SinoTERM365, Bottom-up Representation of China at the Prefectural Level

CoPS Working Paper No. G-285, October 2018

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ISSN 1 031 9034

ISBN 978-1-921654-94-7

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The TERM methodology requires relatively modest data requirements to create a multi-regional, sub-national CGE database. SinoTERM365 is an extreme form of stretching available data, with the master database representing 162 sectors in 365 prefectural regions of the Chinese economy. A collaborative effort is envisaged among users to enable ongoing improvements to the database. The TERM approach facilitates rapid amendments to the database when improved data are available. The alternative, to wait until better data emerge before building a model, may result in less detail and a less versatile framework for analysis. In our example, we consider a downturn in use of coal and coal-generated electricity in China.

JEL codes: C68, D58, R13, R15

Keywords: sub-national general equilibrium modeling; regional structural change; greenhouse gas abatement.

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1. Introduction

China's economy provides a clear example of why sub-national detail is important in a CGE model. Not only are the populations of some provinces in excess of most countries in the world. The composition of the population is changing rapidly. The rural population is shrinking but remains large enough to be important on a global scale. Between 1980 and 2018, China's population grew from 977 million to 1394 million, or 43 percent. This unremarkable statistic, given that global population grew by more than 70 percent in the same period, does not reveal the massive migration of workers from rural areas to cities. This has resulted in growth in some cities within a generation or two that is difficult to comprehend. In 1980, Shenzhen was a settlement of 58,000 surrounded by marshes, located over the border from Hong Kong. Over the next 20 years, Shenzhen transformed into a city of 7 million people. It has continued growing, reaching 11 million by 2018. Shenzhen's neighboring city along the Pearl River delta, Dongguan, grew from 137,000 in 1980 to 7 million in 2018. In the corresponding period, the better known Pearl River delta city of Guangzhou grew from 1.9 million to 14.2 million. These are the biggest three cities/prefectures in Guangdong, a province with a population of a large nation and a GDP which now exceeds that of the Netherlands (International Monetary Fund, World Economic Outlook Database, April 2016 edition). In total, the province contains 21 prefectures, each with a population exceeding 1.5 million. In addition to the abovementioned cities, there are five others within the province with a population exceeding 5 million. Overall, Guangdong has a land area of around 177 thousand square kilometers, equivalent to the combined U.S. states of New York, New Jersey, Massachusetts and Connecticut but with almost 3 times the combined population of these four densely populated states.

Elsewhere in China, cities that were medium sized in 1980 have transformed into mega-cities. Beijing's population grew from 5.4 million to almost 23 million now. In the same period, neighboring Tianjin grew from 3.7 million to 22.2 million, and Shanghai from 6.0 million to 25.8 million. Stunning growth has spread from cities adjacent to the eastern seaboard. The cities of Chongqing and Chengdu, deep inland along the Yangtze, have experienced four- to five-fold population growth in the same time (all population data in this section are from http://population.city). Guiyang, capital of Guizhou, usually listed as the poorest province in China, had the most rapidly growing economy of any Chinese city in 2016. Substantial road and rail building is underway in Guizhou, and an international airport is now operational, so that tourism infrastructure is being transformed. Guiyang is being reinvented as a high-tech hub as the costs of living and doing business in eastern seaboard cities soar (Roxburgh 2017).

Some effects of urban change follow from the population growth. Compounding population pressures, rising incomes have resulted in rising per capita household spending. We can perceive China's economic growth as both a miracle that has lifted hundreds of millions of people out of poverty and as an extreme strain on natural resources and infrastructure. In three decades from 1980, private car ownership increased 35-fold in per capita terms (Huang 2011). Frenzied road construction may not alleviate congestion in the face of rapid growth in private car use. Rising consumptions is also changing dietary habits: China now accounts for one quarter of global meat consumption (Myers 2016). An increase in demand for land and water follows from an increase in demand for meat. Yet the burgeoning cities are encroaching on farmland, so that high-rise buildings and other urban developments are displacing farm activity.

From the perspective of the rest of the world, China's economic growth has buoyed global markets for mineral and agricultural products. Chinese investors have pursued land acquisitions in foreign nations as one way of coping with worsening land and water scarcity at home in the face of rising demand for food. China has changed the global economic structure, accelerating the shrinkage of manufacturing in developed nations at the same time as fueling a tourism boom as an increasing number of cashed-up Chinese citizens explore the world. The GTAP model (Hertel 1997; Corong *et al*., 2017) is an invaluable tool for analyzing the impacts that China is having on the rest of world. Our interest in the present study is to outline a model for analyzing sub-national impacts within China.

1.1 Analyzing regional economic issues in China

The rise of manufactures in China in the early stages of market liberalization affected mainly eastern seaboard cities. Rapid industrialization proceeded with consequent worsening water and air pollution. With rising incomes in cities has come rising costs and changing lifestyles. The demands of citizens change as incomes increase, including the demand for a cleaner environment. Worsening pollution has led to closure of heavy industries near some cities, in particular Beijing. In any case, rising wages in eastern seaboard cities have led to a movement of manufactures into second-string cities where lower wages have provided a comparative advantage. Massive investments in rail and road infrastructure have improved transport links between relatively poor inland cities and the eastern seaboard, thereby contributing to improved competitiveness in such cities.

Worsening water pollution is part of the broader issue of water allocation. Lifestyle changes arising from growing incomes have resulted in rapidly growing urban water demand. In common with the most of the rest of the world, China has been reluctant to introduce market mechanisms to assist in water allocation. In the medium term, increased demand for water has accelerated groundwater extractions. Much of China's response has been through grand engineering schemes, notably the South-to-North-Water-Diversion Project, which has brought water to water-scarce cities including Beijing. There have been losers from the water diversion project, notably the 330,000 people relocated from the surrounds of Danjiangkou Reservoir in Shiyan prefecture, Hubei, in expansion of the reservoir arising from the project. Local officials have described Danjiangkou city as the "saddest city in China" accorded to China Daily (Wu Yan, 2014). In addition to the relocation of inhabitants, many local industries important in regional economic were closed down so as to reduce pollution of the water supply arising from mining and manufacturing activities (Probe International, 2016).

Within provinces, some prefectures have boomed as others have lagged. Shenzhen, Zhuhai and Shantou within Guangdong were designated as "Special Economic Zones" in 1979 to attract foreign investment (Fan, 1995). This resulted in these regions of China being the first to experience accelerated growth: Shenzhen's population has grown 190-fold since 1980, compared with a 40-fold increase in Zhuhai and 10-fold increase in Shantou. Growth in prefectures outside the Pearl River delta in Guangdong was relatively slow in the earlier years of economic reform. More recently, investments in transport infrastructure such as the Jieyang airport (So, 2008) have contributed to tourism growth in lagging regions of Guangdong.

A multi-regional CGE model based on prefectures rather than provinces has the potential to capture some of the starkest contrasts between winners and losers in modelling scenarios. Differences in industry composition are larger at the prefectural than provincial level. For example, several prefectures in Xinjiang, Heilongjiang, Qinghai and Hainan have agricultural income as a share of total income exceeding 40 percent, whereas at the provincial level, only one province, Xinjiang (25 percent), has a corresponding share exceeding 20 percent. Agricultural output grew by around 5% per annum from the 1980s to 2007 (Wang *et al*., 2013), slower than the rest of the economy: World Bank data indicate average annual real GDP growth of 10% per annum between 1980 and 2007. This indicates that provinces and prefectures in which agriculture had accounted for a large share of total income are likely to grow relatively slowly. Agriculture has to cope with worsening water and land scarcity, given the growing demands of urban areas. Moreover, agriculture in some regions has suffered from climate change. So while many cities boom, prefectures in which agriculture remains important are vulnerable to stagnation or decline, unless various adaptations are undertaken so that productivity gains offset worsening input scarcity.

This paper presents details of SinoTERM365, a multi-regional model in the TERM suite of sub-national models (Horridge *et al.*, 2005). The master database of the model contains 162 sectors and 365 bottom-up prefecture-based regions. The model has more sectors than the input-output table published by China's National Bureau of Statistics, with agriculture split into different types of crops and livestock. In addition, the electricity sector has been split into different types of generation, with a separate sector for transmission and distribution.

Section 2 of the paper outlines the TERM approach to sub-national, multi-regional CGE modeling. The theory of TERM is detailed in Section 3. A summary of previous TERM-based models and studies follows in Section 4. Section 5 details the regional impacts of a downturn in coal use in China. Section 6 concludes the paper with a discussion of potential applications of SinoTERM365, including the inclusion of biophysical accounts at a sub-national level.

2. The TERM approach

The TERM (The Enormous Regional Model) methodology circumvents two limitations that in the past have hindered sub-national multi-regional model development. The first is that as the number of sectors and regions increase, simulations may be slow. The second is that regional data may be scarce.

We deal with the first problem of slow simulations through two broad strategies, which are in common with the GTAP approach. First, several multi-dimensional database matrices are partitioned into two smaller matrices. As in

GTAP, the intermediate and final use matrices (a single matrix in the TERM format) include the regional user but not the regional origin. The trade matrices include the regional origin and regional destination but not the user. The small cost that comes with the common sourcing assumption is that the use matrices added up over users must equal the trade matrices summed across regional origins. The separation of full data dimensions into two matrices is an important distinction between TERM and Australia's VURM (Adams et al. 2011), and between GTAP (Hertel ,1997; Corong *et al*., 2017) and its predecessor SALTER (Jomini, *et al*. 1994).

To illustrate the saving of using two matrices instead, consider a model in which there are 20 commodities, 20 industries, 4 final users and 20 sub-national regions plus imports. We assign a domestic and imported subscript to each origin so as to identify international port activity within the model. A use matrix identifying commodities (20), origins (20 x 2, i.e., domestic/imported), destinations (20), intermediate (20) plus final users (4) would contain 384,000 cells (=20x20x2x20x24). If we partition the data into a USE matrix excluding regional origins (20 commodities, 2 domestic\imported origins, 20 destinations and 24 users), with 19,200 cells and a TRADE matrix excluding users (20 commodities, 20 x 2 origins, 20 destinations) with 16,000 cells, the two matrices sum to 9.2% the size of a matrix that includes all relevant dimensions. The market clearing identity that enforces the two matrices to be equal will contain 800 cells (=20 commodities x 2 sources x 20 destinations) and therefore comes with only a small additional computational cost. Horridge (2011) provides more explanation of the structure of TERM and its sourcing mechanisms. Section 3 elaborates the equations including additional market-clearing equations required to implement the common sourcing assumption in TERM (see equations (53) to (55)).

In practice, a second strategy, that of aggregating sectors and regions of little or no interest in a scenario while maintaining detail in sectors and regions of interest, aids in rapid computational times. GTAP users took advantage of the common sourcing assumption and aggregation prior to the development of TERM.

The strategy to deal with scarce sub-national regional data is to keep the data requirements modest while using a reproducible sequence of problems, into which we can alter inputs readily as improved data emerge. The ORANI model (Dixon *et al*., 1982) represented over 100 sectors, and introduced large-scale computable general equilibrium modelling in 1977. The ORANI model included "top-down" sub-national regional representation, based on regional activity shares. "Top-down" regional representation uses these regional shares, with a distinction between local and national industries, to estimate regional impacts based on national industry outcomes. Regions do not have their own labor markets, industry-level production functions or inter-regional trade matrices, as is the case in "bottom-up" representation, such as in TERM. The minimal data requirements for constructing a TERM database are little more than those for a "top-down" multi-regional version of ORANI. Indeed, the standard procedure for preparing a TERM assumes that a working "top-down" database has already been prepared and used for simulations.

In the past, practitioners have often cited two constraints to regional modelling: these concern (1) the limited availability of regional IO tables, and (2) an absence of inter-regional trade detail.

In the case of China, IO tables are available for 30 regions (that is, all provinces [+4 municipalities] excluding Tibet). However, with one or two exceptions, notably Henan, the tables lack sectoral detail. Typically, agriculture, mining and manufacturing are each represented by little more than a single sector. Are these tables useful for control totals? To be useful, regional tables should sum to activities represented in the national table. The authors' checks on China's provincial tables indicate that they often do not sum reasonably to totals in the national table. This is not surprising, given that regional statistical bureaus prepare regional tables, with apparent limited harmonization between bureaus. But even with improved harmonization, a problem would remain, in that available regional IO tables do not take advantage of a great deal of regional data present in other sources. The TERM methodology is to make use of all available relevant data in preparing a multi-regional CGE database, and to allow for the possibility that as better data emerge, modelers can utilize it quickly in revising a CGE database. Section 2.4 details the data sources used in preparation of a disaggregated multi-regional CGE database.

Since sub-national regions do not have customs post, any inter-regional trade data are likely to be patchy. Indeed, Wittwer (2017b) appraised the suitability of U.S. Commodity Flow Survey (CFS) data as an input to a CGE database. While these sample data contained considerable detail concerning inter-regional trade, they were far from comprehensive. They were confined to sectors that covered only 15% of GDP. The data concentrated on bulky goods: mining products excluding oil and gas accounted for more than half of the recorded weight in the survey but less than 4% of the value of recorded trades, and account for only 0.3% of U.S. GDP. Moreover, the data were often incompatible with the trade flows in a CGE database, which concerns product origins and destinations. The CFS data often recorded movements to and from transport nodes, that is, intermediate points rather than origins or final destinations. In the U.S. context, recorded movements may consist of transferring merchandise between different types of vessels along the Mississippi Valley. Wittwer (2017b) concluded that CFS data, invaluable though they may be in analysis of transport logistics, do not supersede the gravity method (outlined in Section 2.5) of allocating inter-regional trades in a regional CGE model.

Before providing more details on the TERM approach, from its inception we intended to apply this framework to a variety of countries. That is, the standard version of TERM avoids mechanisms that might be specific to a particular country or application, by retaining relative simplicity. Rather the emphasis is on allowing a basic multi-regional model to produce simulation results as soon as possible. Very often, analysis of results reveals shortcomings of the model or data, or suggests priorities for improvement. To arrive quickly at this stage is key to the quality of the final model. Section 4 lists the countries for which versions of TERM exist at present.

2.1 Comparison with the GTAP model

GTAP (Hertel, 1997; Corong *et al*., 2017) has a fairly similar structure to TERM. The "regions" of GTAP, however, are countries or groups of countries, whilst in TERM they are regions within a single country. In GTAP, regional trade deficits must sum to zero [the planet is a closed system] whilst in TERM a national trade deficit is possible. There are also differences in data structures: GTAP has a far more detailed representation of bilateral trade taxes than does TERM, reflecting the freer trade that is usually possible within a nation. TERM can accommodate commodity tax rates that vary between regions (North might tax wine more than South) but it does not allow for regional tax discrimination (such as a tax, in North, that applied only to wine from West). Inter-regional labor movements, a rarity in GTAP, are usual in TERM. Finally, TERM has a more detailed treatment of transport margins. While GTAP identifies how much each country contributes to *world* shipping supply, the TERM data structure shows how much each region contributes to supply of transport between all separate pairs of source and destination regions. Domestic margins are now being included in GTAP (Corong, 2018).

2.2 The TERM data strategy

TERM offers a strategy in stark contrast that of practitioners who believe that both regional IO tables and some inter-regional trade are necessary to devise a multi-regional CGE database. We have estimated the SinoTERM365 database from very limited regional data, even scarcer than the data typically used by TERM practitioners. Here we outline the strategy, while Section 2.4 outlines data sources.

The process starts with a national IO table and certain regional data. The *minimum* requirements for regional data are very modest: the distribution between regions of industry outputs and of final demand aggregates. This distribution is based on a set of regional shares, which may in turn be calculated from value data, or on physical units (eg, tons of wheat) or on numbers employed. This flexibility (regarding units) greatly increases the amount of data that may be used. Additional regional detail, such as disaggregated sectoral shares from census data (which improve the quality of sectoral share estimates) or international trade by port, can be added when available.

The process is automated, so that additional detail can easily be added at a later stage. The database is constructed at the highest possible level of detail: 162 sectors and 365 regions in the case of SinoTERM365. Aggregation (for computational and presentational tractability) takes place at the end of the process, not at the beginning. Perhaps surprisingly, the high level of disaggregation is often helpful in estimating missing data. When aggregated, the model database displays a richness of structure that belies the simple mechanical rules that were used to construct its disaggregated parent. For example, even though we normally assume that a given disaggregated sector has the same IO coefficients wherever it is located, aggregated sectors display regional differences in technology. Thus, sectoral detail partly compensates for missing regional data.

Our technique of combining a national IO table with limited regional data to produce a detailed inter-regional table bears many similarities to methods developed over several decades by regional IO modellers. Indeed, published regional IO tables may well be in part constructed rather than observed. Unfortunately, the method of construction may be poorly documented or unrepeatable. Aspiring regional model developers may download the TERM data programs customize them to suit particular needs. They will appeal to the modeler who would prefer to construct a multi-regional database using known assumptions, rather than rely on data constructed somehow by others.

Published regional IO tables may well form part of the inputs to the TERM data process. But they should certainly not constrain the degree of regional or sectoral detail that we aim for.

2.3 Preparation of national database

Regional IO tables usually depict fewer sectors than corresponding national tables, reflecting data accuracy concerns at the sub-national level. The TERM approach differs from this, in that a typical first step is to disaggregate the national table into more sectors. The reason for doing so is that regional data are often available for sectors with more detail than in the national IO table. Beijing's National Bureau of Statistics appears to have followed international convention in providing limited detail on agriculture in the national IO table, a convention that the GTAP creators from the beginning wisely chose not to follow. The official Chinese IO table includes a single crops sector, a single livestock sector and another sector covering services to agriculture. We know that climate, water availability and types of crop vary widely across China. Moreover, even with rapid structural change, around 25% of China's workforce (equal to 5% of the global workforce) is still employed in agriculture. Given that land and water availability is a major policy issue, we split the single crop sector from the available IO table into 14 and the single livestock sector into three. The meat sector is split into two to separate pork from other meat types. Within small regions, we may not know the share of national agricultural activity. But available data may provide good estimates of a region's share of the 14 crops we have chosen to represent. Similarly, herd numbers and other statistics are available for various types of livestock.

A key assumption in the TERM methodology is that an identical technology or input cost structure is imposed on a given industry in all regions. For this assumption not to be burdensome, we undertake sectoral disaggregation at the national level beyond agriculture when it is obvious that technologies vary between regions. For example, hydroelectric generation dominates Sichuan's electricity generation, whereas coal-fired generation dominates Shanxi's generation. In preparing SinoTERM365's database, we split electricity generation in the national database into seven different types of generation. To assume that coal generated electricity in Shanxi has the same technology as in Sichuan is defensible, whereas assuming that a single electricity generating sector in Shanxi has the same technology as Sichuan is not.

2.4 Estimates of the regional distribution of output and final demands

The first version of SinoTERM (Horridge and Wittwer, 2008; Wittwer and Horridge, 2009) represented the 27 provinces and 4 municipalities of China separately. But the populations of a number of Chinese provinces are so large that this remains a relatively coarse level of regional representation. Guangdong, for example, with 102 million inhabitants has a larger population than all but 13 countries. Shandong's population of 95 million is similar to Vietnam's. Third ranked province Henan, with 92 million, comfortably exceeds the population of Germany (82 million), the world's 16th most populous nation (from http://population.city).

Provincial populations are a strong motivation for seeking disaggregation of China's economy to the prefectural level. The prefecture-based regions in SinoTERM365 range in population from 74,000 in Haibei, Qinghai, to 24 million in Shanghai. The mean population of these 365 regions is 3.7 million and the median 3.1 million. This compares with an average population of 43.2 million (exceeded at a national level in only 32 other countries)[1] and a median population of 37.3 for the 31 province-based regions. The prefectural representation, while stretching available data, uses regions with populations closer in magnitude to those of sub-national regions in other TERM-based models.

The idea for a prefectural level SinoTERM arose from a short course held in Beijing in July 2017. A number of participants expressed a desire to build their own database. CoPS made the database generation programs publicly available over a decade ago (see https://www.copsmodels.com/archivep.htm#tpmh0067). The authors thought it preferable to devise a large master database with the objective of providing access to a community of users in China. In this respect, the approach has been inspired by that of the GTAP community. We anticipate that a better database will emerge from a collaboration between different users involved in research on the Chinese economy than if each group builds their own database. Another advantage of this approach is that provision of a basic model will free up research resources for scenarios and CGE analysis. In addition, a basic highly disaggregated database will reduce the effort required to add model extensions such as greenhouse gas, energy or water accounts to a model. This does not mean that developers will preserve all sectoral detail as they add satellites. Rather, it is more likely that the core database will have good coverage of key sectors for particular accounts. For example, a model with greenhouse gas accounts may require some detailed representation of electricity generation, various types of metal production, livestock production and cement production. The developer may choose to aggregate sectors in which greenhouse gas accounts are less important.

As discussed in Section 2.3, the TERM approach is first to disaggregate the national IO table/CGE database. The regional shares required for each sector for devising SinoTERM are production shares of national activities, investment shares (set equal to production shares), household consumption shares, export shares, government spending shares and import shares. We examine data sources for production shares first. The primary source for regional data is Chinadataonline.org (China Data Center, University of Michigan), accessed via the National Library of Australia. In particular, the site provides access to provincial statistical yearbooks.

One of the strengths of the statistical yearbooks produced within the provinces and municipalities of China is that output for a number of crops and livestock products is usually available at the prefectural level. This provides ready data for the desirable split of agriculture. The crops sector is split into rice, wheat, corn,

[1] https://en.wikipedia.org/wiki/List_of_countries_by_population_(United_Nations)

other cereals, soybeans, tubers, other vegetables, cotton, sugarcane, tea, apples/pears, citrus, grapes and other crops. Livestock is split from the original single sector to pigs, sheep/goats and other livestock. Given that China accounts for one quarter of global meat consumption, we also split the downstream meat sector into pork and other meat.

A key weakness relative to the Australian TERM (Wittwer and Horridge, 2010) and USAGE-TERM (Wittwer 2017a) databases is that census data are not highly disaggregated in the sectoral dimension. This means that such data are less specific in estimating regional activities in manufacturing and services sectors than is so for US and Australian census data. The available broad industry census employment numbers for China provide some measure of prefecture-level economic activity. At worst, this means that broad sector outputs (outside of agriculture, for which data are sufficient) are split between the disaggregated sectors of the national database in identical proportions across all prefectures in a given province. In addition, available census data in a number of provinces are only for 2005.

Clearly, relatively recent employment data are preferable to 2005 census data. The 2005 data were used to estimate prefectural shares in Hebei, Inner Mongolia, Jiangsu, Zhejiang, Fujian, Jiangxi, Guangxi, Sichuan, Guizhou, Shaanxi, Qinghai and Ningxia. Employment data for prefectures by national accounts level (19 sectors) were available for either 2013 or 2014 in Liaoning, Anhui, Shandong, Henan, Hainan, Yunnan, Tibet and Gansu. The yearbooks of Jilin, Heilongjiang, and Hunan include 2014 national accounts (GDP) data for 17 broad sectors. Guangdong's 2005 employment census data are supplemented by 2014 GDP data for 9 broad sectors. Regions other than Hubei with limited data include Chongqing (divided into five main regions) and Xinjiang.

For some commodities, we were able to improve on yearbook data. For example, the Liaoning province yearbooks includes employment for a single manufactures sector. An online search indicates that within Liaoning, only Dalian and Shenyang produce motor vehicles, so activities for this sector in other prefectures within the province are set to zero. Prefectural level data are also available for meat products. But in remaining manufactures, the broad manufacturing employment shares provide the sub-provincial split.

Various online sources, including carma.org, provided electricity generation data at the prefectural level. As is evident in Section 5, our initial data sources were deficient, in particular in representing coal-generated electricity output across the prefecture of Shaanxi. We anticipate, as we and other users work with the database, that we will identify and redress various weakness within the database.

Table 1. Summary of prefecture-level data quality

	No. of regions	Agriculture, food processing	Manufacturing	Employment or national accounts data (19 sectors)
Beijing[a]	1	Good	Na	Na
Tianjin[a]	1	Good	Na	Na
Hebei	11	Good	--	2005 census
Shanxi	11	Good	Some	No
InnrMongolia	12	Good	Some heavy industry data	2005 census
Liaoning	14	Good	--	2013
Jilin	9	Good	--	nat ac 17 sectors
Heilongjiang	15	Good	--	nat ac 17 sectors
Shanghai[a]	1	Good	Na	Na
Jiangsu	13	Limited	Very detailed	2005 census
Zhejiang	12	Good	--	2005 census
Anhui	16	Good	--	2013
Fujian	9	Limited	--	2005 census
Jiangxi	11	Good	Moderately	2005 census
Shandong	17	Good	--	2014
Henan	18	Good	Moderately	2014
Hubei	17	Good	--	Broad sector (5)
Hunan	14	Fair	--	nat ac 17 sectors
Guangdong	21	Good	--	2005 census + 2014
Guangxi	14	Fair	--	2005 census
Hainan	18	Fair	Moderately	2014
Chongqing	5	Fair	--	Broad sector (5)
Sichuan	21	Fair	--	2005 census
Guizhou	9	Fair	--	2005 census
Yunnan	16	Good	--	2014
Tibet	7	Good	--	2014
Shaanxi	11	Good	--	2005 census
Gansu	14	Good	--	2014
Qinghai	8	Good	--	2005 census
Ningxia	5	Good	--	2005 census
Xinjiang	14	Good	--	6 broad sectors

a Coverage at 31 region level
nat ac = national accounts
Na = not applicable

Table 1 summarizes data quality. Two neighboring provinces, Henan and Hubei, account respectively for the best and poorest data. Good data for agriculture are accompanied by moderately detailed data for manufacturing and 19 sector employment data for 2014 in Henan. In the case of Hubei, good data are available only for agriculture. Beyond agriculture, the only available data at the prefecture level gleaned from the province's yearbooks are national accounts data for four broad non-agricultural sectors.

Regional household and government spending shares are based on expenditure-side macro accounts from the provincial statistical yearbooks. We assume that the commodity composition of household spending is the same across all regions. More specific data would enable us to alter these shares, based on differences that may arise, for example, from climatic differences across regions.[2]

Another obvious weakness in the initial provincial-level database generated is that international trade activities in the database are calculated from available information on port activities rather than customs data. As with the first version of TERM for Australia (Horridge *et al.*, 2005), we expect initial international trade by port estimates to be superseded by actual customs data.

In summary, there are two broad approaches to maintaining and improving the regional database. The first is that collaboration with model users will improve our access to actual data, in particular for international merchandise trade. The second is that the TERM suite of programs, referenced earlier in this section, enables us to generate a new database rapidly as better data emerge.

2.5 The TRADE matrix

The next stage is to construct a TRADE matrix. For each commodity either domestic or imported, TRADE contains a 365x365 submatrix, where rows correspond to region of origin and columns correspond to region of use. Diagonal elements show production that is locally consumed. We already know from regional shares used to split the national database both the row totals (supply by commodity and region) and the column totals (demand by commodity and region) of these submatrices. We use the gravity formula (trade volumes follow an inverse power of distance) to construct trade matrices consistent with pre-determined row and column totals. In defence of this procedure, note that wherever production (or, more rarely, consumption) of a particular commodity is concentrated in one or a few regions, the gravity hypothesis is called upon to do very little work. Because our sectoral classification is so detailed, this situation occurs more frequently than with a relatively aggregated sectoral dimension.

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[2] The Australian Bureau of Statistics produces the Household Expenditure Survey (HES), which provides disaggregated estimates at the state level for capital and rest-of-state regions. However, HES items do not align well with commodities in Australian CGE models. The U.S. Department of Labor produces household expenditure data for four regions, with a similar commodity alignment issue. Consequently, in the past we have usually chosen to assume the same household spending commodity composition across all regions.

The usual TERM gravity formula, as described in Horridge (2011) is:

$$\frac{V_{r,d}}{V_{\bullet,d}} \propto \frac{\sqrt{V_{r,\bullet}}}{D_{r,d}^{k}} \qquad r \neq d \qquad (1)$$

where
$V_{r,d}$ = value of flow from origin r to destination d
$V_{r,\bullet}$ = production in r
$V_{\bullet,d}$ = demand in d
$D_{r,d}$ = distance from r to d
where K is a commodity-specific parameter valued between 0.5 and 2, with higher values for commodities not readily tradable.

Diagonal cells of the trade matrices are set according to:

$\frac{V_{d,d}}{V_{d,\bullet}}$ = locally-supplied demand in d as share of local production

$$= \min\left\{\frac{V_{d,\bullet}}{V_{\bullet,d}},1\right\}F \qquad (2)$$

where F is a commodity-specific parameter valued between 0.5 and 1, with a value close to 1 if the commodity is not readily tradable.
The initial estimates of V(r,d) are then scaled (using a RAS procedure) so that:
$\Sigma_r V(r,d) = V(\bullet,d)$ and $\Sigma_d V(r,d) = V(r,\bullet)$.
Transport costs as a share of trade flows are set to increase with distance:
$T(r,d)/V(r,d) \propto \sqrt{D(r,d)}$

where T(r,d) corresponds is a matrix or margins on the TRADE matrix (TRADMAR in Section 3, Table 11). Again, the constant of proportionality is chosen to satisfy constraints derived from the initial national IO table.

All these estimates are made with the fully-disaggregated database. In many cases, zero trade flows can be known *a priori*. For example, tea is grown in a limited number of prefectures in which the climate is suitable. At a maximum sectoral disaggregation, the load born by gravity assumptions is minimized.

2.6 Aggregation

Even though TERM is computationally efficient, the master database of 162 sectors and 365 regions is far too large for simulations. The next stage in the data procedure is to aggregate the data to a more manageable size. This stage is automated and effortless. The aggregation choice is application-specific. Our aggregation example is that of the simulation presented in section 5. This concerns a switch away from coal use in industries and in electricity generation. The sectoral aggregation preserves the coal mining sector, coal-generated electricity, hydro-electric generation and electricity distribution from the master database, while aggregating other sectors. There are 21 sectors in the aggregation.

In the regional dimension, three prefectures in which coal accounts for a large share of regional GDP are represented individually. These are Erdos (Inner Mongolia), Shuoxhou (Shanxi) and Huaibei (Anhui). In each case, a regional composite covers the rest of the province. A 7th region is Shaanxi, in which coal accounts for a significant share of provincial GDP, and an 8th region the rest of China. The 365 regions of the master database are aggregated to 8 regions (Figure 1).

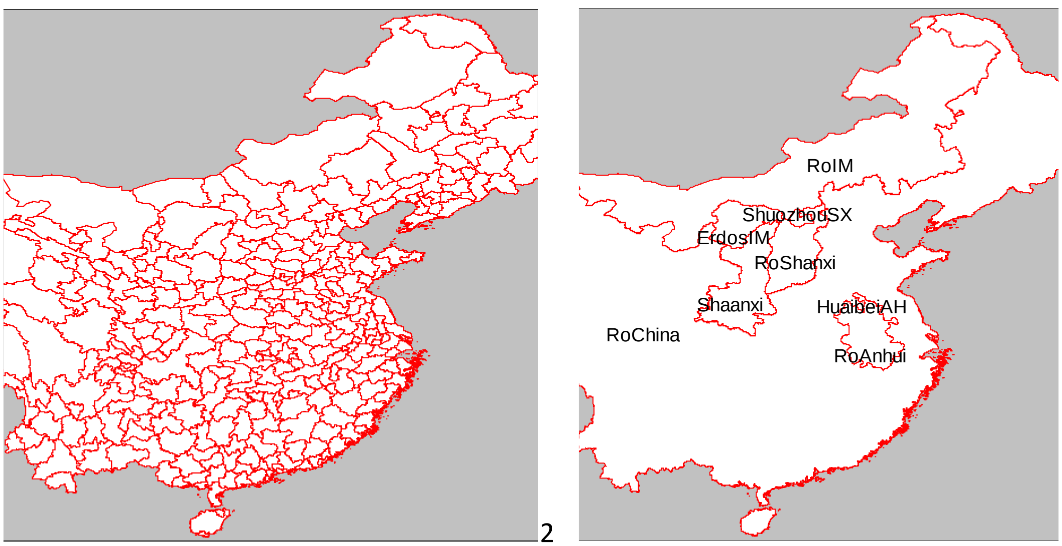

Figure 1. Aggregating from master database to policy simulation regions

3. The equations of TERM

This section elaborates the core theory of the TERM suite of models. The format of this section is to present the levels version of each block of equations. The model is implemented using GEMPACK software (Harrison *et al.*, 2014). TABLO coding of the model's equations follows each block. Within GEMPACK, most equations are presented in a linearized form. Multi-step solution methods (Dixon et al., 1982, chapter 5) enable the modeler to combine the accuracy of the levels form with the relative simplicity and computational speed of linearized equations.

3.1 Production

Each industry uses a combination of intermediate and primary inputs to produce a unit of output. Producer decisions consist of a sequence of CES decisions, with a composite good entering the next stage. Figure 2 shows the production structure.

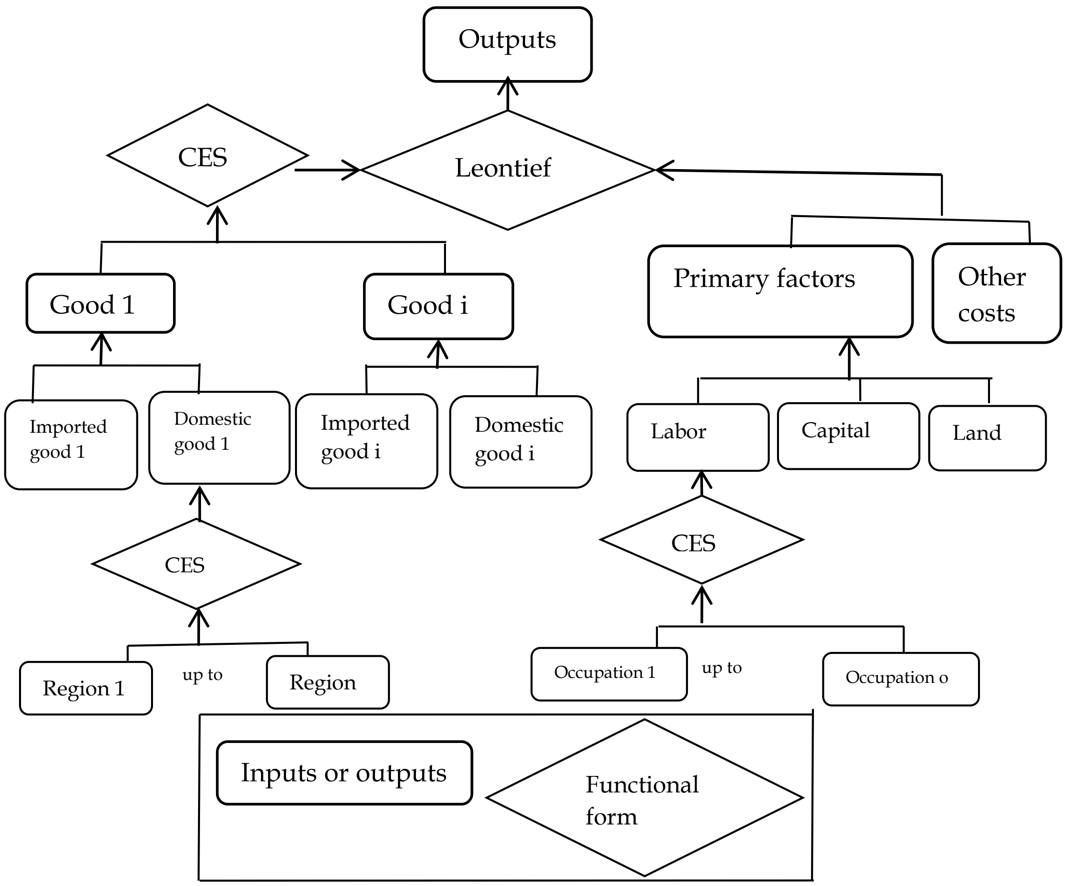

Figure 2. Production structure

Users of commodities minimize costs subject to CES substitutability:

$$X^{cs}_{ud} = f(X1^{c}_{ud}, CES[P^{cs}_{ud} / P1^{c}_{ud}]) \qquad (3)$$

$$P1^{c}_{ud}.X1^{c}_{ud} = \sum_{s} X^{cs}_{ud}.P^{cs}_{ud} \qquad (4)$$

X^{cs}_{ud} is the quantity demand of commodity c from (domestic composite or imported) source s by user u in region d. Users include industries plus final users (households, investors, exporters and government). P^{cs}_{ud} is the corresponding price, and $X1_{ud}^{c}$ and $P1_{ud}^{c}$ the respective domestic-import composite quantities and prices.

Throughout the TABLO notation in this section, the index c refers to commodities (COM), s to domestic or imported source (SRC), d to destination (DST), u to users (USR) and i to industry (IND $\in$ USR).

Table 2. Definitions of variables, values and parameters in intermediate and final usage

Variables	
xint(c,s,i,d)	Source-specific (dom./imp.) intermediate demands
xint_s(c,i,d)	Source-composite intermediate demands
xhou(c,s,d)	Source-specific (dom./imp.) household demands
xhou_s(c,d)	Source-composite household demands
xinv(c,s,d)	Source-specific (dom./imp.) investment demands
xinv_s(c,d)	Source-composite investment demands
ppur(c,s,i,d)	Source-specific (dom./imp.) tax-inclusive com. price for user
ppur_s(c,i,d)	Source-composite tax-inclusive commodity price for user
puse(c,s,u,d)	Source-specific (dom./imp.) commodity price for user
tuser(c,s,u,d)	Powers of commodity taxes
pint(i,d)	Intermediate effective price indices
pinvest(c,d)	Purchaser's price for investment
phou(c,s,d)	Household price
aint_s(c,i,d)	Intermediate tech change
Values, shares and parameters	
PUR_S(c,i,d)	Purchasers' values summed over sources
PUR_CS(i,d)	Purchasers' expenditure summed over commodities
SIGMADOMIMP(c)	CES parameter, domestic v. import sources

Listing 1 shows the percentage change quantity equations concerning equation (3) in TABLO format.[3] The indexes "hou" and "inv" refer to the household and investment elements of the user set.

Listing 1. Intermediate and final usage (partial TABLO coding)

```
xint(c,s,i,d)      = xint_s(c,i,d) -
SIGMADOMIMP(c)*[ppur(c,s,i,d)-ppur_s(c,i,d)];                        (T3a)

xhou(c,s,d) = xhou_s(c,d) -
SIGMADOMIMP(c)*[ppur(c,s,"hou",d)-phou(c,d)];                        (T3b)
```

[3] Note that the TABLO equation numbering follows that of previous equations in text: i.e., (T5) corresponds with (5).

```
xinv(c,s,d) = xinv_s(c,d) -
SIGMADOMIMP(c)*[ppur(c,s,"inv",d)-pinvest(c,d)];                    (T3c)
ppur(c,s,u,d) = puse(c,s,d) + tuser(c,s,u,d);                       (T4a)

PUR_CS(i,d))*pint(i,d)=
sum{c,COM,PUR_S(c,i,d)*[ppur_s(c,i,d)+aint_s(c,i,d)]};              (T4b)

pinvest(c,d) = ppur_s(c,"Inv",d);                                   (T4c)
phou(c,d) = ppur_s(c,"hou",d);                                      (T4d)
```

3.2 Commodity sourcing at the sub-national level

Users in a given region source from sub-national regions in common proportions, so that the user subscript is dropped from the equation for sub-national CES substitution:

$$XT_{rd}^{cs} = f\,(XT1_d^{cs}, CES[PD_{rd}^{cs} / PU_d^{cs}] \tag{5}$$

$$PU_{sd}^{c}.XT1_d^{cs} = \sum_r XT_{rd}^{cs}.PD_{rd}^{cs} \tag{6}$$

The total demand for all users of commodity *c*, domestic or import source *s*, from sub-national origin *r* to destination *d* is XT_{rd}^{cs}. Sub-national source composite demands are denoted by $XT1_d^{cs}$ and user prices by PU_{sd}^{c}. TERM substitutability possibilities involve two stages, between a domestic composite and imports, and between sub-national sources to form the domestic composite.

Table 3. Definitions of variables, values and parameters in trade

Variables	
xtrad_r(c,s,d)	Total demand for regional composite
xtrad(c,s,r,d)	Quantity of good dom/imp commodity delivered from origin r to destination d
pdelivrd(c,s,r,d)	All-user delivered price of good c
Values and parameters	
DELIVRD(c,s,r,d)	Trade plus margins = delivered values
DELIVRD_R(c,s,d)	Demand in region d for delivered goods summed over origins
SIGMADOMDOM(c)	CES parameter for substitution between origins

Listing 2. Inter-regional trade (partial TABLO coding)

```
xtrad(c,s,r,d) = xtrad_r(c,s,d)
SIGMADOMDOM(c)*[pdelivrd(c,s,r,d)-puse(c,s,d)];                    (T5)

DELIVRD_R(c,s,d))*puse(c,s,d) =
sum{r,ORG,DELIVRD(c,s,r,d)*pdelivrd(c,s,r,d)};                     (T6)
```

Table 4. Definitions of variables, values and parameters in primary factor demands

Variables	
xlab(i,o,d)	Labour demands, occupation specific
plab(i,o,d)	Wage rates, occupation specific
xcap(i,d)	Capital usage
xlnd(i,d)	Land usage
pcap(i,d)	Rental price of capital
plnd(i,d)	Rental price of land
plab_o(i,d)	Price of labour composite
xlab_o(i,d)	Effective labour input
wlab_o(i,d)	Wage bills
alab_o(i,d)	Labor-augmenting technical change
acap(i,d)	Capital-augmenting technical change
alnd(i,d)	Land-augmenting technical change
xprim(i,d)	Primary factor composite
pprim(i,d)	Effective price of primary factor composite
Values and parameters	
LAB(i,o,d)	Wage matrix
CAP(i,d)	Rentals to capital
LND(i,d)	Rentals to land
LAB_O(i,d)	Total labour bill in industry i
PRIM(i,d)	Total factor input to industry i
SIGMAPRIM(i)	CES parameter, primary factors

Next, we outline cost minimizing behaviour in primary factor demands by industry users. The occupation *o* mix of labour follows a CES form:

$$L_{id}^{o} = f(L1_{id}, CES[W_{id}^{o} / W1_{id}]) \tag{7}$$

$$W1_{id}.L1_{id} = \sum_{o} L_{id}^{o}.W_{id}^{o} \tag{8}$$

Occupation-specific labor demands are L_{id}^{o} and labour composite demands $L1_{id}$, with the corresponding wages being W_{id}^{o} and $W1_{id}$.

$$L1_{id} = f(F_{id}, CES[W1_{id} / PF_{id}]) \tag{9}$$

$$LND_{id} = f(F_{id}, CES(RLND_{id} / PF_{id}]) \tag{10}$$

$$K_{id} = f(F_{id}, CES(R_{id} / PF_{id}]) \tag{11}$$

$$PF_{id}.F_{id} = LND_{id}.RLND_{id} + L1_{id}.W1_{id} + K_{id}.R_{id} \tag{12}$$

Equations (9) to (12) show primary factor demands for the labour composite $L1_{id}$, capital K_{id} and land LND_{id} subject to a composite factor demand F_{id} by industry i in region d. The factor prices are $W1_{id}$ for composite labour, R_{id} for capital rentals, $RLND_{id}$ for land rentals and PF_{id} for composite prices.

Listing 3. Primary factor demands (partial TABLO coding)

```
xlab(i,o,d) = xlab_o(i,d) –
 SIGMALAB(i)*[plab(i,o,d) - plab_o(i,d)];                              (T5)

LAB_O(i,d))*wlab_o(i,d) =
 sum{o,OCC,LAB(i,o,d)*[plab(i,o,d)+xlab(i,o,d)]};                      (T6a)

LAB_O(i,d))*plab_o(i,d)=sum{o,OCC, LAB(i,o,d)*plab(i,o,d)};            (T6b)

xlab_o(i,d) - alab_o(i,d) =xprim(i,d) -
SIGMAPRIM(i)*[plab_o(i,d) + alab_o(i,d) - pprim(i,d)];                 (T7)

xlnd(i,d) - alnd(i,d) = xprim(i,d) -
SIGMAPRIM(i)*[plnd(i,d) + alnd(i,d) - pprim(i,d)];                     (T8)

xcap(i,d) - acap(i,d) = xprim(i,d) -
SIGMAPRIM(i)*[pcap(i,d) + acap(i,d) - pprim(i,d)];                     (T11)

PRIM(i,d))*pprim(i,d) = LAB_O(i,d)*[plab_o(i,d) + alab_o(i,d)]
+ CAP(i,d)*[pcap(i,d) + acap(i,d)]
+ LND(i,d)*[plnd(i,d) + alnd(i,d)];                                    (T12)
```

The composite factor demand F_{id} is proportional to total output Q_{id} subject to a primary-factor using technology A_{id}.

$$F_{id} = Q_{id}.A_{id} \tag{13}$$

The demand $X1^{c}_{id}$ is related to output Q_{id} by a CES relationship between the composite price $P1^{c}_{id}$ and the price composite of all intermediate goods $P11_{id}$ via a CES function.

$$X1^{c}_{id} = f(Q_{id}, CES[P1^{c}_{id} / P11_{id}]) \tag{14}$$

$$P11_{id}.X11_{id} = \sum_{c} P^{c}_{id}.X1^{c}_{id} \tag{15}$$

The zero pure profit condition is that total revenue, valued at the output price net of production taxes, PC_{id}, multiplied by Q_{id} equals the total production cost.

$$PC_{id}.Q_{id} = \sum_{c} P^{c}_{id}.X1^{c}_{id} + \sum_{o} W^{o}_{id}.L^{o}_{id} + R_{id}.K_{id} + RLND_{id}.LND_{id} \tag{16}$$

Table 5. Definitions of variables and parameters in composite factor demands

Variables	
xtot(i,d)	Industry outputs
atot(i,d)	All-input-augmenting technical change
aint_s(c,i,d)	Intermediate tech change
delPTX(i,d)	Ordinary change in production tax revenue
pcst(i,d)	Ex-tax cost of production
ptot(i,d)	Industry output prices
delPTXRATE(i,d)	Change in rate of production tax
Values and parameters	
SRCSHR(c,s,u,d)	Imp/dom shares
VCST(i,d)	Total cost of industry i
PRODTAX(i,d)	Taxes on production

Next, we introduce production taxes to industry costs. Production tax revenue, $VPTX_{id}$, is calculated as the tax rate $RPTX_{id}$ multiplied by the value of output. The industry output price $PTOT_{id}$ is inclusive of production taxes.

$$VPTX_{id} = RPTX_{id}.PC_{id}.Q_{id} \tag{17}$$

$$PTOT_{id}.Q_{id} = PC_{id}.[1+RPTX_{id}].Q_{id} \tag{18}$$

Listing 4. Composite factor demands (partial TABLO coding)

```
xprim(i,d) = xtot(i,d)+atot(i,d)+aprim(i,d);                          (T13)
xint_s(c,i,d) = atot(i,d) + aint_s(c,i,d) + xtot(i,d)
   -0.15*{ppur_s(c,i,d) + aint_s(c,i,d) - pint(i,d)};                 (T14)
ppur_s(c,u,d)=sum{s,SRC,SRCSHR(c,s,u,d)*ppur(c,s,u,d)};               (T15)
VCST(i,d))*[pcst(i,d)-atot(i,d)] =
   PRIM(i,d)*[aprim(i,d)+pprim(i,d)] + PUR_CS(i,d)*pint(i,d);         (T16)
delPTX(i,d) =0.01*PRODTAX(i,d)*[xtot(i,d)+pcst(i,d)] +
   VCST(i,d)*delPTXRATE(i,d);                                         (T17)
VTOT(i,d))*[ptot(i,d)+xtot(i,d)]=
   VCST(i,d)*[pcst(i,d)+ xtot(i,d)] + 100*delPTX(i,d);                (T18)
```

In applications of the model in which industries have multi-product capability, supplies of commodity c by industry i in region d (MQ_{cid}) follow a CET relationship between industry output prices and the average commodity price $PDOM_{cd}$, which is the basic domestic price (see (50)).

$$MQ_{cid} = f(Q_{id}, CET(PDOM_{cd} / PTOT_{id}]) \tag{19}$$

$$PTOT_{id}Q_{id} = \sum_{c} PDOM_{cd}.MQ_{cid} \tag{20}$$

We assume that the supply of imports is infinitely elastic. Hence, the price of imports, PM_{cd}, depends on foreign import prices, PFM_{cd} and the nominal exchange rate ϕ.

$$PM_{cd} = PFM_{cd}.\phi \tag{21}$$

Table 6. Definitions of variables and parameters in industry supplies

Variables	
xmake(c,i,d)	Output of good c by industry i in d
pmake(c,i,d)	Price received by industries
pdom(c,r)	Output prices = basic prices of domestic goods
xcom(c,d)	Total output of commodities
Values and parameters	
phi	Exchange rate, local currency/$world
pimp(c,r)	Import prices, local currency
pfimp(c,r)	Import prices, foreign currency
SIGMAOUT(i)	Constant elasticity of transformation parameter

The TABLO coding for multi-product industries is:

Listing 5. Industry supplies (partial TABLO coding)

```
xmake(c,i,d)=xtot(i,d)+SIGMAOUT(i)*[pmake(c,i,d) ptot(i,d)];          (T19)
pmake(c,i,d)=pdom(c,d)-0.05*[xmake(c,i,d)-xcom(c,d)];                 (T20)
pimp(c,r) = pfimp(c,r) + phi;                                         (T21)
```

3.3 Household demands

The linear expenditure system (LES) is based on a utility function (U) which splits household spending on each commodity ($XHOU_c$) into two, a subsistence component $XSUB_c$ that depends only on the number of households (N) and preferences, and a luxury component, $XLUX_c$, which depends on prices and income in a Cobb-Douglas form. β_c is the marginal budget (i.e., aggregate spending minus aggregate subsistence spending) share of commodity c. Regional and household dimensions are omitted from equations (22) to (33).

$$U = \frac{1}{N}\prod_c (XHOU_c - XSUB_c)^{\beta_c} \tag{22}$$

Aggregate spending ($WHOU$) is of the form:

$$WHOU = \sum_c P3_c XHOU_c = \sum_c P3_c XSUB_c + [WHOU - \sum_c P3_c XSUB_c] \tag{23}$$

From this, we obtain the linear expenditure function, where $P3_c$ is the price faced by household consumers of commodity c:

$$P3_c XHOU_c = P3_c XSUB_c + \beta_c [WHOU - \sum_d P3_d XSUB_d] \tag{24}$$

Aggregate subsistence expenditure *WSUB* is given by:

$$WSUB = \sum_c P3_c.XSUB_c \qquad (25)$$

The Frisch "parameter" is the (negative) ratio of total expenditure to luxury expenditure:

$$Frisch = -WHOU/[WHOU - WSUB] \qquad (26)$$

The ORANI school (Dixon et al., 1982) typically assigns a Frisch "parameter" of -1.82 to a model for a relatively high income nation.

Differentiating equation (24) with respect to *WHOU*, and multiplying by $WHOU/[XHOU_c.P3_c]$, we calculate the expenditure elasticity EPS_c. This is equal to the marginal budget share divided by the budget share ($SHOU_c=P3_c.XHOU_c/WHOU$) for each commodity:

$$EPS_c = \beta_c.WHOU/[P3_c.XHOU_c] \qquad (27)$$

$BLUX_c$ is the ratio of luxury expenditure to total expenditure on each commodity, given by:

$$BLUX_c = \beta_c[WHOU - WSUB]/[P3_c.XHOU_c] \qquad (28)$$

Substituting equations (26) and (27) into equation (28):

$$BLUX_c = -EPS_c/Frisch \qquad (29)$$

Next, we calculate the matrix of price elasticities implied by LES. By differentiating equation (24) with respect to $P3_d$ [i.e., $dXHOU_c/dP3_d = -\beta_c XSUB_d/P3_c$], we calculate the off-diagonal elements of the price elasticity matrix (η_{cd}):

$$dXHOU_c/dP3_d\,.[P3_d/XHOU_c] =$$
$$-\beta_c.(WHOU)(P3_d XSUB_d)/(WHOU.P3_c).[P3_d/XHOU_c] \qquad (30)$$

$$\eta_{cd} = \beta_c(1-BLUX_d).SHOU_d/SHOU_c \qquad (31)$$

We obtain the diagonal elements by dividing equation (24) by $P3_c$ and differentiating with respect to $P3_c$:

$$dXHOU_c/dP3_c.[P3_c/XHOU_c] = -\beta_c WHOU/[P3_c.XHOU_c] +$$
$$\Sigma\beta_c(WHOU)P3_d.XSUB_d/[(WHOU.P3_c).[P3_c.XHOU_c] \qquad (32)$$

Substituting equations (27) and (31) into equation (32), we obtain:

$$\eta_{cc} = -EPS_c - \sum_{d \neq c} \eta_{cd} \tag{33}$$

LES does not allow for specific substitutability. Where appropriate, specific substitutes could form a CES nest, with the CES composite commodity entering LES within the model. In addition, LES does not allow for goods with negative income elasticities.

SinoTERM365 includes provision for multiple households in each bottom-up region. At present, there is only one household in the database in each region. Individual households are denoted by *h*.

Table 7. Definitions of variables and shares in the household demand system

Variables	
xhouh_s(c,d,h)	Household demands
wlux(d,h)	Total nominal supernumerary household expenditure
xhouhtot(d,h)	Total real household consumption
whouhtot(d,h)	Total nominal household consumption
phouhtot(d,h)	CPI
nhouh(d,h)	Number of households
xlux(c,d,h)	Household - supernumerary demands
xsub(c,d,h)	Household - subsistence demands
alux(c,d,h)	Taste change, supernumerary demands
asub(c,d,h)	Taste change, subsistence demands
ahou_s(c,d,h)	Taste change,household imp/dom compsite
Values and shares	
BLUX(c,d,h)	Luxury share of expenditure on commodity c
BUDGSHR(c,d,h)	Budget share
SLUX(c,d,h)	Marginal budget share

Rather than include the general household demand equation in the model with the elasticities implied by equations (31) and (33), the LES in SinoTERM365 is coded as shown in Listing 5.

Listing 6. Household demand system (partial TABLO coding)

```
xlux(c,d,h) + phou(c,d) = wlux(d,h) + alux(c,d,h);              (T24a)
xhouh_s(c,d,h)=BLUX(c,d,h)*xlux(c,d,h)+[1-BLUX(c,d,h)]*xsub(c,d,h)(T24b)
alux(c,d,h) = asub(c,d,h) - sum{k,COM, SLUX(k,d,h)*asub(k,d,h)}; (T24d)
asub(c,d,h)=ahou_s(c,d,h)-sum{k,COM,BUDGSHR(k,d,h)*ahou_s(k,d,h)};(T24e)
xsub(c,d,h) = nhouh(d,h) + asub(c,d,h);                         (T25)
xhouhtot(d,h)= sum{c,COM,BUDGSHR(c,d,h)*xhouh_s(c,d,h)};
phouhtot(d,h)= sum{c,COM,BUDGSHR(c,d,h)*phou(c,d)};
whouhtot(d,h)= phouhtot(d,h) + xhouhtot(d,h);
```

A formula within the TABLO code calculates the share term $BLUX_c$ from equation (29) and $SLUX_c$ based on equation (25). The Frisch "parameter" and expenditure elasticities are updated as the subsistence share of consumption changes. The usual practice has been to assign $XSUB_c$ as fixed. In modeling relatively local changes, this is not an issue. But in dynamic modeling, particularly when dealing with rapid income growth as in the case of the Chinese economy, growing aggregate consumption results in $XSUB_c$ shrinking as a share of total consumption of each commodity. This implies that the LES system tends towards Cobb-Douglas as the economy grows over time. If this is unsatisfactory in a particular scenario, the modeler may choose to increase per capita subsistence consumption over time. This is justifiable on the basis that yesterday's luxuries are today's necessities. An alternative functional form to LES that copes better with growth in consumption over time is the AIDADS form, which also allows inferior goods (Rimmer and Powell 1996).

To accommodate changes in per capita subsistence quantities, we may add to SinoTERM365 an equation defining the percentage change in the Frisch "parameter", *wfrisch*:

```
wfrisch(d,h) = whoutot(d,h)-wlux(d,h);                              (T26)
```

A subsistence taste shifter *asub_c* is added to the following:

```
xsub(c,d,h) = nhou(d,h) + asub(c,d,h) + asub_c(d,h);                (T24f)
alux(c,d,h) =asub(c,d,h) -asub_c(d,h)
-sum{k,COM, SLUX(k,d)*[asub(k,d,h)-asub_c(d,h)]};                   (T24g)
```

In order to target a given shift in subsistence expenditures, the variable *wfrisch* is made exogenous by swapping with *asub_c*.[4]

3.4 Investment demands

In the ORANI school, the commodity composition of investment varies between industries. The amount of good c demanded by investment industry i in region d, $X2_{id}^{c}$, is proportional to the industry investment quantity, $X2TOT_{id}$, for a given investment technology $A2_{id}^{c}$. $P2_{cd}$ is the commodity-specific investment price.

$$X2_{id}^{c} = A2_{id}^{c}.X2TOT_{id} \tag{34}$$

[4] In a dynamic simulation of an earlier SinoTERM version developed by the authors, aggregate consumption per capita grew by more than 785 percent between 2006 and 2030. In the forecast baseline, shocks to *wfrisch* were set equal to minus 15 percent of the growth in aggregate consumption. Starting with an absolute Frisch ratio of 2.5 in 2007, the ratio had moved in each region of the model to around 1.75 by 2030 (see http://www.copsmodels.com/archivep.htm item TPGW0169).

$$P2_{cd}.X2_{cd} = P1^{c}_{Inv,d}.X1^{c}_{Inv,d} \qquad \text{Inv} \in \text{User (35)}$$

$$PI2_{id}.X2TOT_{id} = \sum_{c} X2^{c}_{id}.P1^{c}_{Inv,d} \qquad \text{Inv} \in \text{User (36)}$$

$$GR_{id} = R_{id} \,/\, PI2_{id} \qquad (37)$$

Equation (34) calculates an industry investment price index. Equation (35) defines the gross rate of return (GR_{id}) as the ratio of the capital rental to the price of new capital (i.e., the industry investment price index).

$$IKRAT_{id} = X2TOT_{id} \,/\, K_{id} \qquad (38)$$

$$IKRAT_{id} = f[(GR_{id})^{2} \,/\, Islack]^{0.33} \qquad (39)$$

Equation (36) defines the investment-to-capital ratio ($IKRAT_{id}$). Typical, the gross rate of return is exogenous in long-run simulations, with capital stocks (K_{id}) endogenous – and the converse in the short run. *Islack* is exogenous except when the simulation is accommodating a macro investment target. Equation (37) follows the ORANI investment rule (Dixon *et al*. 1982). In dynamic applications of TERM, the equations defining capital growth are replaced by a dynamic accumulation equation linking present capital, past capital net of depreciation and past investment (see Dixon and Rimmer, 2002, section 21).

Table 8: Definitions of variables and shares in investment demands

Variables	
xinvitot(i,d)	Investment by industry
pinvitot(i,d)	Investment price index by industry
gret(i,d)	Gross rate of return = Rental/[Price of new capital]
ggro(i,d)	Gross growth rate of capital = Investment/capital
finv1(i,d)	Investment shift variable
invslack	Investment slack variable for exogenizing national investment
fgret(i,d)	Shifter to lock together industry rates of return
capslack	Slack variable to allow fixing aggregate capital
Values	
INVEST_I(c,d)	Investment by commodity and region
INVEST_C(i,d)	Investment by industry and region

Listing 7. Investment demands (partial TABLO coding)

```
xinvi(c,i,d) = xinvitot(i,d);                                        (T34)
INVEST_I(c,d)*xinv_s(c,d)=    sum{i,IND,INVEST(c,i,d)*xinvi(c,i,d)}; (T35)
INVEST_C(i,d)*pinvitot(i,d)= sum{c,COM,INVEST(c,i,d)*pinvest(c,d)}; (T36)
gret(i,d)= pcap(i,d) - pinvitot(i,d);                                (T37a)
gret(i,d) = fgret(i,d) + capslack;                                  (T37b)
ggro(i,d)= xinvitot(i,d) - xcap(i,d);                               (T38)
ggro(i,d)=finv1(i,d)+0.33*[2.0*gret(i,d)-invslack];                 (T39)
```

3.5 Other final demands

Government demands XG_{cd} are independent of prices and proportional to three corresponding shifters. They shift the demand function with different dimensions: by d as FG_c, by c and d, as FGS_{cd} and by c, s, and d, as $FGOV_{csd}$.

$$XG_{cd} = FG_c . FGS_{cd} . FGOV_{csd} \tag{40}$$

Export demands follow a two-stage process. First, regional source-specific exports $X4_{cd}$ form a CES composite $X4NAT_c$:

$$X4_{cd} = f(X4NAT_c, CES[P4_{cd} / P4NAT_c]) \tag{41}$$

$$P4_{cd} = P1^{c}_{Exp,d} \qquad \text{Exp} \in \text{User} \tag{42}$$

$$P4NAT_c . X4NAT_c = \sum_d X4_{cd} . P4_{cd} \tag{43}$$

Next, national exports are linked to international demands. $FP4NAT_c$ and $FQ4_c$ are demand shifters, and γ the export demand elasticity.

$$X4NAT_c = (P4NAT_c / FP4NAT_c)^{-\gamma} FQ4_c \tag{44}$$

Inventories XST_{id} are proportional to $XTOT_{id}$ multiplied by a shifter, FST_{id}.

$$XST_{id} = Q_{id} . FST_{id} \tag{45}$$

Table 9: Definitions of variables and parameters in other final demands

Variables	
ppur_exp(c)	Export price
xpur_exp(c)	National export volume
natfqexp(c)	Export quantity shift variable
natfpexp(c)	Export price shift variable
natfpexp_c	Macro shifter
xexp(c,s,d)	Export of all-region composite leaving port
xgov(c,s,d)	Government demands
fgov(c,s,d)	Government demand shifter
fgov_s(c,d)	Government demand shifter
fgovtot(d)	Government demand shifter
xgov_s(c,d)	Government demands, dom+imp
xstocks(i,d)	Inventories
Values and parameters	
TRADE_D(c,s,r)	TRADE matrix summed across destinations
TRADE_R(c,s,d)	TRADE matrix summed across origins
TRADE_RD(c,s)	TRADE matrix summed across origins and
TRADE_RDimp(c	Imported part of TRADE_RD
EXP_ELAST(c)	Export demand elasticity
PUR(c,s,u,d)	Purchasers' prices

Listing 8. Other final demands (partial TABLO coding)

```
xgov(c,s,d) =  fgovtot(d) + fgov(c,s,d) + fgov_s(c,d);            (T40a)
xgov_s(c,d) = sum{s,SRC, SRCSHR(c,s,"Gov",d)*xgov(c,s,d)};        (T40b)
xexp(c,"dom",d)=xpur_exp(c)-5*[ppur(c,"dom","Exp",d)-
ppur_exp(c)]+ttradEXP(c,d);                                       (T41)
ppur_exp(c)=Sum{d,Dst,PUR(c,"dom","exp",d)*[ppur(c,"dom","Exp",d)] (T43)
xpur_exp(c) - natfqexp(c) =   -EXP_ELAST(c)*
[ppur_exp(c)- phi - natfpexp(c) - natfpexp_c];                    (T44)
xstocks(i,d) = xtot(i,d);                                         (T45)
```

3.6 Margins

TERM separates the market for margins from the market for commodities being delivered by margins *m* (Dixon *et al.*, 1982). Demands for margins XTM_{rd}^{csm} are proportional to commodity demands XT_{rd}^{cs} subject to a margins-using technology ATM_{rd}^{csm} (equation (46)).

$$XTM_{rd}^{csm} = ATM_{rd}^{csm}.XT_{rd}^{cs} \tag{46}$$

In equation (47), $PBAS_r^{cs}$ is the basic commodity price and PM_{rd}^{m} the margins' prices. PU_d^{cs} is the margins-inclusive, tax-exclusive source-composite delivered price that appears in equation (3.4).

$$PD_{rd}^{cs}.XT_{rd}^{cs} = PBAS_r^{cs}.XT_{rd}^{cs} + \sum_m PM_{rd}^{m}.XTM_{rd}^{csm} \tag{47}$$

$$PMR_{rd}^{m}.XMR_{rd}^{m} = \sum_p XMP_{rd}^{pm}.PDOM_r^{m} \tag{48}$$

$$XMP_{rd}^{pm} = f(XMR_{rd}^{m}, CES[PDOM_r^{m} / PMR_{rd}^{m}]) \tag{49}$$

$$PBAS_d^{c,dom} = PDOM_{cd} \tag{50}$$

$$PBAS_d^{c,imp} = PIMP_{cd} \tag{51}$$

A third context is introduced for sub-national regions in equation (46). In addition to regional origins *r* and destinations *d* for good and services, regions *p* also produce margins. A shipping company that moves goods from origin in Chongqing to a destination in Shanghai may be based in Wuhan (i.e., the margins producing region). The Wuhan company competes with shipping companies from other regions through CES substitution between regional providers *p* of margins in equation (49). PMR_{rd}^{m} is the price of margins summed across providers *p*. XMP_{rd}^{mp} is the level of margins provided by *p* to move goods from region *r* to *d* and XMR_{rd}^{m} the provider composite.

Table 10 contains the definition of variables, values and shares concerning margins, followed by the TABLO coding.

Table 10. Definitions of variables, shares and parameters in margins

Variables	
xtradmar(c,s,m,r,d)	Margin m on good c,s going from r to d
atradmar(c,s,m,r,d)	Tech change: margin m on good c,s going from r to d
atradmar_cs(m,r,d)	Tech change: margin m on goods going from r to d
asuppmar(m,r,d,p)	Tech change, Margin m supplied by p on goods passing from r to d
xsuppmar(m,r,d,p)	Demand for margin m (made in p) on goods from r to d
xsuppmar_d(m,r,p)	Total margins on goods from r, produced in p
pdelivrd(c,s,r,d)	All-user delivered price of good c,s from r to d
psuppmar_p(m,r,d)	Price of composite margin m on goods from r to d
xsuppmar_p(m,r,d)	Quantity of composite margin m on goods from r to d
xsuppmar_rd(m,p)	Total demand for margins produced in p
pbasic(c,s,r)	Basic prices
Values, shares and parameters	
BASSHR(c,s,r,d)	Share of basic value in all-user delivered price
MARSHR(c,s,m,r,d)	Share of margin m in all-user delivered price
DELIVRD_R(c,s,d)	Demand in region d for delivered goods from all regions
SUPPMAR_P(m,r,d)	Total demand for margin m on goods from r to d
SUPPMAR_D(m,r,p)	Total demand for margin m (from p) on goods from r
SUPPMAR(m,r,d,p)	Margins supplied by p on goods passing from r to d
SIGMAMAR(m)	Substitution elasticity between margin origins

Listing 9. Margins (partial TABLO coding)

```
xtradmar(c,s,m,r,d)=xtrad(c,s,r,d)+atradmar(c,s,m,r,d);         (T46)
pdelivrd(c,s,r,d) = BASSHR(c,s,r,d)*pbasic(c,s,r)  + sum{m,MAR,
MARSHR(c,s,m,r,d)*[psuppmar_p(m,r,d)+atradmar(c,s,m,r,d)]};      (T47)
SUPPMAR_P(m,r,d)*psuppmar_p(m,r,d) =
sum{p,PRD, SUPPMAR(m,r,d,p)*[pdom(m,p)+asuppmar(m,r,d,p)]};      (T48)
xsuppmar(m,r,d,p) = xsuppmar_p(m,r,d) + asuppmar(m,r,d,p)
-SIGMAMAR(m)*[pdom(m,p)+asuppmar(m,r,d,p)-psuppmar_p(m,r,d)];    (T49)
pbasic(c,"dom",r) = pdom(c,r);                                   (T50)
pbasic(c,"imp",r) = pimp(c,r);                                   (T51)
```

3.7 Market clearing equations and macro equations

Equation (52) is the market clearing condition for industry outputs. Additional market clearing equations are required due to the common sourcing assumption. Equation (53) links non-margins (a subset of commodities, denoted by *nm*) commodity sales summed across destinations to regional supplies and equation (54) does so for the margins subset (*m*). Equation (55) links sales summed across users to supplies summed across regional origins.

$$PTOT_{id}.Q_{id} + XST_{id} = \sum_c MQ_{cid} \quad (52)$$

$$\sum_d PDOM_{rd}^{nm}.XT_{rd}^{nm,dom} = \sum_i MQ_{nm,ir} \quad (53)$$

$$\sum_i MQ_{mip} = \sum_d PDOM_{pd}^{m}.XT_{pd}^{m,dom} + \sum_r \sum_d XMP_{rd}^{pm} \quad (54)$$

$$\sum_u X_{ud}^{cs}.P_{ud}^{cs} = PU_{sd}^{c}.XT1_d^{cs} \quad (55)$$

$$XMR_{rd}^{m} = \sum_c \sum_s XTM_{rd}^{csm} \quad (56)$$

Next, we calculate GDP on the expenditure ($GDPE_d$) and income sides ($GDPE_i$). GDP on each side is set equal by the above market clearing equations.

$$\begin{aligned} GDPE_d = &\sum_u P1_{ud}^{c}.X1_{ud}^{c} + \sum_i PTOT_{id}.XST_{id} - \sum_c \sum_r PT_{dr}^{c,imp}.XT_{dr}^{c,imp} \\ &+ \sum_m \Big(\sum_{dst} PMR_{dst,d}^{m}.XMR_{dst,d}^{m} - \sum_p PMR_{dp}^{m}.XMR_{dp}^{m}\Big) + \sum_c \sum_s \Big(\sum_{dst} PT_{d,dst}^{cs}.XT_{d,dst}^{cs} - PT_{dd}^{cs}.XT_{dd}^{cs}\Big) \\ &- \sum_c \sum_s \Big(\sum_{org} PT_{org,d}^{cs}.XT_{org,d}^{cs} - PT_{dd}^{cs}.XT_{dd}^{cs}\Big) \end{aligned} \quad (57)$$

$$GDPI_d = \sum_i PF_{id}.F_{id} + \sum_i VPTX_{id} + \sum_u \sum_c \sum_s PU_{sd}^{c}.XT1_d^{cs}.(T_{ud}^{cs} - 1) \quad (58)$$

Equation (59) is the consumption function where APC_d is the average propensity to consume based on labor income $LTOT_d \ (= \sum_i \sum_o W_{id}^{o}.L_{id}^{o})$ and a consumption function shifter ($FHOU_d$).

$$WHOU_d = LTOT_d.APC_d.FHOU_d \quad (59)$$

Table 11: Definitions of variables, values and mappings in market clearing and macro equations

Variables	
xtrad_d(c,s,r)	Total direct demands for goods produced(dom) or landed(imp) in r
delXGDPEXP(d,i)	Ordinary change in quantity expenditure G
xgdpexp(d)	Real expenditure GDP
xfin(u,d)	Final user quantity indices
wlnd_i(d)	Total rentals to land
wcap_i(d)	Total rentals to capital
wlab_io(d)	Total wage bill
delTAXint(c,s,i,d)	Ordinary change in intermediate input taxes
delTAXhou(c,s,d)	Ordinary change in household commodity taxes
delTAXinv(c,s,d)	Ordinary change in investment commodity taxes
delTAXgov(c,s,d)	Ordinary change in government commodity taxes
delTAXexp(c,s,d)	Ordinary change in export commodity taxes
delGDPINC(d,i)	Ordinary change in nominal income GDP composition
wgdpinc(d)	Nominal income GDP
houslack	Consumption slack variable to accommodate national constraint
fhou(h,d)	Regional propensity to consume from labour income
Values and mappings	
MAKESHR2(c,i,d)	Industry share in commodity supply
MAKE_I(c,d)	Total production of commodities
SUPPMAR_RD(m,p)	Total demand for margin m produced in p
USE(c,s,u,d)	Delivered value of demands: basic + margins
USE_U(c,s,d)	Total delivered value of regional composite
USE_I(c,s,d)	All-intermediate delivered value of regional composite
TRADMAR(c,s,m,r,d)	Margins on trade matrix
TRADMAR_CS(m,r,d)	Total demand for margin m on goods fro
SCOM2IND	Mapping from SCOM commodity to industry
STOCKS(i,d)	Domestic inventories
LAB_IO(d)	Total wages
LND_I(d)	Total rentals to land
CAP_I(d)	Total rentals to capital
GDPINCSUM(d,i)	Income GDP breakdown
GDPINC(d)	Income GDP

In the TABLO coding, the commodities set is divided into two in (52). MCOM (denoted by *mc*) refers to commodities produced by several industries, and SCOM (*sc*) to commodities produced by a single industry. The set MCOMIND refers to industries producing commodities within the MCOM subset. There are computational efficiency gains from not assuming that all industries are potentially multi-product. Expenditure-side GDP in region q is computed by adding up elements of the set GDPEXPCAT. The set FINDEM (*f*), a subset of USR, refers to final demands. The add-up of income-side GDP follows. The set GDPINCCAT includes all factors, commodity taxes and production taxes.

Listing 10. Market clearing and macro equations (partial TABLO coding)

```
xcom(mc,d)=sum{i,MCOMIND,MAKESHR2(mc,i,d)*xmake(mc,i,d)};       (T52a)
xcom(sc,d)=xmake(sc,SCOM2IND(sc),d);                            (T52b)
xcom(nm,r) = xtrad_d(nm,"dom",r);                               (T53)
MAKE_I(m,p)*xcom(m,p) = TRADE_D(m,"dom",p)*xtrad_d(m,"dom",p)
+ SUPPMAR_RD(m,p)*xsuppmar_rd(m,p);                             (T54)
USE_U(c,s,d)]*xtrad_r(c,s,d) = USE_I(c,s,d)*xint_i(c,s,d)
 + USE(c,s,"hou",d)*xhou(c,s,d) + USE(c,s,"inv",d)*xinv(c,s,d)
+USE(c,s,"gov",d)*xgov(c,s,d)+USE(c,s,"exp",d)*xexp(c,s,d);     (T55)
TRADMAR_CS(m,r,d))*xsuppmar_p(m,r,d) =
sum{c,COM,sum{s,SRC,TRADMAR(c,s,m,r,d)*xtradmar(c,s,m,r,d)}};   (T56)
delXGDPEXP(q,f) =0.01*PUR_CS(f,q)*xfin(f,q);                    (T57a)
delXGDPEXP(d,"Stocks")=
0.01*sum{i,IND,STOCKS(i,d)*xstocks(i,d)};                       (T57b)
delXGDPEXP(q,"Imports") =
-0.01*sum{c,COM,TRADE_D(c,"imp",q)*xtrad_d(c,"imp",q)};         (T57c)
delXGDPEXP(q,"NetMar") = 0.01*sum{m,MAR,sum{r,ORG,sum{d,DST,
SUPPMAR(m,r,d,q)*xsuppmar(m,r,d,q)} -sum{p,PRD,
SUPPMAR(m,r,q,p)*xsuppmar(m,r,q,p)}}};                          (T57d)
delXGDPEXP(q,"Rexports") = 0.01*sum{c,COM,sum{s,SRC,
TRADE_D(c,s,q)*xtrad_d(c,s,q)- TRADE(c,s,q,q)*xtrad(c,s,q,q)}}; (T57e)
delXGDPEXP(q,"Rimports") =-0.01*sum{c,COM,sum{s,SRC,
TRADE_R(c,s,q)*xtrad_r(c,s,q)-TRADE(c,s,q,q)*xtrad(c,s,q,q)}};  (T57f)
GDPEXP(q)*xgdpexp(q)=100*sum{i,GDPEXPCAT, delXGDPEXP(q,i)};     (T57g)
delGDPINC(d,"Land") =0.01*LND_I(d)*wlnd_i(d);                   (T58a)
delGDPINC(d,"Capital") =0.01*CAP_I(d)*wcap_i(d);                (T58b)
delGDPINC(d,"Labour") =0.01*LAB_IO(d)*wlab_io(d);               (T58c)
delGDPINC(d,"ProdTax") =sum{i,IND,delPTX(i,d)};                 (T58d)
delGDPINC(d,"ComTax") =sum{c,COM,sum{s,SRC,
sum{i,IND,delTAXint(c,s,i,d)}+delTAXhou(c,s,d)
+delTAXinv(c,s,d)+delTAXgov(c,s,d)+delTAXexp(c,s,d)}};          (T58e)
GDPINC(d)*wgdpinc(d) =100*sum{i,GDPINCCAT,delGDPINC(d,i)};      (T58f)
whouhtot(d,h)  =  wlab_io(d) + fhou(d,h) + houslack;            (T59)
```

4. Previous multi-regional models using the TERM approach

The first implementation of the TERM approach was to Australia (Horridge *et al*., 2005). Versions for other countries developed in succeeding years cover Brazil (Ferreira Filho and Horridge, 2006), Indonesia (Horridge *et al*., 2006), Japan,[5] China (Horridge and Wittwer, 2008), USA (Wittwer 2017a), South Africa,[6] Finland (Törmä 2008; Simola *et al*., 2011) and Poland (Zawali´nska *et al*., 2011).

[5] See https://www.copsmodels.com/archivep.htm TPSY0054.
[6] See https://www.copsmodels.com/archivep.htm TPMH0126.

Australia and the USA both have extensive regional data that ease the task of estimating regional activity shares. Some shares are easier to manage if the national database, devised from a national input-output table, is split into more sectors. For example, good data are available on crop outputs by region for many nations, yet available input-output tables tend to aggregate agricultural sectors. International trade data are available by port for USA and Australia. In the case of both countries, state level national accounts data are available as control totals. In the US case, value-added data by state cover up to 65 broad sectors, whereas in the Australian case such data cover 19 sectors. The most important data source in each case at the regional level for manufactures and services is census data on employment by industry in small regions. In the U.S. case, the U.S. Bureau of Labor Statistics provides such data at the county level. These are sufficient to provide regional share estimates for around 450 industries. Two master databases are available for USAGE-TERM, the US version of TERM. One represents 512 sectors in 70 regions (i.e., state level with sub-state representation in states with a population exceeding 8 million), the other 121 sectors in 436 congressional districts (Wittwer 2017a).

In the Australian case, census data released by the Australian Bureau of Statistics cover over 700 four-digit ANZSIC (Australia New Zealand Standard Industry Classification) industries at the SA2 level: there are more than 2,000 SA2 regions. However, the ANZSIC industries do not neatly aggregate to a sectoral set that is useful in a CGE model. For example, there are numerous retail and wholesale trade sectors and many service sectors of limited analytical interest. Mining, agricultural and electricity generation regional activity estimates rely on other data sources. The most recent Australian master database represents 192 sectors in 334 regions.[7]

Data used to estimate Indonesian regional shares are based on the National Labor Force Survey, crop data from the Ministry of Agriculture and manufacturing surveys.[8] Regional data in the Brazilian version of TERM draw heavily on Brasileiro Institute of Geography and Statistics IGBE data (dos Santos 2013). Statistic South Africa was the main source for South African regional data.

The Australian TERM (Wittwer 2012), U.S. USAGE-TERM (Wittwer 2017a), Indonesian IndoTERM and an earlier version of SinoTERM (see footnote 4) have been developed further to enable dynamic, variable aggregations. Dynamic models are useful in many contexts. For example, the regional, statewide and

[7] See https://www.copsmodels.com/archivep.htm TPGW0172.
[8] See https://www.copsmodels.com/archivep.htm TPMH0144 for Indonesia

national impacts of a major project with a protracted timeline can be analyzed year-by-year in the construction and operational phases.

5. Simulation: Reducing China's Use of Coal

5.1 Background to scenario

The illustrative simulation concerns a switch from coal-generated electricity to hydroelectric generation. China's use of coal has grown so as to satisfy the nation's burgeoning demand for energy accompanying rapid economic growth. Amid growing concerns of pollution from coal use, China appeared to reach peak coal in 2013 (Qi Ye *et al*., 2016). Qi Ye and Lu Jiaqi (2018) provide several contributors to the fall in coal. First, as China's economy grows, there is a switch in composition from manufacturing towards services, reducing the energy intensity of economic output. Second, rapid technological change in renewables, notably in photovoltaic cells, is resulting in renewables catering for an increasing share of energy needs. Other reasons might include the contribution of more energy-efficient industrial processes as old plants close and a switch to gas.

China's coal use and greenhouse gas emissions are global issues, given that the nation accounts for around 30% of global emissions.[9] Even if coal use has now peaked, emissions will continue to rise until renewable energy displaces non-coal fossil fuel inputs, and further energy efficiency gains and structural change make larger contributions to the nation's greenhouse gas abatement. The Chinese government expects greenhouse gas emissions to peak in 2030. The nation's greenhouse gas emissions increased in 2017 after growing little in the previous two or three years due to an economic lull (Buck and Hornby, 2017).

Some major projects to reduce China's reliance on coal have major environmental issues of their own. The controversial Three Gorges Dam is now the largest hydropower plant in the world.[10] 1.2 million people in two cities and 116 towns along the Yangtze were evacuated prior to construction. Pletcher and Rafferty (2013) indicate that the weight of water in the filled dam may have contributed to the Sichuan earthquake of 2008, the possibility of which was predicted prior to the event (Hvistendahl 2008).[11] In addition, the compensation

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[9] See https://en.wikipedia.org/wiki/List_of_countries_by_carbon_dioxide_emissions.
[10] See https://water.usgs.gov/edu/hybiggest.html.
[11] Hvistendahl's article appeared on 25 March 25 2008. In outlining observed links between dams and earthquakes in southern China, she noted: "Surveys show that the Three Gorges region may be next". The massive Sichuan earthquake occurred weeks later on 12 May 2008, with around 69,000 lives lost, over 18.000 reported missing and over 370,000 reported injuries (https://en.wikipedia.org/wiki/2008_Sichuan_earthquake).

paid to evacuees from the dam site appears not to reflect anywhere near the full costs of relocation.

Increased hydroelectric generation presents an environmental quandary. While generation is of a renewable form, substantial environmental damage is possible. Disrupting natural river flows – and floods – can threaten various plant and animal species. In addition to the earthquake risk in a region crossed by geologic fault lines, the dam has increased the risk of landslides. Whole villages which were relocated suffered problems with subsidence, landslides and ground cracking in new village sites. The dam has flooded some habitats and fragmented lakes elsewhere along the waterway, which will accelerate the loss of plant and animal diversity. Such habitat alterations may have a limited direct effect on human activity, but there are concerns that the dam will increase the frequency of drought and increase the incidence of water-borne diseases. In January 2008, the Yangtze reached its lowest level in 142 years. Ships were stranded in Hubei and Jiangxi provinces (Hvistendahl, 2008).

Further hydroelectric dams are planned in Tibet. These dams will not be constructed in areas with high population densities, but the environmental concerns remain. In addition, the Yarlung Tsangpo River along which dams are planned flows into two other nations, namely India and Bangladesh, so that international tensions may rise. The Zangmu dam was the first to become operational in 2014 (Times of India, 2017). Up to 11 dams are planned along the river. The two largest dams being planned within the Nyingchi prefecture are each to have two or more times the generating capacity of Three Gorges Dam (Yangtso, 2014). Whether all of the planned dams proceed appears to be doubtful: given the massive expenditures planned, it would be surprising if the financial and environmental costs were less than the economic and greenhouse gas reducing benefits. As the costs of wind and solar generation fall, the probable negative net economic outcomes of massive dam construction projects worsen.

5.2 The scenario

The above complexities remind us that there are only certain dimensions of China's future energy mix that we can model in a CGE framework. Even if we extend a model to link an array of environmental accounts to economic activity, there are still externalities that we may not capture.

What follows is a relatively simple long-run scenario consisting of the following shocks:

1. A 20% decrease in coal output, a 10% decrease in coal capital and a 90% decrease in investment in the coal industry.

2. A 10% decrease in coal-generated electricity output, a 20% decrease in coal-generated electricity capital and a 30% decrease in investment in the coal-generated electricity industry.
3. A 50% increase in hydroelectricity output and capital and a 50% increase in investment in the hydroelectricity industry.
4. A 20% decrease in inputs of coal-generated electricity per unit of output and a 50% increase in hydroelectric inputs per unit of output in all industries.
5. A 20% decrease in coal inputs per unit of output in all industries.
6. A 6% switch towards inputs of "other mining" (i.e., gas) in all industries.

Clearly, the comparative static shocks above fall short of depicting the scale of planned expansion of hydroelectricity output. The objective of this exercise is to illustrate the regional impacts of a reduction in reliance on coal.

Table 12. Long-run effects of 20% decrease in coal use and switch to hydropower

	Coal share of GDP %	Coal-generated electricity as share of GDP %	Real GDP	Regional terms of trade	Aggregate consumption	Employ-ment	Real wage	Aggregate capital
					% change from base case			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ErdosIM	57.8	2.2	-10.5	-1.8	-13.5	-7.0	-7.0	-9.2
RoIM	6.2	3.7	-1.3	0.2	-2.0	-1.0	-1.0	-1.9
ShuozhouSX	31.7	1.2	-6.1	-1.9	-9.4	-4.8	-4.8	-4.9
RoShanxi	9.9	5.6	-3.7	0.9	-4.1	-2.0	-2.1	-3.5
Shaanxi	8.7	0.6	-1.9	-0.4	-3.0	-1.5	-1.5	-1.6
HuaibeiAH	20.2	4.1	-3.8	0.4	-4.5	-2.3	-2.3	-3.0
RoAnhui	1.9	2.2	-0.3	0.2	-0.3	-0.1	-0.2	-0.8
RoChina	0.6	1.0	0.3	-0.1	0.3	0.2	0.1	0.1
National	1.5	1.2	0.1	-0.2	0.0	0.0	0.0	-0.1

Source: SinoTERM365 simulation results.

The first two columns of Table 12 show these shares for the regions of the aggregation of SinoTERM365 for this scenario. Coal's share of GDP in ErdosIM (Erdos prefecture, Inner Mongolia), is 57.8% and coal-generated electricity's share is 2.2%. If the outputs of both sectors fall by 20%, that is equivalent to a real GDP loss of 12% (=[0.578+0.022]*20%]. Since real wages in ErdosIM fall by 7.0%, employment losses end up being much less than 12% at 7.0%. That is, a weakened labour market adjusts partly through falling real wages and partly through falling employment. Some industries, notably services that are heavily reliant on local household demands, suffer output decreases due to the decline in local demand. ErdosIM's real GDP falls by 10.5%, yet some sectors including farming, non-coal mining activity and some manufactures increasing output due to improved competitiveness arising from lower real wages. ErdosIM is a net exporter of coal to other regions, so that a decline in national demand for coal has a negative impact on ErdosIM's terms-of-trade (-1.8%). This reduction in spending power implies that real consumption (-13.5%) will fall by a larger percentage than real GDP (-10.5%).

The RoIM (Rest of Inner Mongolia) region has a higher share of coal production in GDP than China overall, and a lower share of the expanding sector, hydro-electric generation. Consequently, the region is a loser with real GDP (-1.3%) and aggregate consumption (-2.0%) both falling. ShuozhouSX (Shuozhou prefecture, Shanxi) suffers losses in real GDP, aggregate consumption and employment reflecting a coal share of GDP that is second only to ErdosIM. RoShanxi (Rest of Shanxi), with a lower coal share but higher coal-generated electricity share than ShuozhouSX, suffers smaller losses due to a small improvement in the terms-of-trade due to coal imported into the region falling in price.

The RoChina (Rest of China) region includes almost 95% of national hydroelectric generating capacity. This sector expands by 20% in the scenario. Therefore, the Rest of China, with a relatively small share of coal and coal-generated electricity output in real GDP, gains more from hydroelectric expansion than it loses from the shrinkage of coal in the economy.

How have the economies of Shanxi and Inner Mongolia fared since 2013, the year of peak coal, given that coal has formed a substantial share of GDP in each province? For a number of years, Shanxi's economy has been among the slowest growing in China, yet Inner Mongolia appeared to exhibit exceptional growth in the same period (i.e., 2012 to 2015). Evidently, statistics in Inner Mongolia were falsified for several years: the reported real GDP for the province in 2017 was almost 16% lower than in the previous year, reflecting at least two years of inflated data (Babones, 2018). We can conclude that both provinces have suffered temporary declines in growth with the passing of peak coal in China. At a prefectural level, the impacts on ErdosIM and ShuozhouSX (real GDP losses of 10.5% and 6.1% respectively) of the move away from coal modelled in our scenario are equivalent to a year or more of lost economic growth.

5.3 Database issues

When we apply SinoTERM365 to new scenarios, we anticipate that some database errors may emerge. We found the following problems with the database in the preliminary run: (1) Shaanxi province's coal-fired generating capacity was understated; and (2) Inner Mongolia's precious mineral production was understated.

The first deficiency was relevant to our scenario: a check of data sources indicated that preparation of SinoTERM365 regions shares did not include representative data for Shaanxi's coal-fired generated. The second deficiency was explored only because for several years, Inner Mongolia's reported real GDP growth was not slower than national growth after the passing of peak coal. Had Inner Mongolia's real GDP in years after the passing of peak coal in 2013 aligned with the eventual 2017 GDP, we may not have searched for sectors contributing to strong economic growth. Baotou prefecture in Inner Mongolia accounts for a significant share of global rare earth production, part of non-ferrous metals in the SinoTERM365 database. Rare earths are used in cell phones, rechargeable batteries and catalytic converters, and consequently are in high demand. Using new data, we amended the regional shares of national output. Since the TERM database generation process is highly mechanized, it is a straightforward matter to create a new database with amended data. It is more efficient to improve the database on a needs basis in response to specific projects rather than wait for better data to emerge.

5.4 Should a large country face infinitely elastic import supplies in a national model?

An instructive exercise among CGE modelers is to compare the national results of a simulation using different models. Indeed, it is possible using GTAP with a top-down sub-national module to run a similar scenario as that above.[12] In some context, the parsimonious top-down method is useful. But the bottom-up scenario provides region-specific price effects, notably real wage movements and terms-of-trade impacts, not captured by a top-down methodology.

In the context of a single country, what do we miss by not using a global model? A single country model is linked to the rest of the world via an export demand equation and an import supply equation. We may wish movements in supply and demand in a single country model to approximate those we would observe if we used a global model such as GTAP for shocks within a single nation. Concerning the case of export demands, Dixon and Rimmer (2002, pp. 222-5) present a derivation of export demand elasticities based on a given Armington parameter, export share of the global market, and given supply and demand elasticities. In the case of a small country, export demand elasticities of around -4 correspond with Armington parameters of around 6.

Turning to imports, the default assumption in TERM models and other national models in the ORANI school is that import supplies are infinitely elastic. In China,

[12] An example is downloadable at https://www.copsmodels.com/archivep.htm TPMH0100.

whose soaring demands for raw commodities led to a resources boom in the first decade of the new millennium, this appears not to be appropriate.

One way of examining the extent to which the assumption of infinitely elastic supplies affects national results is to run a scenario in two models, one in SinoTERM365 with this assumption and the other in GTAP. Our scenario (simpler than the simulation described above) is a 10% fall in coal input requirements in all industries in China. Before running a comparative scenario, we note that in GTAP, China's coal imports as a share of national coal usage is 15%, whereas in SinoTERM365, based on the National Statistical Bureau's input-output table for 2012, it is only 7.3% (the scenario reported above uses an altered database with the higher coal import share).

With the initial import share in SinoTERM, a 10% fall in demand for coal results in the price of coal falling by 4.0% in China. But when we amend the database to raise the import share to 15% (i.e., consistent with the 2011 GTAP database), a 10% fall in demand results in a price fall of only 3.6%. Running a GTAP simulation in which China's demand for coal falls by 10%, the import price of coal faced by China falls by 5.6%.[13] Running the import shrinkage scenario again in SinoTERM using an import price shock to replicate the GTAP result (an additional price shock of -5.6% to the coal import price), the national price now falls by 4.1% instead of 3.6%.

The import supply elasticity depends on a combination of China's share of global trade plus the fixed factor share of total costs. In GTAP, the natural resource share of total costs in coal production exceeds 20% globally. This limits the supply elasticity of coal even in the long run, hence the 5.6% fall in China's import price. In practice, we might expect mine closures to follow any downturn in demand for coal, particularly given global concerns about the contribution of coal to greenhouse gas emissions. Therefore, we might expect the natural resource factor for coal to diminish over time rather than being fixed. In the SinoTERM365 simulation, capital stocks in coal production fall around 9% when the price of coal falls by 4.1%, or around 8% when the price falls by 3.5%. Any adjustment in a GTAP run to reflect a diminution of the natural resource factor would reduce the fall in price of imported coal and result in an even smaller difference in the price paid by China's coal users relative to assuming infinitely elastic supplies in SinoTERM.

[13] Files to reproduce the GTAP simulation are downloadable from https://www.copsmodels.com/archivep.htm TPGW0171.

6. Potential Model Developments

Any modeling development entails trade-offs. The GTAP model has global breadth so that we can examine the implications of one nation's policy and market changes on the rest of the world. Standard GTAP is limited to 57 sectors, albeit with considerable agricultural detail (and individual modelers may split sectors in the standard database) which had provided a platform for numerous natural resource and environmental extensions.

A sub-national representation has several advantages. First, it enables us to capture region-specific characteristics that we may gloss over in a global model. One example concerns water allocation in the Murray-Darling Basin in Australia. In the southern basin, water is tradable between users and catchment regions. This gives farmers considerable flexibility in production. Annual crops such as rice and cotton may be grown in years when water is abundant, but in drier years, annual crop growers may choose instead to sell part or all of their irrigation water allocation (at many-fold the wet year trading price) to perennial growers. In the northern basin, water is tradable between users but not between regions, which are based on far-flung tributaries of the basin. This makes the northern basin farm production less flexible than in the southern basin (Wittwer, 2012).

An example of a GTAP-based model that captures some of the factor flexibility of TERM-H20 is GTAP-AEZ (Haqiqi *et al*., 2016) which deals with river-basin level farm activities. Instead of representing the entire economy of each basin region, relevant region-specific farm sectors are depicted individually while maintaining national-level representation in non-farming sectors. This method captures much of the salient detail of interest in water allocation scenarios without burdening the model with sub-national detail in sectors of little interest.

However, regional outcomes have a political dimension best captured with bottom-up analysis of regional economies. One example is that Dixon *et al*. (2011) found in Australia's Murray-Darling Basin that water buybacks by government could increase spending power in irrigation regions, because government purchases of water entitlements raised the price of water. This in turn raised farmers' terms-of-trade, more than offsetting the reduction in farm output due to reduced water inputs. Without bottom-up modeling, this insight may not have been evident.

In the political dimension, false attribution of the impacts of policy reforms often arises. In Australia, water scarcity due to the drought has a scapegoat in the 2007 Water Act, which aimed to reduce the volume of water extracted for economic purposes. A quarter of a century ago, protectionists attributed job losses due to a global recession to reductions in import tariffs and removal of import quotas. More recently, trade reforms have become the scapegoat for job losses in manufacturing, when ongoing technological change and changing consumer tastes have played significant roles in the decline of manufactures in high income nations. In this context, sub-national detail helps quantify impacts in regions most exposed to structural change. CGE modelers undertaking policy analysis are likely to have their results disputed by interests opposed to economic reforms. Sub-national regional implications of policy become the topic of heated debate in part because structural change at the regional level tends to be more extreme than at the national level.

In the context of China, a prefectural representation may provide a framework for examining the impact of major projects on regions. The dilemma for modelers within China is that there may be limited appetite in the current political environment for quantitative studies which conclude that a particular major project is not welfare enhancing.

Other applications are easier to communicate. For example, an earlier version of SinoTERM (see footnote 4 for an example of the dynamic model), to which Feng *et al.* (2018) added greenhouse gas accounts following Adams and Parmenter (2013), has been applied to carbon emissions trading between regions. This is a carbon trading policy that the central and provincial governments have agreed to in principle (Harvey, 2017).

More generally, as incomes in China increase, the value that society places on the environment is also likely to increase. On this basis, there is a likely to be a growing role for sub-national CGE modeling that includes various satellite accounts covering pollution, water, greenhouse gases and biophysical attributes. Users who modify the core SinoTERM365 model with theory and satellite accounts will broaden the potential array of research issues covered by the model.

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