect to data processing. In order to analyze the changes in labor productivities from 1997 to 2002, data in constant prices were required. Given the limited availability of such data, a new estimation procedure has been proposed in Chapter 4. The information that was available covered the price indices for the value added of sectors at the national level (i.e. summed over the regions) and of regions at the aggregate level (i.e. summed over the sectors). What was required for the analysis was the value added in constant prices of sector $i$ in region $k$. We proposed to use the geometric average of the results obtained from two separate estimates, each obtained from applying the well-known RAS updating method.

### 6.4 Opportunities for Future Research

The research as reported in this thesis has led to a number of new insights, with respect to both methodological issues and empirical aspects. Examples in the first category are the introduction (in Chapter 2) of certain econometric techniques—such as robust regression and threshold regression—that were novel in the literature on estimating non-survey IO tables, and the introduction (in Chapter 5) of the minimum spanning tree for multilateral structural decompositions. Examples in the second category are related to the question whether individual cells or entire sectors are to be surveyed when collecting superior data (in Chapter 3), or to finding the underlying reasons for the disparities in regional labor productivity levels (in Chapter 4) or the regional concentration of the ICT manufacturing and ICT services sectors (in Chapter 5).

Despite these new insights, many problems have been willfully neglected—given the focus of the thesis—and are, therefore, still unsolved and open for future research. One good example is related to the fact that in the Chinese regional tables intermediate inputs are defined so as to include both intraregionally produced and imported goods and services. Because the intra-regional intermediate inputs are not singled out, the Chinese regional IO tables yield “regional technical coefficients.”
(which measure the total amount of input of good \(i\)—no matter whether it is produced within the region, in another region, or abroad—per unit of output in sector \(j\) in the region). For several types of studies, however, the regional input coefficients (which measure the input of good \(i\) produced within the region per unit of output in sector \(j\) in the region) are required. This means that the imported products should be removed from intermediate inputs in the current IO tables, so that they better reflect the intra-regional purchases and sales patterns. Another example is related to the use of the cross-regional methods of Chapter 2 for other cases. It should be borne in mind that the methods that work well in developed countries may not be suitable for a fast developing economy like China (and vice versa). Replications of our analysis for Chinese regions on other datasets might shed more light on the extent to which our conclusions are valid for regions in less heterogeneous and dynamic countries. The scarcity of databases that are comparable in terms of numbers of regions included and similarity of sector classifications poses problems in this respect. Given the increasing availability of databases of IO tables for large sets of countries, it might be possible to test whether the methods in Chapter 2 are also valid in an international context. And, if so, they might be applied to estimate IO tables for countries with incomplete information.

Other examples concern economic applications of the Chinese regional IO tables. Chinese economic growth has been miraculous, the economy being ten times larger than it was 30 years ago and continuing to grow at a rate of approximately 10% annually. This development is unprecedented in economic history and therefore raises many questions. For example, what exactly happened in China during the past three decades and why does the growth miracle continue? The survey-based regional IO tables cover both a temporal and a spatial dimension, and describe the production and consumption patterns in the economy at a very detailed sectoral level. As such, they

\[^3\] Examples of such databases are the one compiled by the OECD (http://www.oecd.org/sti/inputoutput) or within the WIOD project led by the University of Groningen (http://www.wiod.org). If the WIOD project is finished, for example, one could act as if the European Union is a single country and consider the member states (or a subset of these) as regions, to see to what extent the results would be similar for a somewhat less heterogeneous and dynamic set of regions.
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provide a very useful and valuable tool for approaching economic questions. In this thesis, we have only carried out some preliminary attempts at using the dataset. A lot of opportunities are still open for future work, studying the dynamics and strengths of the economy. Examples are with respect to inter-provincial trade patterns, geographical concentration, intra-regional industrial clusters, the upgrading of Chinese regions in global value chains.

Next to these applications that focus particularly on describing and explaining the past, traditional regional impact and scenario analyses would focus on the economic consequences of the things to happen. Despite the unprecedented growth in the past, there are clear signs that also China might be facing bad weather in the not too distant future. An issue that was discussed in this thesis—albeit from a descriptive and explanatory perspective—was the regional inequality. Other issues that are expected to become relevant or even pressing are: the growing costs of labor and land, which may cause China to lose its comparative advantage (often due to assembly activities) in the global manufacturing chain; the upcoming problems due to the demographic time bomb, which was caused by the one-child policy; the serious shortage of energy and resources (on a per capita basis) due to the increase in welfare of a very large population. All of these issues may contribute to a slowdown in China’s growth rate and eventually may lead to a series of social, economic and environmental problems. By combining the regional IO tables with satellite accounts (e.g. for energy use and emissions, or labor by skill type) and other complimentary data (e.g. for land use) and methods, many general issues and problems in social, economic and environmental fields might be tackled.