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Drivers of intersectoral metal consumption intensity in China: A combined input-output and sensitivity analysis

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ABSTRACT

As a country with a high level of metal consumption, China must urgently formulate effective policies to improve its metal use efficiency. This article identifies the key sectors with the highest metal consumption intensity (MCI) and investigates the effect of the (pure) technical and final demand coefficients on the MCI of key sectors using a combined input-output and sensitivity analysis. The results show that the average MCI of key industries increased from 7.37 tonnes per ten thousand yuan to 32.13 tonnes per ten thousand yuan during the period from 2002 to 2012, and the manufacturing and processing of the metals sector (n14) revealed the greatest MCI. Moreover, the elasticity of the MCI in terms of the (pure) technical and final demand coefficients of key sectors also increased rapidly from 2002 to 2012, and the number of corresponding transactions leading to the increase in key sectoral MCI significantly increased. In terms of the elasticity of the technical coefficients, their sensitivity exceeded that of the pure technical coefficients in most cases due to the influence of the demand structure, and direct transactions between sectors had important impacts on the MCI in most key industries. Meanwhile, almost all the sectors exerted direct or indirect effects on the MCI of the mining of metal ores industry (n4). In addition, the manufacturing of general and special purpose machinery (n16), manufacturing of electrical machinery and apparatus (n18) and construction (n22) exerted influences on most sectors. Concerning the final demand coefficient elasticity, the gross fixed capital formation of most sectors induced the greatest elasticity in the corresponding sectors, and the greatest elasticity of all the sectors was related to the gross fixed capital formation of n22.

1. Introduction

As the basic and most important strategic materials for national economies, metals are closely related to human life and social development in building, transport, and communication (Wiedmann et al., 2015). In recent years, increased economic development and urbanization along with a growing population have stimulated substantial consumption of metal resources. In 1987, 3.54 billion (metric) tonnes of metals were extracted for consumption or use in production processes. By 2012, this amount had increased to 8.11 billion tonnes (Fig. 1). As globalization has progressed, China has played an important role in stimulating the provision and use of metals. In 2002, China accounted for 10.40% of worldwide metal consumption, and by 2012, this proportion had grown to 32.66% (Fig. 2). Although China's demand growth rate for some bulk metals, such as iron, has been decreasing in recent years, the country's total demand is still increasing, leading to severe environmental consequences. As a result, issues of resource utilization efficiency have aroused widespread concern in China and even the world (UN Environmental Program, 2011; Zhong et al., 2018). China has clearly recognized the need for the comprehensive conservation and efficient use of mineral resources in the National Mineral Resources Plan (2016–2020) and the Thirteenth Five-Year Plan, and the 19th National Congress of the Communist Party of China proposed improving the country's resource utilization efficiency. Under these circumstances, it is urgently necessary for the Chinese government to undertake effective measures to reduce its MCI and improve the metal utilization efficiency.

Recent research has found a strong coupling of metal use and economic development (Zheng et al., 2018; Wiedmann et al., 2015),

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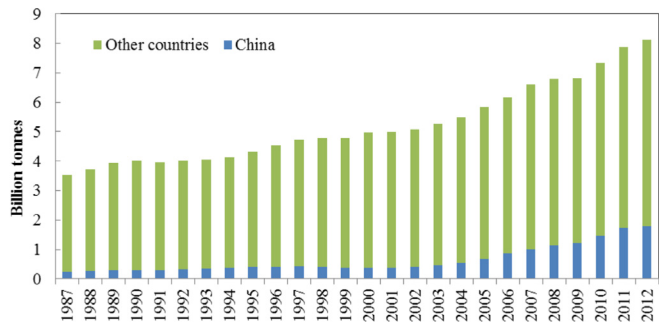

Fig. 1. Metal extraction statistics for China and other countries during the 1987–2012 period.
Date source: www.materialflows.net.

and reducing MCI is of great significance in limiting this unsustainable development pattern (Li et al., 2017). Considering that certain metals are indispensable to certain sectors, improving metal use efficiency by reducing the total metal consumption in each sector is impractical. However, reducing the MCI of different sectors would be feasible. In fact, there are direct or indirect relationships between different sectors and final demand, and changes in the resource use efficiency in an industry can directly or indirectly influence the output of other industries (Liu et al., 2016). This effect comes from technical factors and final demand factors. In terms of technical factors, the sales of one sector to another might cause higher metal consumption than its sales to other sectors because the products sold to the respective sectors are different, leading to different amounts of metal consumption. Thus, the MCI of production linkages between sectors is worth exploring. In terms of final demand factors, a 1% increase in the demand for the metal products of one sector may cause a larger increase in total metal consumption that the same level of increase in the demand for the products of other sectors. Those composition of final demand (public and private consumption, gross fixed capital formation, and net exports), which contribute most to the MCI should be identified. Therefore, both effects above can directly or indirectly affect the MCI of various departments through the industrial chain.[1] The purpose of this paper is to identify technical effect and final demand effect whose minimal variations lead to the highest changes in sectoral MCI. Accordingly, the following three questions must be answered. Which sectors show high MCI (defined as the key sectors)? Which factors primarily affect the MCI of these key sectors? What are the relationships among these key sectors? To answer these questions, a sensitivity analysis of China's intersectoral MCI based on an input-output model is proposed.

Many studies have empirically investigated the drivers, focusing mainly on energy, carbon emissions and materials use. These studies can be divided into three groups in terms of the methodologies employed.

(1) Factor decomposition analyses, i.e., structural decomposition analysis (SDA), index composition analysis (IDA) and production-theoretical decomposition analysis (PDA). These methods have been widely used to analyse the relationships between certain indicators and their drivers. Numerous

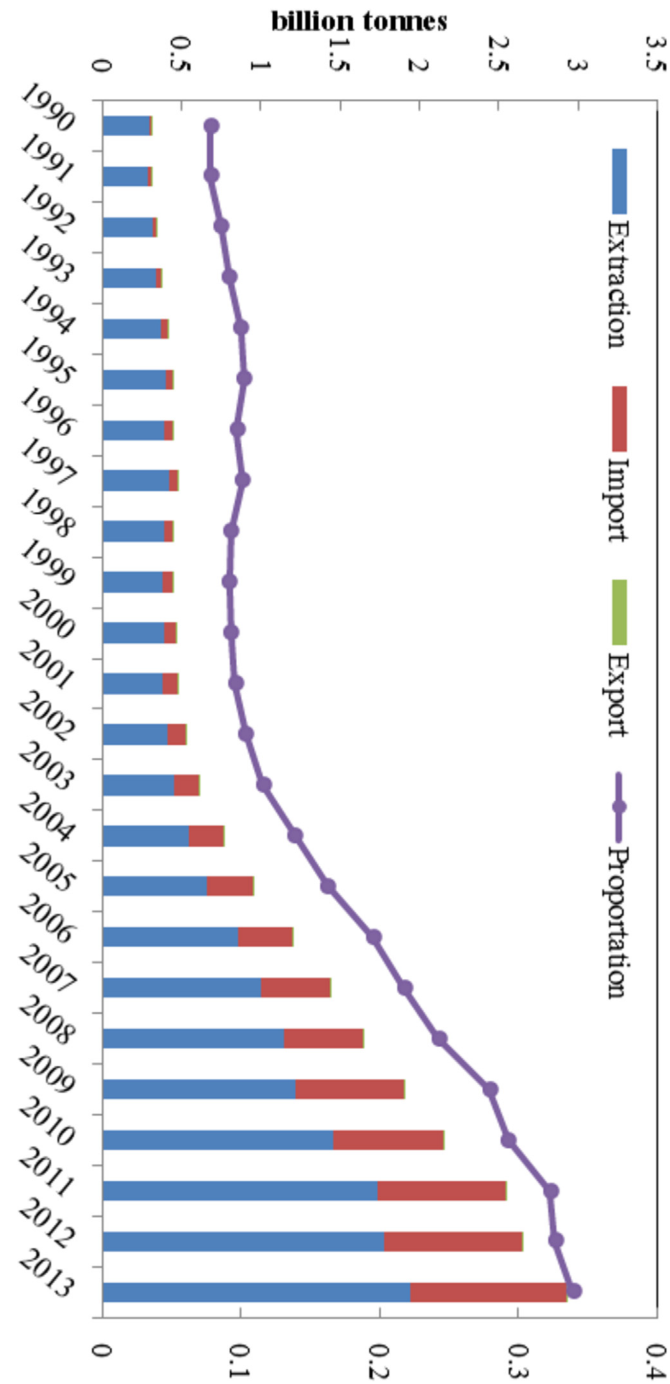

Fig. 2. Metal consumption in China and China's share of global consumption during the 1990–2013 period.
Date sources: www.materialflows.net and calculated based on our study.

scholars have applied SDA to investigate the drivers of energy and CO_2 emissions (Chang et al., 2008; Guan et al., 2008; Tian et al., 2013; Geng et al., 2013; Wang et al., 2013; Su and Ang, 2012). In addition, studies have used SDA to examine the drivers of materials use in different cases (Muñoz and Hubacek, 2008; Wood et al., 2009; Weinzettel and Kovanda, 2011). Compared with other methods about decomposition, the analysis of SDA on driving forces is more comprehensive and thorough, but the requirement on data is higher than the other methods. The second method is IDA,

[1] MCI could be affected by direct or indirect transaction relations. Direct effects refer to changes in the MCI of a sector caused by changes in the transactions between this sector and either another sector or its final demand composition. In contrast, changes in the MCI of a sector that are linked to either changes in the transactions between two other sectors or changes in the final demand composition of other sectors are considered to be indirect effects.

Table 1
Studies of CO_2 emissions drivers using the LMDI.

Studies	Decomposition factors
Liu et al. (2007)	Carbon emissions coefficients of heat and electricity, energy intensity, industrial structural, industrial activity and final fuel shift
Fan et al. (2007)	Real energy intensity, energy policies, primary energy mix
Zhang et al. (2009)	CO_2 intensity, energy intensity, structural changes, economic activity
Zhang et al. (2013)	Economic activity effect, electricity generation efficiency effect
Xu et al. (2014)	Energy structure, energy intensity, industry structure, economic output, population scale effects
Ren et al. (2014)	Industry structure, economic output, energy structure, energy intensity
Zhang and Da (2015)	Economic growth, energy intensity, final energy consumption structure,
Moutinho et al. (2015)	Population, the size and structure of the countries, the value added
Wang and Yang (2015)	Energy structure, energy intensity, industrial structure
Lin and Long (2016)	Output per worker, industrial economic scale, energy intensity, energy structure
Zhang et al. (2016)	Energy consumption intensity and proportions, technology, energy structure
Shao et al. (2016)	R&D intensity, investment intensity, R&D efficiency, output scale, industrial structure
Lin and Liu (2017)	Labor productivity, energy intensity, industry scale
Wang and Feng (2017)	Population effect, economic output, industrial structure, energy intensity, energy structure, carbon dioxide emission coefficient

which has relatively lower requirements for data and is widely used in energy-environmental analysis. In practice, the logarithmic mean Divisia index (LMDI) has been frequently employed in IDAs to explore the drivers of energy decomposition (Ang and Liu, 2001; Ang, 2004), water use (Zhao and Chen, 2014), carbon emissions (Table 1), food and crop production (Kastner et al., 2012; Liu et al., 2013; Zhen et al., 2017), toxic chemical management (Fujii and Managi, 2013), resource use intensity (Zhang, 2014; Pothen and Schymura, 2015), materials use (Wang et al., 2017), and energy consumption (González et al., 2014; Xu et al., 2012; Wang et al., 2014; Dai and Gao, 2016). PDA is the third most extensively applied decomposition tool to investigate the drivers of carbon emissions (Zhou and Ang, 2008; Zhang et al., 2012; Li, 2017; Song et al., 2018) since it requires only aggregate panel data (Zhou and Ang, 2008), which are easy to collect.

(2) Applying econometric models to investigate the relative effects of different factors. Studies have investigated the relationships between CO_2 emissions and the industrial structure, the population, lifestyles, urbanization, technology, GDP, the environment, affluence, energy intensity, and even democracy and financial openness (Table 2). However, this method can reveal only the relative effects of different factors, and it is not applicable for investigating intersectoral relevance.

(3) Sensitivity analysis based on the input-output technique. The input–output model can be classified into the Leontief input–output model (Leontief, 1936) and the Ghosh input–output model (Ghosh, 1958). Compared with the Ghosh input–output model, the application of Leontief model is more sophisticated and popular. Several branches of the input-output model have been applied to the research field of energy/CO_2 emission, including energy consumption/carbon emission accounting and development trend analysis (Chen and Zhang, 2010; Zhu et al., 2012), structural decomposition analysis (SDA) for the driving factors (Duarte et al., 2013; Su and Ang, 2014; Liu et al., 2015), analysis on the influence of production/supply structure change (Zhang, 2010; Tarancón et al., 2010), etc.

Tarancón et al. (2007, 2007) creatively combined Leontief input-output model and sensitivity analysis to evaluate the transactions between sectors that led to the highest CO_2 emissions in Spain from demand side. On this basis, Morán et al. (2008) used this method to analyse the drivers of CO_2 emissions in the Spanish electricity generation sector. Since then, input-output models combined with sensitivity analysis have been employed in the energy consumption field. Tarancón et al. (2010) quantitatively researched the main manufacturing sectors with the greatest impact on electricity demand in 15 European countries, and the sectors most sensitive to changes in electricity prices were identified. Subsequently, Tarancón et al. (2011) studied the effects of the structure and technology of manufacturing sectors on electricity consumption in Spain. Tarancón and Del Río (2012) provided an overview of sensitivity analysis based on the input-output technique. Based on previous research, Yan et al. (2016) conducted a sensitivity analysis based on the Ghosh model to identify the drivers of six energy-intensive industries in China, and they compared the results with a sensitivity analysis based on the Leontief model. Liu et al. (2016) applied sensitivity analysis based on the Leontief input-output model to investigate the drivers of intersectoral CO_2 emissions. So far, this method hasn't been widely used and the related literature is scant.

In summary, the existing studies related to driver decomposition methods have focus mainly on the drivers of CO_2 emissions/energy consumption, and many of these studies were from the perspective of industries (as shown in Table 1). However, there have been no studies examining the transactions between different sectors and final demand that affect the MCI in China. The aim of this paper is to fill this gap using sensitivity analysis based on Leontief input-output model. This method allows for a detailed and coherent analysis of the metal consumption flows between sectors and final demand, and it could help us obtain a “map” of hot spots of the metal consumption system, i.e., identify the transactions between sectors and final demand that contribute more to the reduction of the MCI of the key sectors. Other methods do not allow us examine as deeply the internal productive linkages within the economic system with implications for the MCI. Moreover, data complexity of this method is relatively low.

This article makes three contributions: First, although a few studies have proposed that the MCI should be reduced (Zheng et al., 2018; Li et al., 2017; Wiedmann et al., 2015),[2] there has been a lack of research on its driving factors. This article studies the factors driving the key sectors with high MCI in China from the intersectoral perspective, quantifies the relevance between sectors and explores the critical paths influencing the MCI of key sectors, providing a basis for the policies improving metal use efficiency. Second, the paper applies sensitivity analysis based on an input-output model to the field of MCI for the first time, thus

[2] Although Zheng et al. (2018) and Wiedmann et al. (2015) studied the metal footprint, their purpose is to reduce MCI and improve the efficiency of metal use.

Table 2
Studies of the decomposition factors using econometric models.

Studies	Decomposition factors
Fan et al. (2006)	Population, affluence and technology
Martínezzarzoso et al. (2007)	Population growth
Lin et al. (2009)	Population, urbanization level, GDP per capita, industrialization level, energy intensity
Hubacek et al. (2011)	Affluence, population growth, lifestyles and technology
Shuai et al. (2011)	Per capita output, industrial growth, energy efficiency, R&D intensity
Wei et al. (2011)	Energy utilization, technology, policies and international carbon market mechanisms
Li et al. (2011)	GDP per capita, industrial structure, population, urbanization level and technology
Zhu and Peng (2012)	Population size, population structure, and consumption level
Wang et al. (2012)	Urbanization level, economic level, industry proportion, tertiary industry proportion, energy intensity, R&D output
You et al. (2015)	Democracy and financial openness
Zhou and Zhao (2016)	Population, affluence and technology

expanding the application of this method and enriching the research on metal consumption. In addition, it provides a good reference for the study of driving factors in other related industries.

The paper is structured as follows. The basic model is provided in section 2, together with a description of the data sources. The results of the empirical application are discussed in section 3. Finally, the paper ends with conclusions and corresponding policy recommendations in section 4.

2. Methodology and data

2.1. Input-output technique

This paper adopted sensitivity analysis based on an input-output technique (Tarancón and Delrio, 2007; Tarancón et al., 2010, Tarancón et al., 2011, Tarancón and Delrio, 2012) to identify the effects of the (pure) technical coefficient, the final demand coefficient on the intersectoral MCI.

The output of an activity branch i can be expressed as follows:

$$x_i = x_{i1} + x_{i2} + \dots + x_{in} + y_{i1} + y_{i2} + \dots + y_{im} = \sum_j x_{ij} + \sum_l y_{ip} \quad (1)$$

where x_{ij} refers to the purchase consumption by sector j, and y_{ip} represents the final demand, including public and private (household) consumption, gross fixed capital formation, and net exports. Meanwhile, the technical coefficient represents the amount of value consumed by sector j per unit of output by sector i:

$$a_{ij} = \frac{x_{ij}}{x_j}\ (i = 1, 2, \&, n\ and\ j = 1, 2, \&, n) \quad (2)$$

Let g_p denote the final demand aggregate p, and let y_{ip} denote the production requirements for the final demand aggregate p by sector i. Thus, the final demand coefficient can be expressed as follows:

$$h_{ip} = \frac{y_{ip}}{g_p}\ (i = 1, 2, \&, n\ and\ p = 1, 2, \&, m) \quad (3)$$

The vector $M(n \times 1)$ of metal consumption by activity can be calculated as follows:

$$C_i = \frac{M_i}{x_i}\ (i = 1, 2\&, n) \quad (4)$$

where M_i refers to the metal consumption of sector i. Integrating Eqs. (2)–(4), we can obtain the calculation formula for the metal consumption of branch i:

$$M_i = \sum_{j=1}^{n} C_i x_{ij} + \sum_{p=1}^{m} C_i h_{ip} g_p \quad (5)$$

The equation above can be rewritten in matrix form for all the sectors as follows:

$$M = \widetilde{C}(Ax + Hg) = \widetilde{C}BHg \quad (6)$$

$\widetilde{C}$ is the $(n \times n)$ diagonal matrix of the metal consumption per unit of output. A is the $(n \times n)$ matrix of the technical coefficients, x is the $(n \times 1)$ vector of sectoral outputs, H is the $(n \times m)$ final demand coefficients matrix, and g is the $(m \times 1)$ demand aggregates vector. The Leontief inverse matrix can be defined as $B = (1 - A)^{-1}$, which identifies the direct and indirect metal resources used for one unit of output per sector.

2.2. Sensitivity analysis of the technical coefficients

Metal consumption intensity (MCI) has been defined as follows:

$$I_i = \frac{M_i}{VA_i} = \frac{C_i \cdot x_i}{VA_i} \quad (7)$$

where VA_i represents the value added of sector i (as shown in Table 3). Let sector i be a key sector with regard to its contribution to the overall MCI of a country. Thus, the elasticity of I_i with respect to the change in the coefficient a_{kl} can be expressed as follows:

$$\varepsilon_{M_i a_{kl}} = \frac{\Delta I_i}{I_i} \Big/ \frac{\Delta a_{kl}}{a_{kl}} \quad (8)$$

Clearly, a change in the technical coefficient a_{kl} will induce a change in the elements of the Leontief inverse matrix b_{ij}, and this relationship is specified in Eq. (9), which was proposed by Sherman and Morrison (1950):

$$\Delta b_{ij} = \frac{b_{ik} b_{lj} \Delta a_{kl}}{1 - b_{lk} \Delta a_{kl}} \quad (9)$$

Thus, the change in I_i can be expressed as follows:

Table 3
Compendious Chinese input-output table.

Input-output	Intermediate use	Final use	Total output
Intermediate input	x_{ij}	y_{ip}	x_i
Value added	VA_j		
Total input	x_j		

$$\Delta I_i = \sum_{j=1}^{n} \frac{C_i b_{ik} b_{lj} \Delta a_{kl}}{VA_i (1 - b_{lk} \Delta a_{kl})} y_j = \frac{C_i}{VA_i} \times \frac{b_{ik} x_l \Delta a_{kl}}{1 - b_{lk} \Delta a_{kl}} \tag{10}$$

Therefore, the elasticity of M_i to the change in the coefficient a_{kl} can be expressed as follows:

$$\varepsilon_{M_i a_{kl}} = \frac{\Delta I_i}{I_i} \bigg/ \frac{\Delta a_{kl}}{a_{kl}} = \frac{b_{ik} a_{kl}}{1 - b_{lk} \Delta a_{kl}} \bullet \frac{x_l}{x_i} \tag{11}$$

where a_{kl} represents the technological coefficient, $a_{kl} = (x_{kl}/x_l)$ with $k = (1, 2, \ldots, n)$ and $l = (1, 2, \ldots, n)$, x_i and x_l express the output of sectors i and l, respectively, and $\varepsilon_{M_i a_{kl}}$ denotes the elasticity of MCI in response to a 1% change in the technical coefficient. It can be observed that this elasticity depends not only on the technical changes in sector k but also on the final demand structure (Tarancón and Del Rio, 2007; Tarancón et al., 2011). To independently research how a change in technology influences the MCI, let $y_j = 1$; thus, the following formula can be obtained:

$$\Delta I_i = \frac{C_i}{VA_i} \sum_{j=1}^{n} \Delta b_{ij} = \frac{C_i}{VA_i} \sum_{j=1}^{n} \frac{b_{ik} b_{lj} \Delta a_{kl}}{1 - b_{lk} \Delta a_{kl}} \tag{12}$$

Therefore, the elasticity of the MCI in response to a change in the pure technical coefficient can be expressed as follows:

$$\varepsilon^{*}_{M_i a_{kl}} = \frac{\Delta I_i}{I_i} \bigg/ \frac{\Delta a_{kl}}{a_{kl}} = \frac{\Delta \sum_{j=1}^{n} b_{ij} \Big/ \sum_{j=1}^{n} b_{ij}}{\Delta a_{kl} / a_{kl}} = \frac{\sum_{j=1}^{n} \frac{b_{ik} b_{lj} \Delta a_{kl}}{1 - b_{lk} \Delta a_{kl}} \Big/ \sum_{j=1}^{n} b_{ij}}{\Delta a_{kl} / a_{kl}}$$
$$= \frac{b_{ik} a_{kl}}{1 - b_{lk} \Delta a_{kl}} \frac{\sum_{j=1}^{n} b_{lj}}{\sum_{j=1}^{n} b_{ij}} \tag{13}$$

2.3. Sensitivity analysis of the final demand coefficients

The following expression can be obtained in terms of Eqs. (1), (3) and (7):

$$\varepsilon_{M_i h_{kl}} = \frac{\Delta I_i / I_i}{\Delta h_{kl} / h_{kl}} = \frac{b_{ik} h_{kl} g_l}{x_i} \tag{14}$$

where $\varepsilon_{M_i h_{kl}}$ represents the percentage change in the MCI of sector i in response to a 1% change in the final demand coefficient, reflecting the influence of the final demand structure (including public and private consumption, gross fixed capital formation, and net exports) on the MCI.

2.4. Data sources

2.4.1. Input-output table

The original data come from the basic flow tables of China's input-output tables for 2002, 2007 and 2012. To eliminate the impact of inflation in different years, the original input-output tables have been adjusted to comparable price input-output tables (with constant 2002 prices) using GDP deflators. The GDP deflators originate from the National Bureau of Statistics. The basic form of the input-output table is shown in Table 3. Given that the sector of input-output tables is not the same in different years, to facilitate comparisons of data, 42 sectors have been merged into 25 sectors based on the close relationships between certain sectors, and the detailed sector classification is presented in Appendix A.

2.4.2. Metal consumption data

The metal extraction data for China are obtained from www.materialflows.net. The extraction data are provided for both used and unused extractions and are measured in 1000 (metric) tonnes (kt). Regarding the extraction of used metal entering the economic system exclusively, we exclude unused metal.

Metal consumption derived from domestic material consumption (DMC), one of the most popular current indicators of materials use, has been widely used across both fields and regions by numerous institutions (Wang et al., 2017). Given that metal is included under materials, metal consumption is calculated by the extraction in the domestic territory plus all physical imports minus all physical exports. For sectoral metal consumption, we first calculate the complete consumption coefficient based on the input-output table. The specific calculation formula is as follows:

$$D = (I - A)^{-1} - I \tag{15}$$

where D refers to the matrix of total consumption coefficients, A is the matrix of the technical coefficients, and I is the unit matrix. Metal other than energy enters the value chain only through the extraction process. Our approach allocates these metals to the industries that use the output of the metal extraction sectors. The calculation of the metal consumption data is based on the premise that extraction sector prices are identical, regardless of whom the sector sells its output to, which indicates that a certain value of goods and services from the metal extraction sector will always contain an identical amount of metal. Thus, sectoral metal consumption can be expressed as follows:

$$M_i = M \times D_{mi} \tag{16}$$

where M denotes total metal consumption (referring to domestic metal consumption), and D_{mi} represents the metal extraction sector consumption coefficients.

3. Results and discussion

3.1. Metal consumption intensity at the sectoral level in China

This paper chooses the top ten sectors on the MCI index in 2012 as the key sectors, the metal consumption of which accounted for 82.79% of the total. Table 4 shows China's MCI and the share of consumption for the key sectors in 2002, 2007 and 2012. It can be observed that the MCI of each sector increased rapidly from 2002 to 2012, while the consumption structure of the industrial sector did not change significantly.

Table 4
The MCI and share of total metal consumption for key sectors in China.

Sector	2002		2007		2012	
	Intensity	Share (%)	Intensity	Share (%)	Intensity	Share (%)
n14	21.72	31.89%	54.96	36.57%	100.56	37.60%
n15	12.67	7.04%	25.66	5.28%	42.70	5.14%
n18	7.53	5.07%	26.21	6.77%	42.12	6.60%
n4	7.14	1.75%	16.53	1.99%	28.56	2.62%
n16	6.00	8.57%	17.22	8.76%	26.87	7.92%
n17	4.99	4.94%	15.78	5.65%	23.75	5.75%
n22	4.65	12.00%	11.72	9.49%	16.54	11.47%
n19	3.43	3.66%	10.37	3.94%	15.81	3.29%
n20	3.76	0.64%	8.89	0.51%	15.12	0.35%
n13	1.78	1.33%	4.76	1.66%	9.26	2.05%

Notes: The intensity unit is tonnes per ten thousand yuan.

In general, the average MCI of the ten key industries increased from 7.37 tonnes per ten thousand yuan in 2002 to 32.13 tonnes per ten thousand yuan in 2012. Specifically, n14 was the sector with the highest MCI among all sectors, which accounted for 37.60% of total metal consumption in 2012. The combined results in Table 4 and Fig. 3 show that the output for n14 did not match its high metal consumption. The sector with the lowest MCI was n13, the value of which increased from 1.78 in 2002 to 9.26 in 2012. With the rapid industrialization and economic growth over the past two decades, China has increased its investment in infrastructure construction (Schandl and West, 2010). As a result, China's consumption of steel and other metals has increased significantly, and it has even exceeded the growth rate of GDP (Wiedmann et al., 2015; Humphreys, 2010), leading to a substantial increase in the MCI, which indicates that China has gained less economic welfare from the use of metal resources. Thus, it is urgently necessary to reduce the MCI of metal-related industries.

3.2. The trends of the elasticity of (pure) technical coefficients and final demand coefficients

3.2.1. The trends of the elasticity of (pure) technical coefficients

Considering the closeness of the intersectoral linkages, we mainly present sectoral transactions of technical elasticity values that exceed 0.1%, which are considered to be critical transactions (as shown in Table 5). Taking the first line of n14 in 2002 as an example, $\varepsilon_{M_i a_{kl}} = 0.46$ indicates that for every 1% decrease in self-supplied intermediate products provided by n14 for itself, the MCI of n14 decreases by 0.46%.

(1) Most of the elasticity values of the (pure) technical coefficients in different industries showed increasing trends during the 2002–2012 period. For example, the highest elasticity values of the technical coefficient and pure technical coefficient of n14 were both 0.46 in 2002, and the elasticity values increased to 0.59 in 2012, indicating that sector links had been enhanced. The rapid growth of metal consumption acted as a significant factor leading to the increase in the technical coefficients. As shown in Fig. 2, the metal consumption increased from 0.53 billion tonnes to 2.65 billion tonnes in 2012. Examining the different effects in different periods, the growth rate of the elasticity values during the 2002–2007 period was greater than that during the 2007–2012 period. It is well known that China's metal-related industries flourished in the early 21st century due to industrialization and urbanization. High industrial-scale growth along with the low utilization efficiency of metal resulted in a sharp increase in the sensitivity of the MCI of key sectors during the 2002–2007 period. With the development of technology and the reduction in industrial scale attributed to the financial crisis, the key sectors experienced a slow increase in the sensitivity of the MCI during the 2007–2012 period.

(2) Most transactions between sectors leading to changes in the MCI of key sectors increased from 2002 to 2012, and the most increased transactions were related to n4 and n19. Table 5 shows that the transactions leading to the change in the MCI of n4 increased by 10 from 2002 to 2012 and that the application of intermediate products of n4 expanded from n12, n14, n15, n16, n18 and n22 to n1, n7, n9, and n17. Since the application versatility of metal ores in China has expanded rapidly, the consumption has increased accordingly (Humphreys, 2010). Statistics show that the amount of metal consumption for n1, n7, n9 and n17, respectively, increased by 193.31%, 320.94%, 943.43% and 788.10% from 2002 to 2012, which enhanced their effects on the MCI of n4. In addition, for n19, the transactions related to n19 applied to n20, n24 and n25 had a more significant influence on the MCI of n19 in 2012 compared with 2002, which occurred because the demand from education, culture, infrastructure and other construction for electronic communication equipment increased rapidly, thus increasing its influence on the MCI of n19.

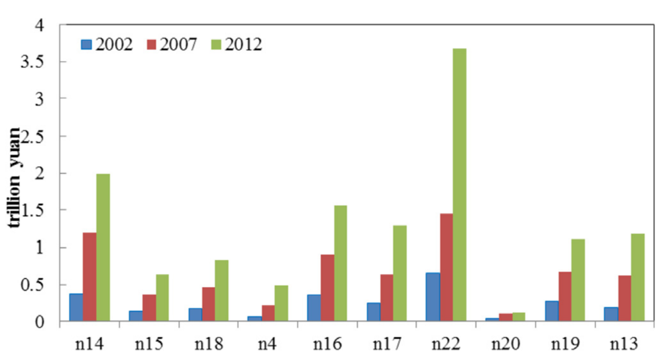

Fig. 3. The value added of ten key sectors in China in 2002, 2007, and 2012. Date source: Input-output table for China.

3.2.2. The trends in the elasticity of final demand coefficients

Considering the importance of intersectoral linkages, elasticity values corresponding to the final demand coefficients that exceed 1% are selected as the key elasticity values (as shown in Table 6). Taking the first line of n14 in 2002 as an example, $\varepsilon_{M_i h_{kl}} = 1.21$ indicates that if the gross fixed capital formation of n14 decreases by 1%, the MCI of n14 will decrease by 1.21%.

(1) Most elasticity values in different industries increased constantly from 2002 to 2012, indicating that the effect of the final demand structure (public and household consumption, gross fixed capital formation, and net exports) on the MCI continually increased. Over the last two decades, consumption, investment and exports have been regarded as "the troika" for China's economic growth – especially investment and exports, which have contributed greatly. Accordingly, the effects of the final demand on the MCI of different industries have increased rapidly. However, the contributions of exports and investment to economic growth have tended to decrease since the onset of the financial crisis, leading to the growth rate of the elasticity values during the 2007–2012 period was less than that during the 2002–2007 period.

(2) The final demand relations leading to changes in the MCI of key sectors showed an increasing tendency from 2002 to 2012, and almost all the newly added final demand relations were related to gross fixed capital formation, except for n17. In recent years, China's investment in metal-related industries has rapidly increased. As a result, the influence of gross fixed capital formation in these industries on the MCI of key sectors has increased accordingly. The one exception is that the newly added final demand relations leading to changes in the MCI of n17 were related to household consumption demand for n17. According to statistics published by the China Association of Automobile Manufacturers, automobile production and sales volume in China have been ranked first worldwide since 2009 and have shown rapid growth in recent years. The growth rate of the annual production and sales volume in 2016 reached 14.76% and 13.7% (compared with the previous year), respectively.

Table 5
The sensitivity trends for the MCI of key industries corresponding to the (pure) technical coefficients.

Key industry	2002				2007				2012			
	i	*k*	$\varepsilon_{M_i a_{kl}}$	$\varepsilon^*_{M_i a_{kl}}$	*i*	*k*	$\varepsilon_{M_i a_{kl}}$	$\varepsilon^*_{M_i a_{kl}}$	*i*	*k*	$\varepsilon_{M_i a_{kl}}$	$\varepsilon^*_{M_i a_{kl}}$
n14	n14	n 14*	0.46	0.46	n 14	n 14*	0.56	0.56	n 14	n 14*	0.59	0.59
	n14	n 15	0.24	0.19	n 14	n 15	0.28	0.22	n 14	n 15	0.27	0.22
	n 14	n 16	0.29	0.15	n 14	n 16	0.38	0.20	n 14	n 16	0.32	0.17
	n 14	n 17	0.06	0.06	n 16	n 16	0.14	0.07	n 16	n 16	0.12	0.07
	n 14	n 18	0.15	0.13	n 14	n 18	0.23	0.20	n 14	n 18	0.22	0.18
	n 14	n 22	0.28	0.03	n 14	n 22	0.41	0.05	n 14	n 22	0.42	0.05
n4	n 12	n 12	0.11	0.02	n 4	n 4	0.12	0.12	n 12	n 1	0.11	0.00
	n 4	n 14*	1.08	0.29	n 7	n 7	0.13	0.01	n 4	n 4	0.17	0.17
	n 14	n 14	0.50	0.13	n 12	n 12	0.23	0.04	n 7	n 7	0.11	0.01
	n 4	n 15	0.11	0.02	n 4	n 14*	1.85	0.49	n 14	n 9	0.14	0.02
	n 14	n 15	0.26	0.06	n 14	n 14	1.02	0.27	n 4	n 12	0.10	0.02
	n 14	n 16	0.32	0.04	n 14	n 15	0.50	0.11	n 12	n 12	0.24	0.04
	n 16	n 16	0.10	0.01	n 14	n 16	0.69	0.10	n 4	n 14*	2.17	0.57
	n 14	n 18	0.16	0.04	n 16	n 16	0.26	0.04	n 14	n 14	1.27	0.33
	n 14	n 22	0.30	0.01	n 14	n 17	0.12	0.04	n 14	n 15	0.58	0.12
					n 14	n 18	0.42	0.09	n 15	n 15	0.10	0.02
					n 13	n 22	0.12	0.00	n 14	n 16	0.69	0.10
					n 14	n 22	0.74	0.02	n 16	n 16	0.27	0.04
									n 14	n 17	0.15	0.05
									n 17	n 17	0.10	0.03
									n 14	n 18	0.46	0.10
									n 18	n 18	0.11	0.02
									n 13	n 22	0.14	0.00
									n 14	n 22	0.89	0.03
									n 15	n 22	0.11	0.00
n15	n 15	n 15	0.13	0.13	n 15	n 15*	0.15	0.15	n 15	n 15	0.16	0.16
	n 15	n 22*	0.20	0.03	n 15	n 16	0.12	0.08	n 15	n 16	0.12	0.08
					n 15	n 22	0.14	0.02	n 15	n 22*	0.17	0.03
n18	n 18	n 16	0.10	0.07	n 18	n 16	0.14	0.09	n 18	n 16	0.14	0.09
	n 18	n 18*	0.11	0.11	n 18	n 18*	0.18	0.18	n 18	n 18*	0.20	0.20
	n 18	n 22	0.11	0.02	n 18	n 22	0.16	0.02	n 18	n 22	0.14	0.02
n16	n 16	n 16*	0.23	0.23	n 16	n 16*	0.30	0.30	n 16	n 16*	0.30	0.30
n17	n 17	n 17*	0.41	0.41	n 17	n 17*	0.51	0.51	n 17	n 17*	0.47	0.47
	n 17	23	0.26	0.12	n 17	n 23	0.29	0.14	n 17	n 23	0.30	0.14
					n 17	n 25	0.13	0.03				
n22	n 22	n 23	0.01	0.08	n 22	n 25*	0.01	0.02	n 22	n 22*	0.03	0.03
	n 22	n 24*	0.03	0.05								
n20	n 20	n 22*	0.22	0.01	n 12	n 12	0.16	0.04	n 20	n 10	0.11	0.07
	n 20	n 25	0.16	0.01	n 20	n 20	0.12	0.12	n 20	n 20	0.16	0.16
					n 20	n 25*	0.29	0.02	n 20	n 25*	0.19	0.02
n19	n 19	n 16	0.12	0.04	n 19	n 16	0.16	0.06	n 16	n 16	0.11	0.04
	n 19	n 19*	0.86	0.86	n 19	n 18	0.19	0.11	n 19	n 16	0.29	0.11
	n 19	n 24	0.24	0.13	n 19	n 19*	1.15	1.15	n 19	n 18	0.15	0.09
					n 19	n 20	0.14	0.25	n 19	n 19*	1.05	1.05
					n 19	n 24	0.14	0.08	n 19	n 24	0.13	0.07
					n 19	n 25	0.16	0.02	n 19	n 25	0.19	0.03
n13	n 13	n 22*	0.23	0.06	n 13	n 13*	0.20	0.20	n 13	n 13*	0.25	0.25

Note: * represents the most important sector linked to the MCI of the corresponding key industries.

3.3. Discussion of the elasticity of technical coefficients and final demand coefficients

Sensitivity analyses of the technical coefficients and final demand coefficients for the MCI of key sectors based on the input-output table in 2012 were conducted, and the results are shown in Fig. 4. It should be noted that the solid lines represent direct effects, the dotted lines represent indirect effects, and the arc lines represent self-use relationship effects. For example, for the MCI elasticity of n4, the elasticity of 2.17 involved in the demand of n14 for n4 has a direct influence on the MCI of n4; the value of 0.17 is caused by the self-supply by n4; and the elasticity of 0.46 caused by the demand of n18 for n14 has an indirect impact on the MCI of n4.

3.3.1. The elasticity of technical coefficients in 2012

(1) For the mining of metal ores sector, the technical coefficients involved in the self-supply by n4, n12 and n16, the direct transaction related to the purchase of n4 by n14, and the indirect transactions related to the sales of n14 to n15, n16, n18 and n22 each changed by 1%, the MCI of n4 would change by 0.17, 0.24, 0.27, 2.17, 0.58, 0.69, 0.46, and 0.89, respectively, as shown in Fig. 4. China is a country with a high level of metal consumption, and given the relatively backward technical conditions, the waste of mineral resources in mining is serious, and the use efficiency is consequently low (Chen and Cheng, 2015), leading to the high MCI in n4.

(2) The purchase of products from n14 by n14, n15, n16, n18 and n22 had a direct impact on the MCI of the manufacturing and processing of the metals sector, as shown in Fig. 4. The two highest elasticity values were 0.59 and 0.42, which were related to the purchase of n14 to support the production of n14 and n22. This result occurred because the exploitation and smelting of metals require a significant amount of metal ore, and even construction also requires metals as inputs. Statistics show that in 2012, the metal consumption in n14 and n22 accounted for 37.60% and 11.47% of the total amount of metal consumption, respectively. Moreover, the transaction

Table 6
The trends in the elasticity of the final demand coefficients.

Industry	2002			2007			2012		
	i	k	$\varepsilon_{M_i h_{kl}}$	i	k	$\varepsilon_{M_i h_{kl}}$	i	k	$\varepsilon_{M_i h_{kl}}$
n14	n14	3	1.21	n 14	3	2.11	n 14	3	2.71
	n16	3	2.57	n 16	3	4.48	n 16	3	5.74
	n22	3*	7.12	n 17	3	1.21	n 17	3	1.56
				n 18	3	1.14	n 18	3	1.46
				n 22	3*	12.43	n 22	3*	15.95
				n 25	2	1.18	n 25	2	1.66
n 4	n 14	3	1.35	n 14	3	2.35	n 14	3	3.02
	n 16	3	3.26	n 15	3	1.06	n 15	3	1.36
	n 22	3*	8.46	n 16	3	5.70	n 16	3	7.31
	n 25	2	1.04	n 17	3	1.46	n 17	3	1.87
				n 18	3	1.32	n 18	3	1.70
				n 22	3*	14.76	n 21	3	1.05
				n 25	2	1.54	n 22	3*	18.94
							n 25	2	2.17
n 15	n 15	1	1.42	n 15	1	2.13	n 15	1	2.93
	n 15	3	2.15	n 15	3	3.75	n 15	3	4.81
	n 15	4	1.90	n 15	4	1.08	n 15	4	1.35
	n 16	3	1.25	n 16	3	2.18	n 16	3	2.80
	n 22	3*	4.90	n 22	3*	8.55	n 22	3*	10.97
				n 25	2	1.17	n 25	2	1.64
n 18	n 16	3	2.07	n 16	3	3.61	n 16	3	4.64
	n 18	1	2.58	n 18	1	3.87	n 17	3	1.02
	n 18	3*	4.24	n 18	3*	7.40	n 18	1	5.31
	n 22	3	3.08	n 22	3	5.38	n 18	2	1.17
				n 25	2	1.02	n 18	3*	9.49
							n 22	3	6.90
							n 25	2	1.43
n 16	n 16	3*	10.83	n 16	1	1.25	n 16	1	1.72
	n 22	3	2.66	n 16	3*	18.91	n 16	3*	24.26
				n 22	3	4.65	n 17	3	1.27
				n 25	2	1.00	n 22	3	5.96
							n 25	2	1.41
n 17	n 17	3*	10.23	n 16	3	1.48	n 16	3	1.89
	n 22	3	2.12	n 17	3*	17.86	n 17	3*	22.91
	n 23	4	1.30	n 22	3	3.69	n 21	3	1.02
				n 25	2	1.23	n 22	3	4.74
							n 23	1	1.07
							n 25	2	1.73
n 22	n 22	3*	16.86	n 22	3*	29.44	n 22	3*	37.76
n 20	n 16	3	1.21	n 16	3	2.11	n 16	3	2.71
	n 20	3*	10.33	n 20	3*	18.03	n 20	3*	23.13
	n 22	3	2.14	n 22	3	3.73	n 22	3	4.78
	n 25	2	1.88	n 25	1	1.07	n 25	1	1.47
				n 25	2	2.77	n 25	2	3.90
n 19	n 19	1*	6.43	n 19	1*	9.64	n 16	3	1.17
	n 19	3	4.86	n 19	3	8.48	n 19	1*	13.22
				n 22	3	1.10	n 19	3	10.88
				n 25	2	1.20	n 22	3	1.41
							n 25	2	1.69
n 13	n 13	3	1.54	n 13	3	2.68	n 13	3	3.44
	n 13	4	1.38	n 16	3	1.13	n 16	3	1.45
	n 22	3*	11.09	n 22	3*	19.36	n 22	3*	24.84
							n 25	2	1.36

Note: * represents the most important final demand linked to the MCI of the corresponding key industries.

involving the self-provision of n16 had an indirect influence on the MCI of n14 because the production of n16 indirectly consumed the products of n14.

(3) For the manufacturing of the fabricated metal products sector, direct transactions related to the sales of n15 to n16 and n22 and the self-provision by n15 had the greatest effects on the MCI of n15, the elasticity values of which were 0.12, 0.17 and 0.16, respectively, as shown in Fig. 4.
(4) The highest direct impact on the MCI of the manufacturing of electrical machinery and apparatus sector was related to its self-use and its linkages with n16 and n22. Since n18 provides power devices for the production of its own sector, n16 and n22, it is important to improve the production efficiency and extend the service life of mechanical and electrical equipment in n18, n16 and n22.
(5) For the manufacturing of transport equipment sector, the direct transaction related to the self-supply of intermediate products provided by n17 for itself had the greatest effect on the MCI of n17, followed by the sales of n17 to n23. Since n17 provides conveyances for its own production and for the transportation, storage and delivery of goods, it would be helpful to improve the transport efficiency by promoting the recycling of scrap vehicles and rationally distributing the cargo load of vehicles.
(6) For construction, the highest direct elasticity value induced by self-use was 0.03. Compared to the technical coefficient elasticity in other key industries related to n22, the elasticity of the technical coefficients in n22 was quite small. The reason for this result is that n22 is in the downstream portion of the industrial chain, and its demand for metal resources from other industries has a strong impact on the MCI of the corresponding industries.
(7) Sectors n10, n20 and n25 had direct effects on the MCI of n20, with elasticity values of 0.11, 0.16 and 0.19, respectively. The reason for this result is that the products of n20 are the main production inputs for sectors n10, n20 and n25.
(8) The transactions involving the application of n16, n18, n19, n24 and n25 to n19 had the greatest direct influences on the MCI of the manufacturing of communication equipment, computers and other electronic equipment sector, as shown in Fig. 4. The greatest direct effect on the MCI of n19 was from self-use by n19 because n19 requires a considerable amount of communication equipment, computers and other electronic equipment as inputs to meet its production demand. Moreover, the self-supply by n16 had an indirect impact on the MCI of n19.
(9) Transactions involving self-use by the manufacturing of general and special purpose machinery sector had a direct influence on its own MCI. Similarly, transactions related to self-use by the manufacturing of nonmetallic mineral products sector also had a direct effect on its own MCI.

3.3.2. *The elasticity of final demand coefficients in 2012*

(1) The greatest MCI elasticity of final demand in 2012 was the gross fixed capital formation of construction, which had an elasticity value of 37.76. The reason for this result is that the proportion of gross fixed capital formation in construction to the total gross fixed capital formation was 93.00% in China in 2012. Moreover, with respect to the MCI of n14, n4, n15, n18, n16, n17, n20 and n13, the greatest elasticity values were also related to the gross fixed capital formation of their respective industries, which were 15.95, 18.94, 10.97, 9.49, 24.26, 22.91, 23.13 and 24.84, respectively, as shown in Fig. 4. Since the 1990s, investment by the Chinese government in infrastructure construction and public services has increased by more than 20% annually (Wang, 2014). Statistics show that China's construction area has increased rapidly, and the commercial and residential building area increased by an average of 39.30% per year from 2000 to 2015 (National Bureau of Statistics, 2016). However, due to its relatively short life span and high vacancy rate, the utilization efficiency of Chinese architecture is very low (Huang et al., 2018). Therefore, the Chinese government should undertake more effective measures to improve the efficiency of buildings and reduce the consumption of metal materials for new buildings to some extent.

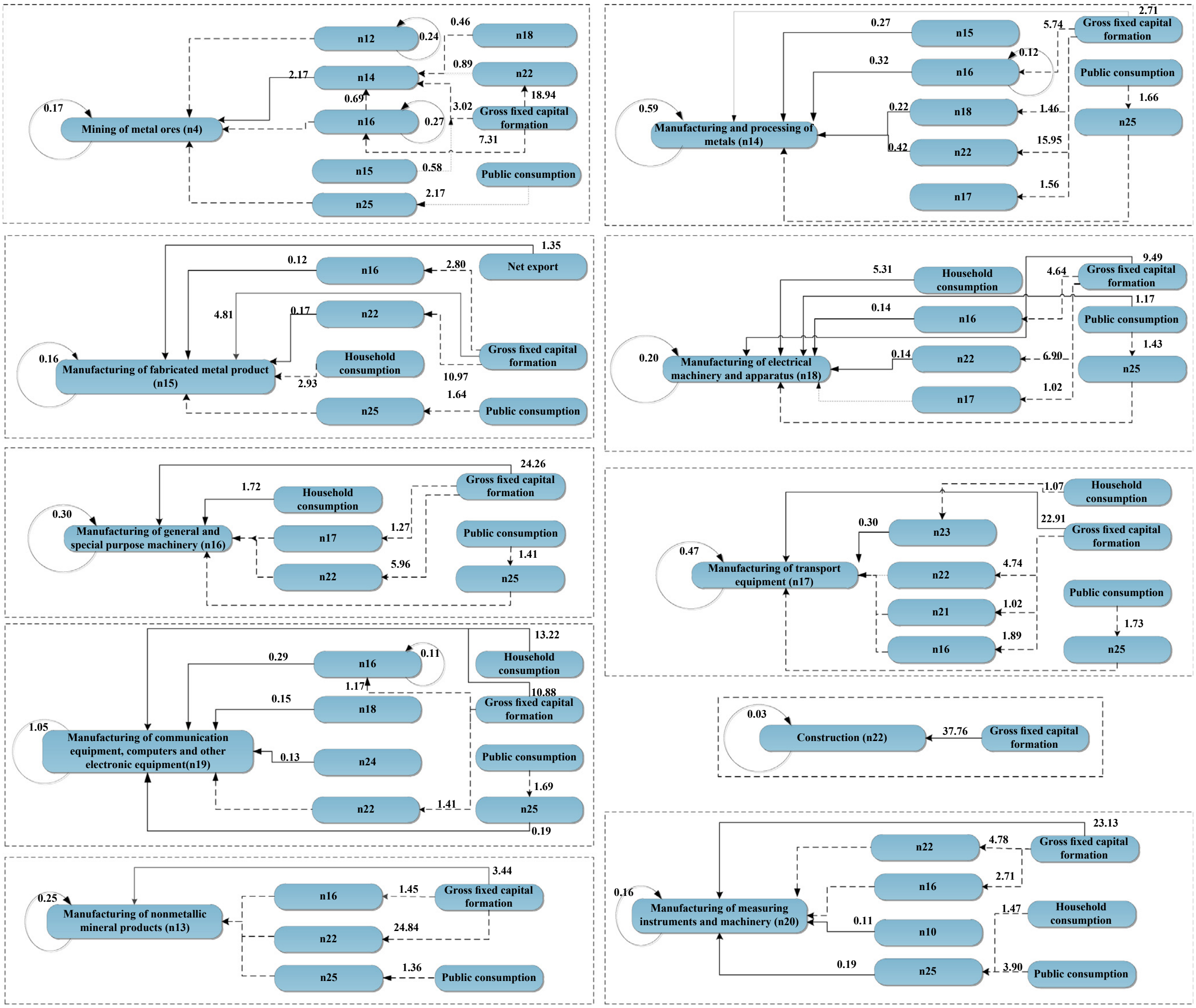

Fig. 4. The main MCI elasticities of key sectors in China based on the 2012 input-output table.

(2) The highest MCI elasticity for household consumption demand was related to sector n19, indicating that the users of communication devices are mainly private consumers. Regarding direct effects, the MCI elasticity for n19 from household consumption demand was 13.22; for the MCI of n15, the elasticity of household consumption demand was 2.93; for n18, the elasticity was 5.31; and for n16, the elasticity was 1.72. Moreover, the household consumption demand for n23 and n25 had an indirect influence on the MCI of n17 and n20, and the elasticities were 1.07 and 1.47, respectively.

(3) Public consumption demand for n25 had an indirect effect on the MCI of n14, n4, n15, n18, n16, n17, n20, n19 and n13, which had elasticities of 1.66, 2.17, 1.64, 1.43, 1.41, 1.73, 3.90, 1.69 and 1.36, respectively. Among them, the public consumption demand for the products of sector n25 made the greatest indirect contribution to the MCI of n20. Moreover, the public consumption demand for the products of sector n18 had a direct effect on the MCI of n18, with an elasticity of 1.17.

(4) The net export coefficient of sector n15 directly influenced its own MCI, and the elasticity was 1.35. It should be emphasized that net exports represent exports minus imports. The net export coefficient of n15 was positive in 2012, indicating that the exports of n15 were greater than the imports in that year. Currently, China's metal exports are mostly oriented towards primary products, and the value added is low. Thus, it is necessary to improve the metal product processing technology to increase the exports of high-tech metal products instead of primary metal products.

3.4. Overall analysis of the critical links

3.4.1. The critical links in terms of (pure) technical coefficients

(1) The MCI of most key industries except for n4 was mainly affected by the technical coefficients concerning direct transaction relations. Table 5 shows that these production transactions related to n14, n15, n18, n16, n17, n22, n20, n19 and n13 with other industries predominantly had direct influences on their own MCI. Among them, changes in production technology for n14, n18, n16, n17 and n19, which consumed self-supplied intermediate products, had the

greatest influence on their MCI. Simultaneously, changes in production technology for n15, n22, n20 and n13, which supplied intermediate products for other industries, exerted the greatest effect on their own MCI. It is worth nothing that the MCI of n4 was affected not only by the direct transactions but also by the indirect transactions.

(2) Comparing the elasticity values of the technical coefficients and pure technical coefficients from different years in Table 5 clearly shows that under most circumstances, $\varepsilon_{M_i a_{kl}} \geq \varepsilon^*_{M_i a_{kl}}$ is established. This result indicates that the production technology impact on the MCI of key industries is enhanced after considering the effect of the demand structure. Thus, for these industries, attention should be paid to adjusting the product consumption structure while promoting technology innovation in related industries. In addition, the elasticity values of the technical coefficients and pure technical coefficients are equal for industries that consume self-supplied intermediate products. That is, if $i = k$, then $\varepsilon_{M_i a_{kl}} = \varepsilon^*_{M_i a_{kl}}$ under general conditions. The implication is that self-supplying industries are not affected by structural correlations and should emphasize improving their own production technology.

(3) In terms of the industry chain, sectors n4, n14 and n15 are located upstream in the supply chain, and their MCI is influenced more by the production efficiency and the demand structure of the downstream industries since their products are mostly inputs for other sectors. Moreover, sectors n23, n24 and n25 are located at the end of the industry chain, so their production efficiency has a substantial impact on the MCI of the upstream metal-related industries, such as n17 and n19.

(4) From an overall perspective, sectors n16, n18 and n22 have significant impacts on the MCI of most key sectors. Sectors n16, n18, and n22 are in the middle and lower reaches of the industry chain, large quantities of metallic raw materials are required from the production activities, so their own productivity will affect the MCI of the upstream sectors. In recent years, despite constant breakthroughs attained in the production technology of metal smelting and machinery manufacturing, there remain an enormous number of backward production facilities, especially in small and medium-sized enterprises (Shao et al., 2016). Therefore, strengthening the management and promoting collaborative innovation will be conducive to improving the production efficiency in these industries, which could lower the MCI of the whole industry chain.

3.4.2. The critical links in terms of final demand coefficients

(1) The MCI of most industries was mainly affected by the gross fixed capital formation in corresponding industries, and the greatest MCI elasticity value was induced by the gross fixed capital formation in n22. Moreover, the elasticity values increased each year. As mentioned above, the rapid economic growth in China, especially since 2000 (Schandl and West, 2010), has led to massive metal ore extraction and a sharp rise in global metal prices (Wiedmann et al., 2015), resulting in a flood of capital investment into metal-related industries. As a result, metal-related industries have suffered from severe overcapacity, especially soon after the Chinese government launched a 4 trillion yuan rescue plan. Therefore, resolving the overcapacity in metal-related industries, reducing the amount of blind investment and applying funds to technology research and development could help reduce the MCI. It is also worth noting that the greatest MCI elasticity for n19 is household consumption demand because the products of n19 are used mainly to meet the human need to exchange and obtain information. According to the China Statistical Yearbook, in 2002, the number of personal computers owned per 100 urban households in China was 20.63, but by 2012, this number had grown to 87.

(2) In terms of critical demand, the gross fixed capital formation of n16 and n22 and the public consumption demand for n25 had significant effects on the MCI of all key sectors, so more attention should be focused on these sectors. As previously discussed, the significant impact of the gross fixed capital formation of n16 and n22 on the MCI can be attributed to serious overcapacity and blind investments in metal-related industries. Regarding the public consumption demand for n25, it should be clear that rapid growth in China's infrastructure construction has led to substantial improvements in the infrastructure for transport, telecom and the energy supply. Statistics show that investments in these three types of infrastructure increased from 637.65 billion yuan in 2003–4033.99 billion yuan in 2014, for an average annual growth rate of 18.26%. It is worth noting that some infrastructure construction should be attributed to the pursuit of political objectives by sub-national governments in China, resulting in serious resource waste (Xu, 2011). Therefore, the central government should pay greater attention to such investments.

4. Conclusions and policy recommendations

To investigate MCI and the corresponding drivers from the intersectoral perspective in China, this paper first identified the ten sectors with the greatest MCI according to the Chinese input-output tables for 2002, 2007 and 2012. Then, sensitivity analysis of the MCI of key industries based on the Leontief input-output model of 25 sectors was conducted in an effort to explore the relationships among sectoral MCI, intersectoral linkages and final demand, which could guide policy interventions promoting the effective use and conservation of metal resources. The conclusions are as follows.

(1) From 2002 to 2012, the average MCI of key industries increased from 7.37 tonnes per ten thousand yuan to 32.13 tonnes per ten thousand yuan, and the effect of (pure) technical coefficients and final demand coefficients on the MCI in key sectors was correspondingly enhanced. From a sectoral perspective, sector n14, n15 and n18 had the greatest MCI, indicating that metal use in these sectors is relatively inefficient, and more attention should be paid to them.

(2) In terms of the critical path, direct transactions between sectors proved to be the dominant contributor to the changes in most sectoral MCI. For instance, the MCI of n5, n14, n16, n17 and n18 were mainly affected by their own production efficiency. In addition, sectors n16, n18, and n22 exerted a great effect on the MCI of most sectors, and the MCI of n4 was directly or indirectly affected by most sectors.

(3) In terms of critical demand, the gross fixed capital formation of the corresponding sectors had a significant impact on the MCI, and the greatest contributor was the gross fixed capital formation of construction. Moreover, the gross fixed capital formation for n16 and the public consumption demand for n25 made significant contributions to the MCI of most sectors.

Based on the above conclusions, we propose the following relevant policy recommendations to reduce China's MCI.

(1) The Chinese government should pay attention to the country's MCI since it reflects the resource utilization efficiency. Since technological progress can affect metal use efficiency through the comprehensive utilization of resources, improving the amount of recycling of mineral resources and reducing resource consumption (Habib and Wenzel, 2014), it is appropriate for the Chinese government to reduce its MCI by improving the current technology and developing new technology for metal picking, smelting and calendar processing, machinery manufacturing and other industries. Specifically, the government could formulate preferential policies to attract currency capital and human capital into metal-related industries and could use R&D subsidy policies and tax incentives to encourage mining companies to implement technical innovations and adopt energy-saving technologies. In addition, appropriate production standards could be formulated according to the specific characteristics of industries with high MCI to improve production efficiency and production quality and to promote the recycling of metal resources.

(2) To improve the metal utilization efficiency of sectors with high MCI, attention should be paid to the technical level and demand structure of the transition processes between sectors with large elasticity values. Policy measures should be predominantly sector specific and should consider the linkages between departments, especially the direct transactions between sectors. For instance, it would be helpful to improve the production technology of n16 to reduce its demand for electronic equipment, which would reduce the MCI of n19. Moreover, since sector n4 is situated in the upper reaches of the industrial supply chain, its products are basic materials for most metal-related industries and are difficult to substitute. Thus, the government should improve the efficiency of metal mining by strengthening management and establishing a reasonable mineral property development system. Meanwhile, it would also be helpful to improve the production technology and optimize the consumption structure of downstream industries such as n16, n18, and n22.

(3) China's government should place a high value on the effect of the gross fixed capital formation of various sectors. Effective policies are urgently needed to resolve overcapacity in metal-related industries, to reduce blind investments and to guide investments towards technology research and development in metal-related sectors. Since the gross fixed capital formation of construction is the highest, it would be useful to maintain and repair existing buildings to extend their service life, thereby reducing the MCI by improving housing utilization. Meanwhile, a rational housing tax could be imposed to reduce the housing vacancy rate, and advanced technologies such as 3D printing could be used to reduce the consumption of certain metals. Moreover, China's government should focus more on the production efficiency and consumption structure of n16, n22 and n25 because these sectors have a significantly direct or indirect impact on the MCI of most industries. In addition, the central government should improve its supervision to prevent sub-national governments from blindly engaging in infrastructure construction in pursuit of higher GDP.

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Appendix A. Sector classification of the Chinese input-output table with the corresponding codes.

Code	Sector	Code	Sector
n1	Agriculture	n14	Manufacturing and processing of metals
n2	Mining and washing of coal	n15	Manufacturing of fabricated metal products
n3	Extraction of petroleum and natural gas	n16	Manufacturing of general and special purpose machinery
n4	Mining of metal ores	n17	Manufacturing of transport equipment
n5	Mining of nonmetallic minerals	n18	Manufacturing of electrical machinery and apparatus
n6	Manufacturing of foods and tobacco	n19	Manufacturing of communication equipment, computers and other electronic equipment
n7	Manufacturing of textile, leather, fur, feather and its products	n20	Manufacturing of measuring instruments and machinery for cultural activities and office work
n8	Processing of timbers and manufacturing of furniture	n21	Other manufacturing (including scrap and waste)
n9	Papermaking, printing and manufacturing of articles for culture, education and sports activities	n22	Construction
n10	Production and supply of electricity, steam and water	n23	Transport, storage and post
n11	Manufacturing of refined petroleum and coke products and processing of nuclear fuel	n24	Renting and leasing, business services, wholesale and retail trades, finance, real estate, hotel and catering services
n12	Manufacturing of chemicals and chemical products	n25	Public utilities, services to households and other services, education, culture, sports and entertainment, scientific research and technical services, administration and others
n13	Manufacturing of nonmetallic mineral products		

Appendix B. Final demand classification of the Chinese input-output table with the corresponding codes.

Code	Final demand	Code	Final demand
1	Household consumption	3	Gross fixed capital formation
2	Public consumption	4	Net exports

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