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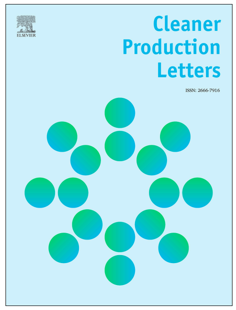

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Assessing urban carbon metabolism using network analysis across Chinese and European cities

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Abstract

Urban metabolism uses the idea that cities are resource consuming systems that are supported by flows of energy and materials, and they produce goods and wastes, which generate greenhouse gas emissions both directly and indirectly. This research builds on other recent applications of input-output and ecological network analyses to urban metabolism with added value of comparing in one study both approaches across Europe and China specifically at the city scale. We use input-output (IO) and ecological network analyses (ENA) in a study of the urban metabolism of four cities, Vienna, Austria, Malmö, Sweden, Beijing and Shanghai, China. Based on economic input-output tables and environmental weighting coefficients, we create a connected network of flows between 17 economic sectors that captures the carbon emissions from transactions in a producer orientation. Ecological network analysis is conducted to identify the main sectors contributing to the direct and indirect carbon emissions in the four cities. Our results reveal these to be Transportation, Manufacturing, and Electricity production. Furthermore, we show that final demand in terms of domestic export is the highest contributor in each city, indicating that each city is a producer overall in the countries' economies generating carbon flows that are consumed elsewhere.

Key Words: urban carbon metabolism; input-output analysis, ecological network analysis, carbon flow

1. Introduction

1.1 Cities as economic engines and Greenhouse Gas emitters

With human urban activities emitting approximately 80% of global greenhouse gas emissions, cities are playing a significant role in the global carbon balance (Chen and Chen, 2020, Li et al., 2021). According to previous studies on the greenhouse gas emissions of 167 major cities throughout the world, Asian cities are the biggest carbon emitters, and the top 25 (15%) of the 167 cities accounted for 52% of the total GHG emissions, which are mainly from Asia and Europe (Wei et al., 2021). In this research, we compare the urban carbon metabolism of four cities, namely Beijing and Shanghai, China, Vienna, Austria, and Malmö, Sweden. Together the four cities provide a glimpse across two continents and two orders of magnitude in scale with populations in Malmö ~0.25M, Vienna ~2.5M and Beijing and Shanghai both ~25M. A brief overview of the carbon emissions of the four cities is given next. We provide a comparison of direct and indirect emissions using both input-output methods and network analysis in order to answer the question which sectors are most responsible for emissions, which sectors have most control on other sector emissions, and if the overall state of the urban socio-economic system is sustainable in terms of trophic level structure.

In 2017, global carbon dioxide emissions amounted to 33.51billion tons, of which China' s carbon dioxide emissions were 10.10 billion tons, accounting for 30.14% of the total, and the EU-27 contributing 2.93 billion tons or 8.74% of the total (World bank, 2018). Beijing and Shanghai are the political and economic centers of China, as well as the gateway cities of China to the world, and as such are high greenhouse gas emitters in Asia. The carbon emissions of Beijing and Shanghai were 85.56 million tons and 196.15 million tons, and per capita carbon emissions were 3.89 tons and 8.11 tons, respectively (CEADs, 2021). According to Greenhouse gas emissions statistics from the Environment Database of the Organization for Economic Cooperation and Development official website (https://stats.oecd.org/), Austria' s carbon emissions were 69.59 million tons in 2017 and Sweden's carbon emissions amounted up to 42.70

million tons in the same year. Vienna is the capital and largest city of Austria, with carbon emissions of 20.2 million tons and emissions per capita of 11.10 tons. Malmö is the third largest city in Sweden, with carbon emissions of 3.3 million tons and emissions per capita of 9.88 tons. It is vital for both researchers and policy makers to have city-level information regarding carbon emissions in order to achieve the carbon emission reduction targets for these cities. For example, Shanghai's objective is to obtain peak carbon emissions by 2025, Beijing' s goal is attaining carbon neutrality by 2050, and the realization of the Paris Agreement limits the increase in global average temperature to 1.5℃ target.

Table 1. Comparison of carbon emissions in 2017 for the four case cities

	Total carbon emissions (million tons)	Carbon emissions per capita (tons)	Data sources
Beijing	85.56	3.89	www.ceads.net.cn
Shanghai	196.15	8.11	www.ceads.net.cn
Vienna	20.20	11.10	https://citycarbonfootprints.info/
Malmö	3.3	9.88	www.sei.org/projects-and-tools/tools/konsumtionskompassen/

Background of the four case study cities

Urban carbon emissions are closely related to the economic characteristics of cities. Vienna is an important transportation hub in Austria, whose economic growth rate is higher than the EU average. Vienna's service industry is highly developed, and the service industry brings Vienna's economy to about 72.51% of its total output. The primary sector (*Agriculture, forestry and fishing*) accounts only for 0.05% of the total output in Vienna. The *Manufacturing sector* accounts for 13.3% of output in Vienna, which is the largest among all the sectors in 2017. The *Pharmaceuticals and chemicals industry* is also important in Vienna, accounting for 4.6% of the total output.

Malmö is the third most populous city in Sweden. Its industrial structure is dominated by the tertiary industry, and the output value of agriculture as the primary industry accounts for less than 1% of the total output value. Among all service industries, *Professional, scientific and technical activities, administrative and support service activities* is the most active, accounting for 24.39% of the total value. In addition, *Information and communication and real estate* accounted for more than 10% of the total output value.

Beijing and Shanghai are important megacities in China, and their urban economic characteristics are representative. As a metropolis with a high degree of modernization, the industrial structures of Beijing and Shanghai are also dominated by the tertiary industry, and the output of agriculture as the primary industry accounted for less than 1% of the total output. Among all service industries, Real estate activity is the most active in Shanghai and Beijing, contributing more than 10% of total output. Manufacturing output is the highest among all sectors, not only in the secondary industry. Especially in Shanghai, the output of the manufacturing accounts for 37.87% of the total output, which is undoubtedly an important pillar industry.

In order to further analyze the characteristics of carbon metabolism activities in cities and their economic drivers, this paper will conduct research through input-output analysis and ecological network analysis.

1.2 Cities as metabolic systems

The concept of urban metabolism was proposed to provide a framework to analyze the structure and features of an urban system (Wolman et al., 1965; Decker et al. 2000). Urban metabolism, like biological metabolism, refers to the process of a city taking in, consuming, and discarding material and energy, similar to the way individual eats, digests, breathes and performs work, which emits heat and carbon dioxide. To further conduct an inquiry into the role of cities in the global carbon cycle, carbon flows associated with cities need to be systematically measured and modeled as the input and output of material and energy results in environmental impacts (Tjallingii et al., 1993). Tracking the carbon flow within the urban framework offers a deeper comprehension of the intricate interplay between socio-economic and natural metabolic processes, along with the inherent characteristics of carbon metabolism. Urban metabolism, deriving from natural metabolic processes, amalgamates various economic sectors within urban socio-economic sub-systems, leading to considerable changes in the natural process. Efficient carbon flow tracking also facilitates identification of crucial sectors and critical paths within the system, enabling targeted mitigation strategies for high-emitting sectors and their interdependencies (Chen and Chen, 2017). Some studies have investigated the carbon emissions of typical cities. For example, Villalba et al. (2011) analyzed the carbon emissions of transportation activities in port cities and the carbon emissions of energy consumption in residential areas in Xiamen. Kennedy et al. (2010) investigated the carbon emissions of 10 cities including Los Angeles and Prague to measure activities such as resource and energy consumption, increased transportation and electricity, and built-up area design. Croci et al. (2011) compared the carbon emission characteristics of seven global cities - Bangkok, Chicago, London, Madrid, Mexico City, Milan and New York City. Ou et al. (2013) quantitatively investigated how urban form influences urban carbon emissions by establishing a panel data model.

At present, two types of metabolism-orientated approaches have been applied to the investigation of carbon metabolic processes. One is based on the metabolic inventories to quantify and decompose life cycle emissions (Liu et al., 2012; Wang et al., 2013; Liu et al., 2014) through inventory accounting, decomposition analysis (Jung et al., 2012, 2014), and life cycle assessment (Hashimoto et al., 2010; Kantor et al., 2012; Dong et al., 2013). The other one is process-based method tracking metabolic flows using material flow analysis (Tian et al., 2013; Zhang et al., 2014; Yu et al., 2014). Nevertheless, using these two methods it is difficult to identify how the internal sectors of the system participate in the carbon metabolism process and the key characteristics of the system's metabolic structure and function. It is also hard to quantify the indirect interactions between non-directly related sectors, to comprehend better the processes of urban carbon metabolism.

Ecological network analysis (ENA) regards an ecosystem as a network where ecological flows and functional compartments are depicted, by quantifying the carbon flow direction and intensity between nodes, and quantifying the direct and indirect relationships in the system. ENA can elaborate relations in any network effectively, which is conducive to exploring the design of an urban metabolic system (Fath and Patten, 1999; Jørgensen and Fath, 2006; Fath et al., 2007). ENA is also useful to envisage the structure of the system by constructing the "feeding" level of the city's carbon metabolism represented by ecologically-equivalent trophic levels of producers, consumers, and decomposers (Hardy and Graedel, 2002).

Since Hannon (1973) first applied the ecological network method to simulate the structural distribution of the ecosystem and the relationship between various nutrient levels, ecological network analysis was first extensively applied to natural ecosystems. Recently, ecological network analysis has been broadly introduced in socio-economic system. For example, Zhang et al. (2010) introduced this approach into urban water metabolism analysis. Zhang et al. (2014) identified the energy flow processes between 28 socio-economic sectors such as industry and transportation, constructed a Beijing urban network model and estimated its carbon footprint. Also, Zhang et al. (2010, 2016) analyzed the ecological network utility of urban energy metabolism, water metabolism, and nitrogen metabolism systems, and revealed the features of urban material and energy exchange. In the construction of the urban carbon metabolism network model, the system is divided into internal and external environments. This simplifies intricate interaction between the city and the surrounding environment as it is reflected in the ecological network analysis.

Urban carbon metabolism is not only influenced by economic activities, but also by the industrial structure and carbon efficiency. In the network of urban systems, alterations to the industrial structure can influence the network characteristics, potentially impacting carbon metabolism (Zhang et al, 2015). For example, if the share of the electricity sector in total output rises, it can result in higher energy requirements and, consequently, modifications to the flow paths among interconnected sectors. Some studies had analyzed the carbon metabolism of different cities; however, few studies compared the carbon metabolism difference under the same accounting framework. Given this, in this study, we established an ecological network of carbon metabolism of four typical cities from China and Europe. The remainder of the paper is organized as follows. Section 2 shows the method of constructing ENA analysis based on IOA model to simulate urban carbon metabolism. Section 3 compares and analyzes the carbon flow, industrial metabolic scale, intersectoral interaction and system characteristics of the four cities. Section 4 summarizes the conclusions, clarifies the use of ecological network analysis to assess urban carbon metabolism, the significance of these results to their respective cities, as well as the uncertainty and limitations associated with the results, and discusses the possible schemes for cities to achieve emission reduction.

2. Methodology

2.1 Network construction and Input-output analysis

Input-output analysis (IOA) has been shown to be a useful top-down method to distribute emissions to final demand in a consistent framework. It was first developed by Leontief and further modified to evaluate the environmental impacts of resource use (Miller and Blair, 2022). This method distinguishes the direct and indirect emissions embodied in trade from interconnected economic sectors and distributes supply-driven impacts along the supply chain to reflect the embodied emission flows across sectors. We used Matlab for the IOA calculation.

It should be clarified that some pivotal assumptions have been made to set the system boundary and avoid double counting. First, the study is conducted within the administrative boundary of the city in question (Beijing, Shanghai, Vienna, or Malmö) to examine the sectoral interactions through the economic activities more deeply. Second, those goods and services imported from other regions or countries are assumed to have the same emission coefficient as local products.

$$x_i = \sum_{j=1}^{n} X_{ij} + y_i \tag{1}$$

where x_i is the total economic output of the ith sector; n refers to the number of economic sectors; X_{ij} represents the monetary flows from the ith sector to the jth sector; y_i is the final demand of sector i.

The technical coefficient matrix A is calculated as:

$$A = X_{ij}/x_j \tag{2}$$

Combining Eqs. (1) and (2), we can get

$$x = (I - A)^{-1} y \tag{3}$$

where x is the vector of sectoral output; I represents the identity matrix; y refers to a vector of final demand; $(I - A)^{-1}$ is known as the Leontief inverse matrix, which depicts the total production of each sectors required to meet a particular final demand in monetary value (Miller and Blair, 2022).

Environmental impact intensity (carbon emission in this study) from each sector can be calculated by:

$$k_i = E_i/x_i \tag{4}$$

where E_i stands for the total carbon emission from sector i; k_i is the carbon emission coefficient which is calculated by total carbon emission from each sector divided by total output of the corresponding sector. To convert the monetary flow into environmental flow, the equations (3) and (4) should be combined:

$$E_i = k_i (I - A)^{-1} y \tag{5}$$

By extending Eq. (5), we can get:

$$E_i = (k_i y + k_i A y) + (k_i A^2 y + k_i A^3 y + \cdots) \tag{6}$$

Referring to structural path analysis, which is widely used to disaggregate indirect environmental impacts of emissions, indirect carbon emissions can be defined from perspective of paths (Defourny and Thorbecke, 1984). Sectors are directly linked through direct paths, and also have multiple links through longer paths. Considering paths of length greater than 1, emissions generated due to indirect paths can be identified (Wang and Chen, 2021). Then, the direct and indirect carbon emission can be calculated as:

$$D_e = k(I + A)y \tag{7}$$

$$I_e = k(I - A)^{-1}y - D_e \tag{8}$$

where D_e and I_e represent direct and indirect carbon emissions. Thus, the amount of direct and indirect carbon emission from each sector can be separated from the total ones.

2.2 Ecological network analysis

Ecological network analysis regards an ecosystem as a network of compartmental nodes connected by flows of matter or energy (Han, 1993a, 1993b). In urban metabolism research, ecological network analysis can be used to capture the amount of carbon flows through carbon metabolism sectors and paths, which serve as nodes and connections to form the network system. It has an advantage in identifying carbon reduction pathways by reflecting the ecological relationship and system function along with the trophic level structure among the various components (Lindeman,1942). Specifically, here we apply flow analysis, control analysis, and trophic level structure analysis. Characterizing the operating status and characteristics of the metabolic system is conducive to in-depth research on urban carbon metabolism. We used MATLAB for the ecological network analysis.

(1) Flow Analysis

Flow analysis calculates the material flux through each sector, reflects throughflow of each node as well as the overall throughflow of metabolism, and then characterizes contribution of each node to the system activity (Borrett, 2013). Assuming that the system is in steady state, the input-output flow should be in equilibrium, where the sum of inflows equals to the sum of outflows. It can be calculated by:

$$T_i = T_{i,in} = \sum_{j=1}^{n} f_{ij} + z_i \tag{9}$$

$$T_j = T_{i,out} = \sum_{j=1}^{n} f_{ji} + y_j \tag{10}$$

$$TST = \sum_{j=1}^{n} T_j \tag{11}$$

where n is the total amount of metabolic sectors within the urban administrative boundary; f_{ij} represents the carbon flow from the *j* sector to the *i* sector; f_{ji} represents the carbon flow from the *j* sector to the *i* sector; z_i and y_j are the total carbon flow to the *i* sector's input flow and the total carbon flow of the output flow of the *j* sector to the external environment, respectively; T_i is the total flow of the input flow of the *i* sector, which also represent as $T_{i,in}$; T_j represent the total outflow from *i* sector to other sectors, which also represent as $T_{I,out}$. When in steady-state system, $T_{I,in}=T_{I,out}$. TST is the system carbon flux.

(2) Control Analysis

The basis of this method comes from the observation of the flow between various sectors in network analysis and inventory analysis[1] to quantitatively characterize the control level of each sector over other sectors or the entire network system (Fath, 2004b). In the control analysis, network flow interactions are divided into the direct and integral parts. The nondimensional direct flow matrices ***G*** and ***G***', representing how much of input carbon flow is actually used in total carbon flow exchanges between each pair of sectors (Fath and Patten, 1999). They can be calculated as:

$$\boldsymbol{G} = [g_{ij}] = \left[\frac{f_{ij}}{T_j}\right] \tag{12}$$

$$\boldsymbol{G'} = [g'_{ij}] = \left[\frac{f_{ij}}{T_i}\right] \tag{13}$$

where f_{ij} represents the specific ecological flow from sector *j* to sector *i*; T_j represents the total flow of all output from the *j* sector; T_i represents the total flow of all input to the *i* sector. g_{ij} represent nondimensional flows from sector *j* to sector *i*. And based on the nondimensional direct flow matrices, the integral flow matrices $\boldsymbol{N}$ and $\boldsymbol{N'}$ are calculated as following:

[1] Inventory analysis in ENA refers to the quantitative assessment of the flow of energy, matter, and information among different components of the system (Ulanowicz, 1995).

$$N = [n_{ij}] = G^0 + G^1 + G^2 + \cdots + G^m = (I - G)^{-1} \quad (14)$$

$$N' = [n'_{ij}] = G'^0 + G'^1 + G'^2 + \cdots + G'^m = (I - G')^{-1} \quad (15)$$

where I represents the identity matrix, n_{ij} represents the integral dimensionless value of g_{ij}. The self-feedback matrix (G^0) reflects flows that originate in and return to the sector. The matrix G^1 reflects the direct flows between any pair of sectors in the network. The matrix G^2 represents the flows that pass through two sectors, m is the maximum number of steps in the system's pathways, and G^m ($m \geq 2$) reflects the indirect flows of length m between sectors.

Finn (1980) defined the Finn Cycling Index (FCI) as the cycled fraction of total throughflow, which represents how much of the flow would revisit the same node multiple times before exiting the system. It can be calculated as:

$$FCI = \frac{\sum_{j=1}^{m} \left(\frac{(n_{jj} - 1) T_j}{n_{jj}} \right)}{TST} \quad (16)$$

Based on n_{ij} and n'_{ij}, the network control matrix ***CA*** and dependency matrix ***DA*** (Chen and Chen, 2012) that reveal the controllability and dependence of the system can be established respectively, as shown below:

$$CA = [ca_{ij}] \equiv \begin{cases} ca_{ij} = \frac{n_{ij} - n'_{ji}}{\sum_{i=1}^{m} (n_{ij} - n'_{ji})}, & n_{ij} - n'_{ji} > 0 \\ ca_{ij} = 0, & n_{ij} - n'_{ji} \leq 0 \end{cases} \quad (17)$$

$$DA = [da_{ij}] \equiv \begin{cases} da_{ij} = \frac{n_{ij} - n'_{ji}}{\sum_{j=1}^{m} (n_{ij} - n'_{ji})}, & n_{ij} - n'_{ji} > 0 \\ da_{ij} = 0, & n_{ij} - n'_{ji} \leq 0 \end{cases} \quad (18)$$

where ca_{ij} represents the control level of sector j over sector i, $ca_{ij} \leq 1$; da_{ij} represents the level of dependence of sector j on sector i, $da_{ij} \geq 0$.

(3) Trophic Structure Analysis

A city has a resource chain akin to an ecological trophic level and an industrial symbiosis network of material and energy flows, which constitute the basic structural form, process, and function of the metabolic system (Hardy and Graedel, 2002). Trophic structure theory was first applied to ecosystems to observe the transfer of nutrition and energy from one component (as prey) of the system to another (as predator) (Lindeman, 1942). Artificial systems such as cities also have network characteristics of energy and material transferring through pathways, so it is feasible to apply trophic level analysis to urban metabolism. By dividing the trophic level of the carbon metabolism system, the structure and function of the urban carbon metabolism system are revealed. The trophic level can be calculated by:

$$L = 1 + \sum_{i=1}^{n}(P_i \cdot L_i) \quad (19)$$

where L represents the trophic level of a specific sector; P_i represents the percentage that sector's i-th input flow to its total input; L_i represents trophic level corresponding to the n-th input; n is total amount of input flows Similarly, a trophic pyramid in ecology shows stability of the system structure and good functions of each component. In typical ecosystems, the trophic structure of energy is usually a pyramid shape and does not exceed five levels due to the loss of energy transfer from one level to another. However, in urban carbon metabolism, the trophic structure can appear as an irregular pyramid since the conversion efficiency of carbon varies in different sectors and the import of resources from the outside system. Nevertheless, in the form of discussion, we still described the structure of carbon metabolism in terms of the degree of similarity to the pyramids (Yan et al.,2010).

The system structure index STI is established to characterize the structural characteristics of the network system (Lu et al. 2015), as shown below:

$$STI = \sum_{p=1}^{n} r_p \cdot Sign(r_{p-1} - r_p) \quad (20)$$

where p represents the number of trophic levels; r_p represents the ratio of the carbon flux of the p-th trophic level to the overall carbon flux of the system; n is the maximum number of trophic levels; $Sign(r_{p-1} - r_p)$ represents the carbon flux flow relationship between two adjacent trophic levels. Taking a standard pyramid shape as an example, which means that all trophic levels have a higher share than the next level, $Sign(r_{p-1} - r_p)$ takes the value of 1, and STI becomes the sum of the shares of each sector, and therefore is 1. By similar analysis, four scenarios are possible as described below:

1) When *STI=0*, a uniform shape is reflected, indicating the system is deficient in differentiation and specialization;
2) *0<STI<1*, the system structure appears to be an irregular pyramid (such as a barbell structure), indicating that the system is in a moderate condition despite of some structural defects;
3) *STI=1*, the structure of the studied system presents a pyramidal structure, indicating that the structure is stable, mimicking closely an ecological structure;
4) STI<0, the system shows an inverted pyramid with poor stability and few resources supporting the upper sectors.

2.3 Data sources

Data for the carbon emission of Beijing and Shanghai were collected from Carbon Emission Accounts and Datasets(www.ceads.net). It mainly includes carbon emission data (in million tonnes) for Beijing and Shanghai in 2017. Energy consumption data (in tonnes standard coal equivalent) for Beijing and Shanghai were collected from the energy balance tables in the Beijing Statistical Yearbook, Shanghai Statistical Yearbook, China Energy Statistical Yearbook and CEADs Database (www.ceads.net/). The input-output data (in million USD) for Beijing and Shanghai are from the China Input-Output Association. The sector classification and match relationship of four cities is presented in the Appendix, the aggregated sectors and corresponding codes can be found in Table 2, the final demand categories of the four cities can be found in Table 3.

Despite generally improving regional data availability in the EU countries, publicly available city-level IO tables produced by national statistical offices are still scarce (Jahn, 2017). In particular, there are no publicly available IO tables for Vienna and Malmö to date.

In such cases, non-survey methods and publicly available data such as national IO tables, regional accounts and structural business statistics are often used to develop approximations of regional (subnational) IO tables. One of the most widely used non-survey approaches to developing regional IO tables is using so-called location quotients (LQs) (Flegg, 1997). Among several distinct implementations of LQs (for a review, see (Bonfiglio and Chelli, 2008)), Flegg's location quotient (FLQ), which shows good performance, has been widely used for estimating single-region IO tables (Flegg and Tohmo, 2016).

For the purpose of this study, we estimated technical coefficient matrices, flows between sectors and final demand for Vienna and Malmö using the FLQ method and national input-output tables for Austria and Sweden provided by the OECD (stats.oecd.org/) as well as data on sectoral employment on national and regional level and data on population, disposable income of households and gross regional product provided by the national statistical offices, Statistics Austria (www.statistik.at/en/) and Statistics Sweden (www.scb.se/en/). The data for 2017 were used.

More concrete, for each pair of sectors $i, j = 1, \dots, 17$,

$$FLQ_{ij} = \lambda^* \frac{e_i^R / e_i^N}{e_j^R / e_j^N}, \tag{21}$$

where $e_i^{R(N)}$, $i = 1, \dots, n$ is the regional (national) employment in sector i, and $e^{R(N)}$ is the total regional (national) employment, and $\lambda^* = \left[\log_2\left(1 + \frac{e^R}{e^N}\right)\right]^{\delta}$, $0 \le \delta \le 1$ (Flegg and Weber, 1997). The value of λ^* reflects the size of a subnational region (e.g., a city) and increases with its size. It depends on a parameter δ, which is region-specific and generally unknown. The larger is δ, the smaller is λ^*; if $\delta = 0$, then $\lambda^* = 1$. Therefore, a larger value of δ enables a greater adjustment for inter-regional imports for smaller regions (Jahn, 2017).

Since for Vienna and Malmö there are no empirical data available to estimate δ, we used the formula suggested by Lehtonen & Tykkyläinen (2014):

$$\delta = \frac{\log_2\left[\frac{e^R}{e^N} / \left[\log_2\left(1 + \frac{e^R}{e^N}\right)\right]\right]}{\log\left[\log_2\left(1 + \frac{e^R}{e^N}\right)\right]}. \tag{22}$$

It yields $\delta = 0.224$ for Vienna and $\delta = 0.118$ for Malmö. Thus, $\lambda^* = 0.777$ for Vienna and $\lambda^* = 0.99$ for Malmö.

Finally, the regional direct requirement coefficients $a_{ij}^R, i,j = 1,\dots,17$ are estimated as follows (Flegg and Weber, 1997):

$$a_{ij}^R = \begin{cases} (FLQ_{ij})a_{ij}^N, & \text{if } FLQ_{ij}^R < 1 \\ a_{ij}^N, & \text{if } FLQ_{ij}^R \geq 1 \end{cases}, \quad (23)$$

where $a_{ij}^N, i,j = 1,\dots,17$ are the corresponding national direct requirement coefficients.

Table 2. Sector codes (in parentheses – according to the statistical classification of economic activities in the European Community, NACE Rev. 2) and names.

Sector Code	Aggregated Sector Name	Sector Code	Aggregated Sector Name
S1 (A)	Agriculture, forestry and fishing	S10 (J)	Information and communication
S2 (B)	Mining and quarrying	S11 (K)	Financial and insurance activities
S3 (C)	Manufacturing	S12 (L)	Real estate activities
S4 (D)	Electricity, gas, steam and air conditioning supply	S13 (M+N)	Professional, scientific and technical activities+ administrative and support service activities
S5 (E)	Water supply; sewerage, waste management and remediation activities	S14 (O)	Public administration and defense; compulsory social security
S6 (F)	Construction	S15 (P)	Education
S7 (G)	Wholesale and retail trade; repair of motor vehicles and motorcycles	S16 (Q)	Human health and social work activities
S8 (H)	Transportation and storage	S17 (R+S)	Arts, entertainment and recreation + other service activities
S9 (I)	Accommodation and food service activities		

Table 3. Final demand categories of 4 cities

Cities	Final demand categories
Beijing, Shanghai	Urban household consumption
	Rural household consumption
	Government consumption
	Fixed capital formation

Vienna, Malmö	Inventory increase management
	Exports abroad
	Outflow to provinces
	Household consumption
	Government consumption
	Investment
	Domestic export
	Foreign export

3. Results and Discussion

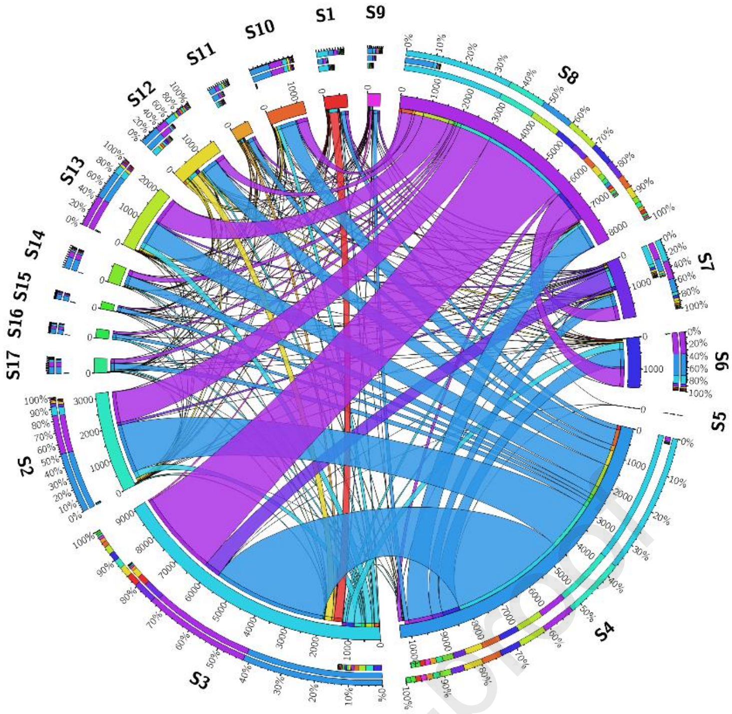
The paper focuses on the carbon flows exchanged among sectors in four cities and the above analysis allows us to calculate the network metrics for multiple mediums including economic flows, energy flows, and carbon flows between sectors. Because the three layers are built off the same network structure, they differ primarily in numbers but not in main conclusions. Therefore, the decision here in the results is to present only for carbon which is most closely aligned with the climate decarbonization goals.

3.1 Carbon emission flows

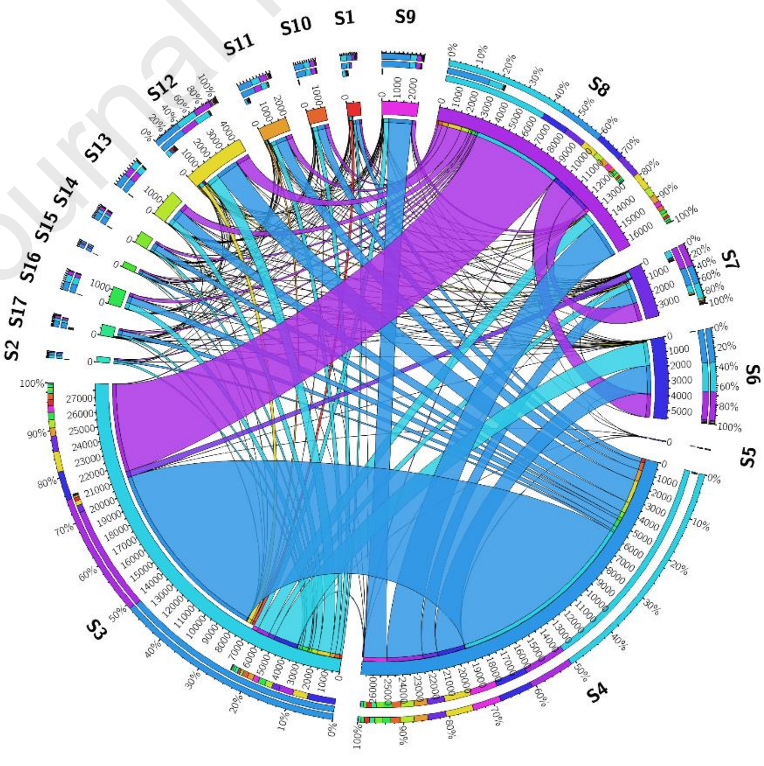
First, we show the overall carbon flow pattern between sectors for each city (Fig.1) where the flow width corresponds to the amount of flow between sectors. With a unique color of each sector, when the color of a flow aligns with the color of a sector, it can be inferred that the flow is sourced from that sector. The directions of flows can tell us the role of the sectors in the urban network. One sector requires inputs from other sectors for production, and also exports products to other sectors. The carbon embedded in matter and energy then follows transactions to transfer between sectors, and the direction of the flows reflect the upstream and downstream dependencies. Table 4 demonstrated direct, total carbon emissions and per capita carbon emission based on IOA of four case cities in 2017.In Beijing, the total CO_2 emissions were 366.28 Mt, which were 4.28 times larger than the emissions in Table 1, and the per capita carbon emission were 16.69 t, which were 4.08 times larger than the emissions per capita in Table 1. These numbers included the direct and indirect CO_2 emissions, which is why the values of carbon emissions and carbon emissions per capita were greater than that in Table 1. In 2017, the four largest CO_2 flows were from S4 (Electricity) to S4, S8 (Transportation) to S8, S4 (Electricity) to S3 (Manufacturing), and S8 (Transportation) to S3 (Manufacturing). They account for 18.44%, 12.27%, 10.29% and 7.71% of the total CO_2.

Table 4 Direct and total carbon emissions based on IOA of four case cities in 2017

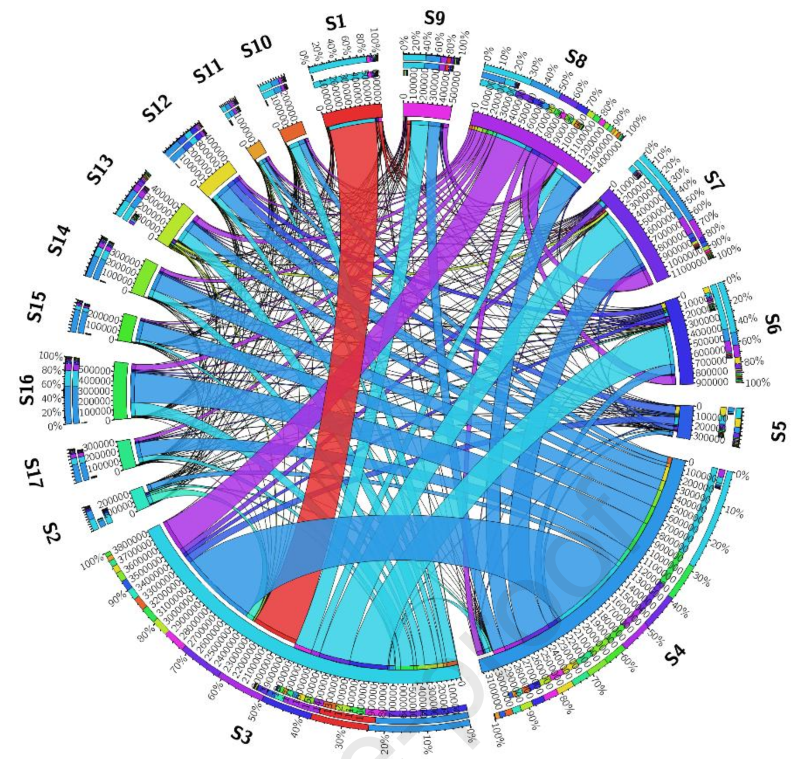
	Direct carbon emissions (million tons)	Total carbon emissions (million tons)	carbon emissions increase (times)	per capita carbon emission (tons per capita)	per capita carbon emission increase (times)
Beijing	85.56	366.28	4.28	16.69	4.08
Shanghai	196.15	774.94	3.95	32.04	3.95
Vienna	20.20	84.21	4.17	44.83	4.04
Malmö	3.3	12.00	3.64	38.87	3.93



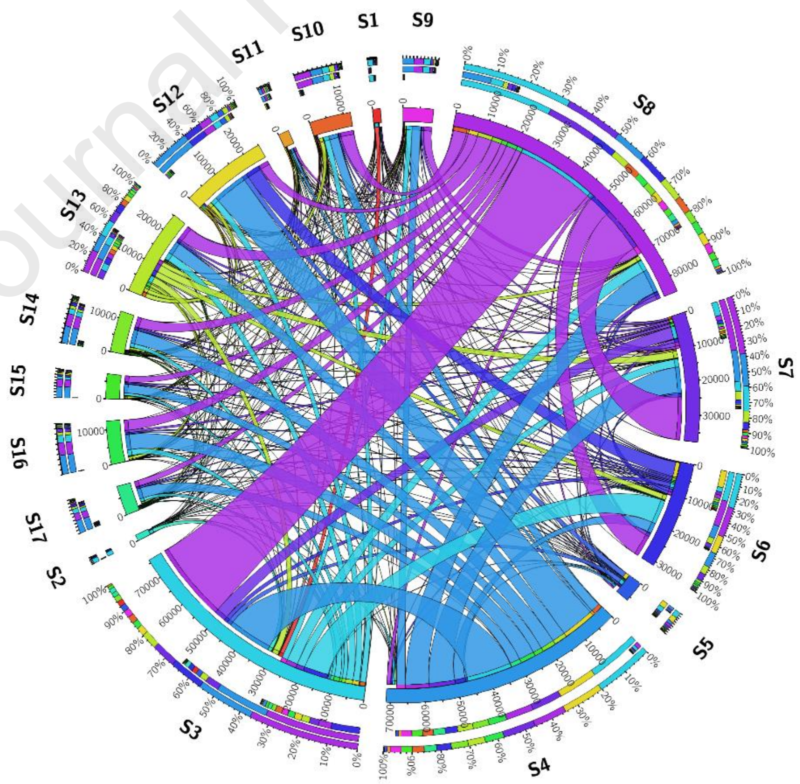
a) Beijing



b) Shanghai



c) Vienna



d) Malmö

Figure 1. Carbon emission flows among sectors in 2017 in a) Beijing, b)

Shanghai, c) Vienna, and d) Malmö. Figures do not include self-loops.

In Shanghai, the total CO_2 emissions were 774.94 Mt and the per capita carbon emission were 32.04 t in 2017 (Fig. 1b). The two largest CO_2 flows were from S3 (Manufacturing) to S3 which accounts for 21.95% of the total CO_2 emissions and S4 (Electricity) to S3 (Manufacturing) which accounts for 17.61% of the total CO_2 emissions.

For Vienna, the total CO_2 emissions were 84.2Mt and the per capita carbon emissions were 44.83 t in 2017 (Fig. 1c). The two largest CO_2 flows were from S4 (Electricity) to S3 (Manufacturing) and S1 (Agriculture) to S3 (Manufacturing), which account for 11.39% and 6.85% of the total CO_2 emissions, respectively. These findings differ from studies of Chen and Chen (2012), which showed that the main carbon flows were from agriculture to the energy production sector and the building sector, probably due to the different scope of nodes and the changing structure of the Chinese economy. The food industry accounts for 1.2% of the total output, which is the fourth largest in manufacturing, suggesting a closed link between manufacturing the agriculture (www.stats.oecd.org/). High emissions of agriculture sector may also be related to high direct energy consumption and energy importing form outside of Vienna (Statistics Austria, 2015). Compared to the other three cities with high population density and arable land constraints, farming in a larger scale may contribute to the high carbon emissions.

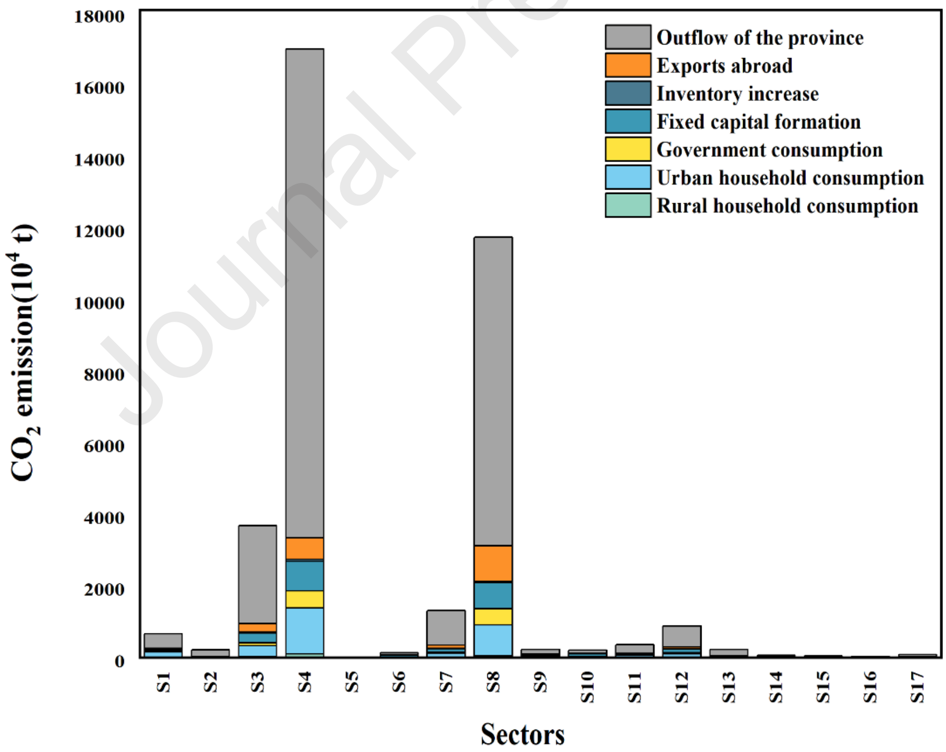
Lastly, for Malmö the total CO2 emissions were 12.0 Mt and the per capita carbon emission were 38.87 t in 2017. The two largest CO2 flows were from S8 (Transportation) to S3 (Manufacturing) and S4 (Electricity) to S3 (Manufacturing) which accounts for 11.34% and 6.46% of the total CO2 emissions.

3.2 Sectoral carbon emission driven by final demand

Embodied carbon is present in all resource flows. It is useful to show the amount of carbon coming from each sector that is associated with final demand.

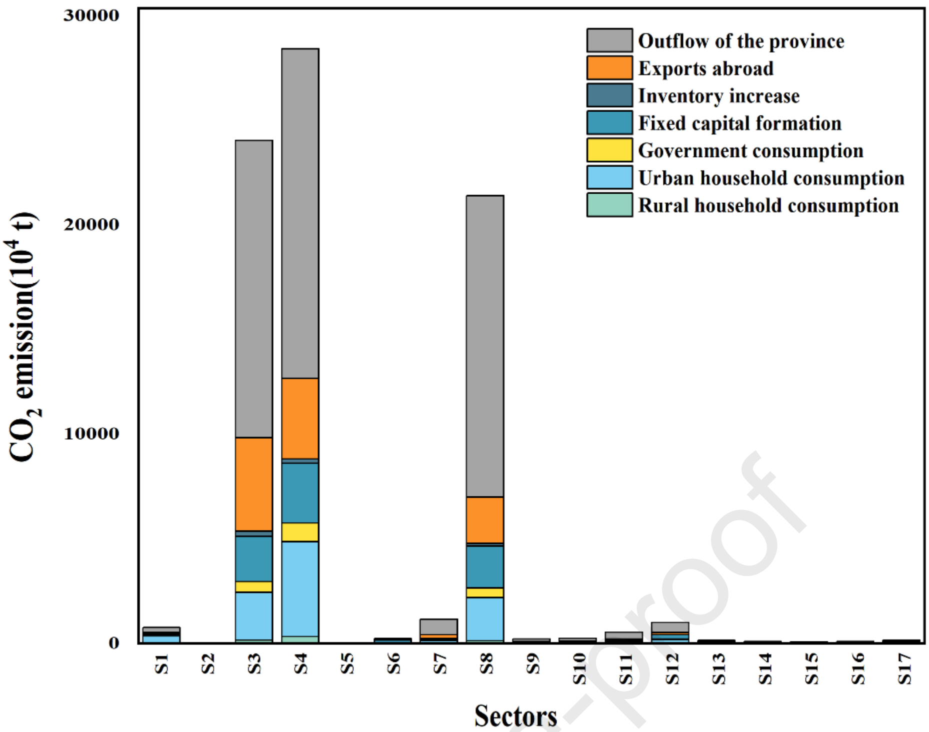
Final demand categories of Beijing and Shanghai include outflow to provinces, exports abroad, inventory increase, fixed capital formation, government consumption, urban household consumption, and rural household consumption. Final demand categories of Vienna and Malmö include household consumption, government consumption, investment, and domestic and foreign export. Fig. 2 compares these results for the four case study cities.

In Beijing (Fig. 2a), the top three leading consumers of carbon emission are S4 (Electricity), S8 (Transportation), S3 (Manufacturing) (46%, 31%, 10% of the total carbon emission). From the perspective of final demand, the share of outflow of the province is relatively large.



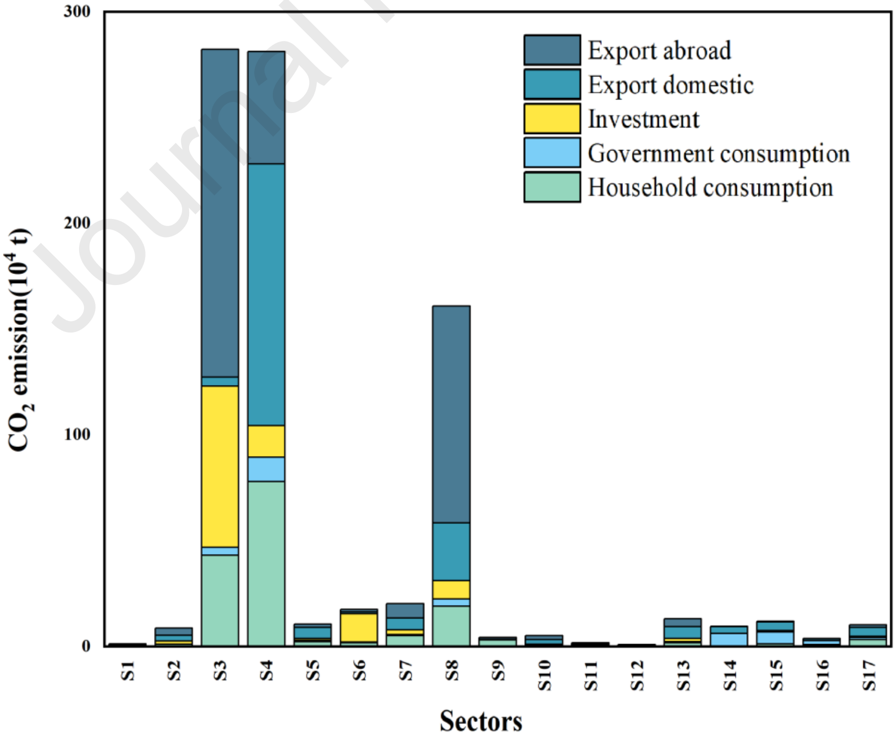
a)

Beijing

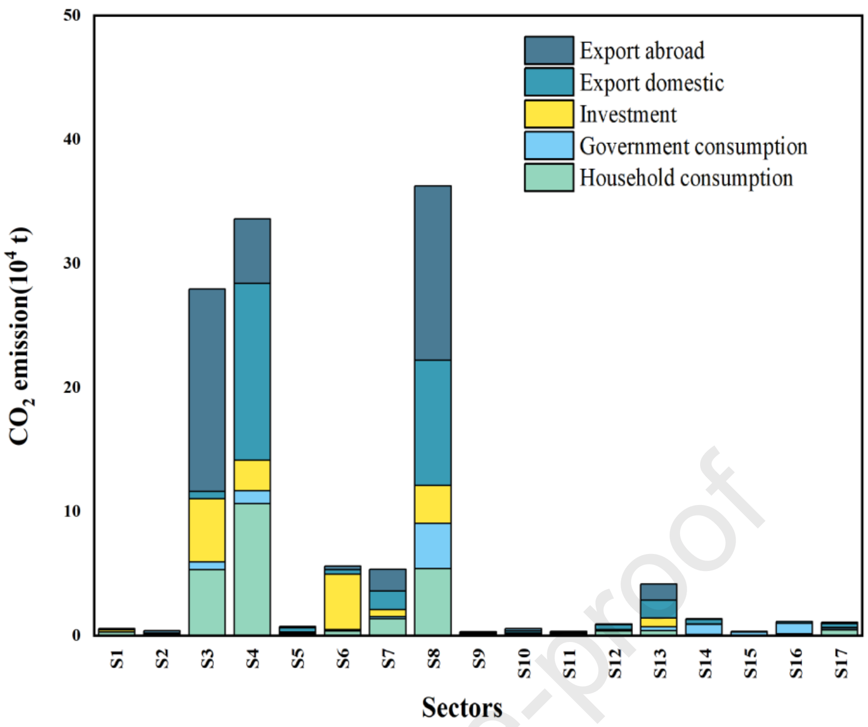


b)

Shanghai



c) Vienna



d) Malmö

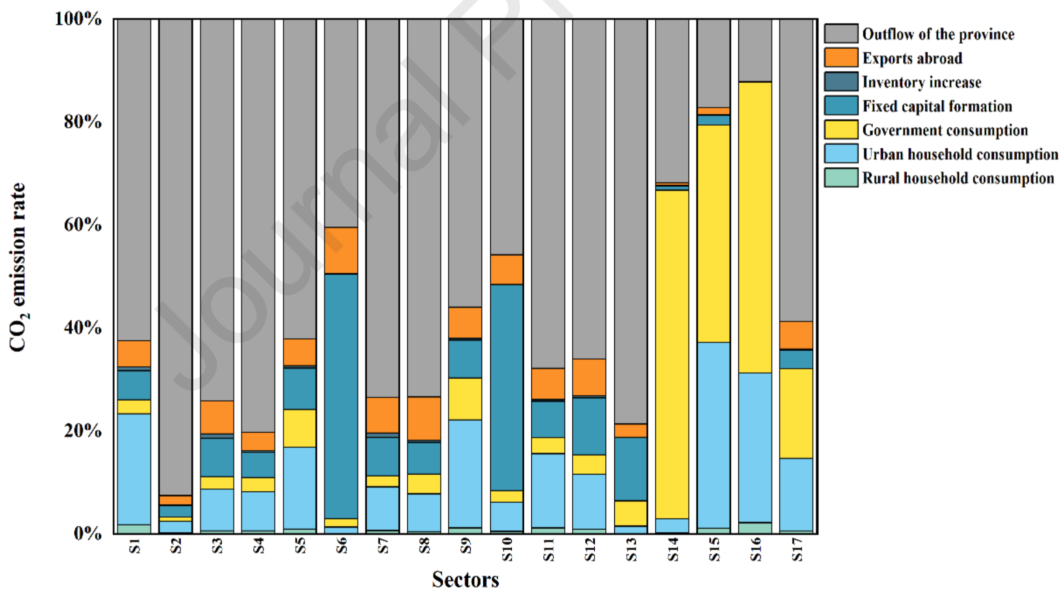
Figure 2. Sectoral carbon emission driven by final demand in 2017 in a) Beijing, b) Shanghai, c) Vienna, d) Malmö.

In Shanghai (Fig. 2b) the top three consumers are the same sectors S4, S8, and S3 (36%, 27%, 30% of the total carbon emission). This differs from Beijing, in that S3 takes more proportion of carbon emission than S8 in Shanghai. From the perspective of final demand, the share of outflow of the province is also relatively large. In Vienna (Fig. 2c), the top three leading consumers of carbon emission are by S3, S4, S8 (34%, 33%, 19% of the total carbon emission). From the perspective of final demand, the share of export abroad is relatively large. In Malmö (Fig. 2d), the top three consumers of carbon emission are by S9, S5, S4 (30%, 28%, 23% of the total carbon emission). Again, the share of export abroad is relatively large.

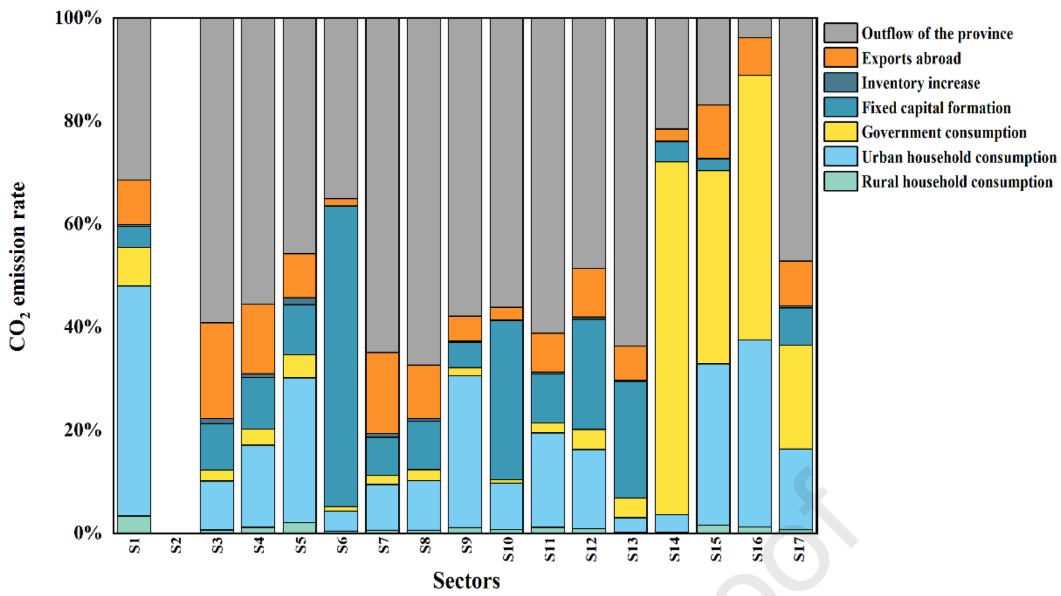
Fig.3 shows the share of carbon emissions driven by different categories of final demand in the total emissions of each sector, which present a relative contribution to carbon footprint by source sector induced by categories of final demand. This shows more clearly for each sector where the final demand emissions end up (Fig. 3). From the perspective of sectoral contribution of carbon emission driven by final demand, domestic export accounts for the largest share in most sectors in all four cities.

In Fig. 3a, we can see that in Beijing the domestic export accounts for the largest share in most sectors. The share of fixed capital formation, government consumption and urban household consumption are relatively large in certain sectors. Fixed capital formation accounts for the largest proportion in S6. Government consumption accounts for the largest proportion in S14, S15 and S16.

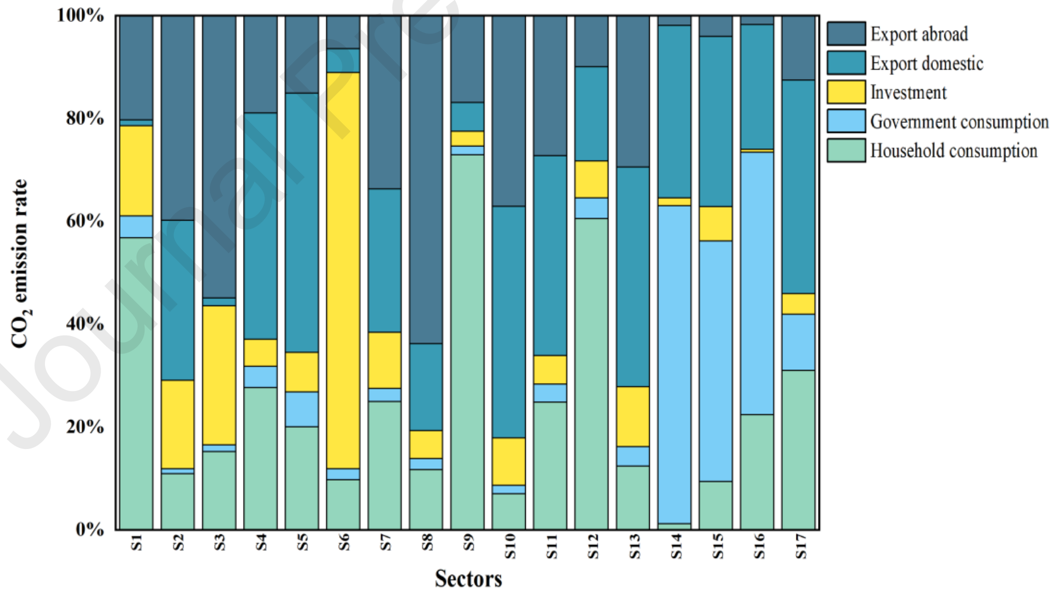
Similarly, in Shanghai (Fig. 3b), domestic export also accounts for the largest share in most sectors and the share of fixed capital formation, government consumption, and urban household consumption are relatively large. For example, urban household consumption accounts for the larger share in S1; Fixed capital formation has a relatively large share in the S6 and S10. Government consumption accounts for a relatively large proportion in the S14, S15 and S16.



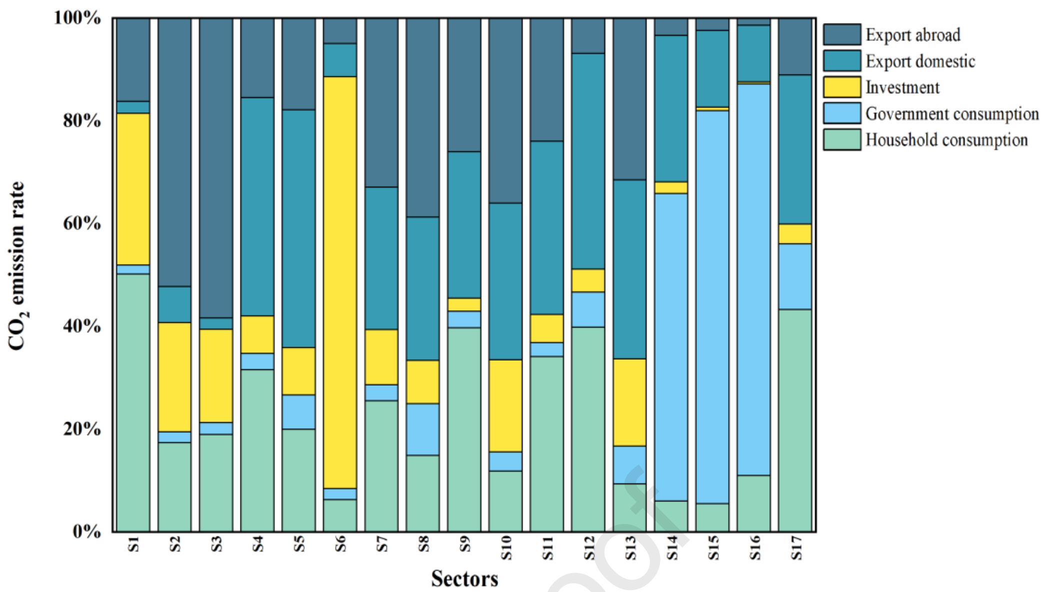
a) Beijing



b) Shanghai



c) Vienna



d) Malmö

Figure 3. Sectoral contribution of carbon emission driven by final demand in 2017 for a) Beijing, b) Shanghai, c) Vienna, and d) Malmö

In Fig. 3c, we can see that in Vienna domestic export accounts for the largest share in most sectors. The share of household consumption, government consumption, investment, and export abroad. are relatively large in certain sectors. Household consumption accounts for the largest proportion in S1, S9 and S12. Government consumption accounts for the largest proportion in S14, S15 and S16. Investment accounts for the largest proportion in S6. Export abroad accounts for the largest proportion in S2, S3 and S8.

Similarly, in Fig 3d, we can see that in Malmö domestic export accounts for the largest share in most sectors. The share of household consumption, government consumption, investment, and export abroad are relatively large in certain sectors. Household consumption accounts for the largest proportion in S1. Government consumption accounts for the largest proportion in S14, S15 and S16. Investment accounts for the largest proportion in S6. Export abroad accounts for the largest proportion in S2, S3 and S8.

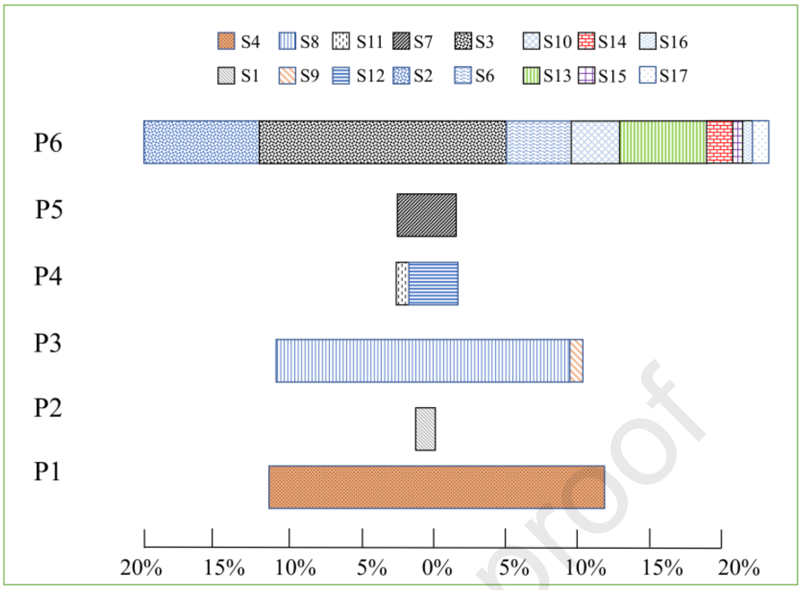
3.3 The system structure

We calculated the trophic levels of the urban carbon metabolism by using Equation 19 and assigned each sector a classification based on the value of L. For instance, when $1 \le L < 2$, the sector was classified as P1, as shown in Table 5. We adopted the ecological concept and identified the trophic roles of each sector, which include producers (P1), primary consumers (P2), secondary consumers (P3), and higher-level consumers. Lower trophic levels provide materials and energy to support higher trophic levels. In the context of urban carbon metabolism, the producers can be seen as suppliers of carbon, while the consumers derive economic value from the processed resources provided by the producers. Theoretically, healthy structure should reflect to the pyramid shape, however in reality pyramid structure exhibits 'zero' growth for complex socio-ecological systems.

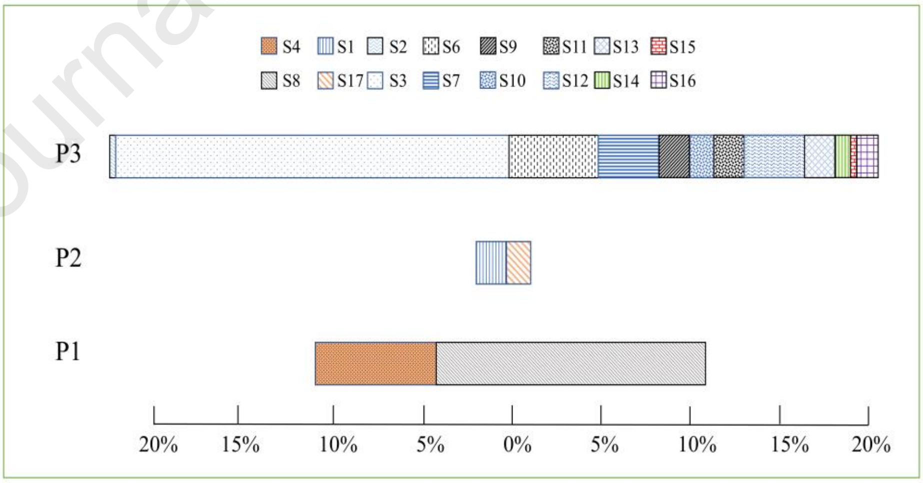
Fig.4 shows the percentage of carbon fluxes in each sector to the total fluxes and the trophic level of each sector. In Beijing (Fig. 4a), the weight of ultimate consumers is the highest, followed by tertiary consumers and then producers. S4 (Electricity), as the largest contributor of carbon fluxes and the only producer, shows its importance in the energy supply of Beijing. Beijing has an irregular pyramid structure of the network, due to the low proportion of primary and secondary consumers and the high proportion of ultimate consumers. This conclusion of irregular pyramid structure is consistent with the ENA analysis of Beijing based on 2007 data (Zhang et al., 2014). In Shanghai (Fig. 4b) the weight of secondary consumers is the highest, followed by primary consumers and then producers. S3(Manufacturing) is largest contributor of carbon fluxes and the carbon consumer, which indicates a large energy demand. The trophic level of Shanghai consists of only three levels, indicating that its energy is more directly transformed between sectors. The trophic level structure of Shanghai shows a dumbbell shape, the high proportion of secondary consumers.

In Malmö (Fig. 4c), the weight of primary consumers is the highest, followed closely by producers and less so by the tertiary consumers. S8 (Transportation) is the largest contributor of carbon fluxes and the only primary consumer, indicating it as key transformation sector. The trophic level structure of Malmö mostly shows a regular pyramid with large bottom, which is different from Beijing and Shanghai with large weight of ultimate consumer. In Vienna (Fig. 4d), the weight of secondary consumers is the highest, followed closely by producers and the primary consumers. S3 (Manufacturing) is the largest contributor of carbon fluxes and the only secondary consumer, indicates a large energy demand from the bottom trophic level. These results differ slightly from those of the perfect pyramid shape of the system structure in Vienna in the studies conducted by Chen and Chen (2012), probably attributed to the inclusion of the external environment in the system boundary of their study. The trophic level structure of Vienna shows a pyramid similar to Malmö, but with higher weight of secondary consumer. In this analysis, both Malmö and Vienna are nearing to the ecological standard that shows higher level consumers adequately supported by lower level production.

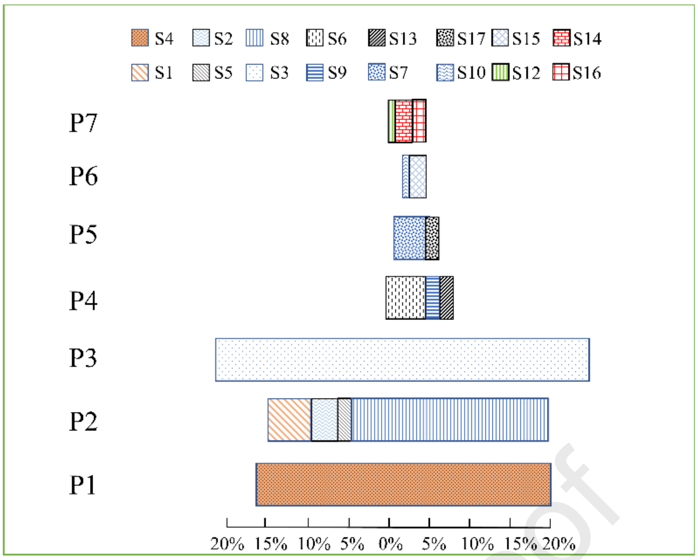
The different network hierarchy structure of the four cities may be attributed to varying industrial structures. The tertiary industry accounts for 61.16% and 53.03% of the total output in Beijing and Shanghai, mostly are at a higher trophic level of consumers. They rely on the bottom of network providing resources, resulting in in a larger upper end of the trophic structure. In addition, S1 (Agriculture) and S17 (Arts) as primary consumers in Shanghai, however, have a low share of economic output (0.31%, 1.50% of the total output) which may lead to low carbon footprints from consumption, resulting in the network hierarchy structure of Shanghai similar to a barbell. Malmö is an important trading center with active trade and transportation activities and a well-developed shipbuilding industry. The mature transportation and manufacturing industries which are the only tertiary consumer and primary consumer, contribute a relatively large share of fluxes, resulting in an irregular pyramid shape. Vienna has a flourishing machinery industry and manufacturing remains a significant source of energy consumption and CO_2 emissions, which is the second largest energy consumer among all sectors (Birgit et al, 2019). The high share of emissions from manufacturing, exceeding producers and primary consumers, contributes to the irregularity of the pyramid structure.



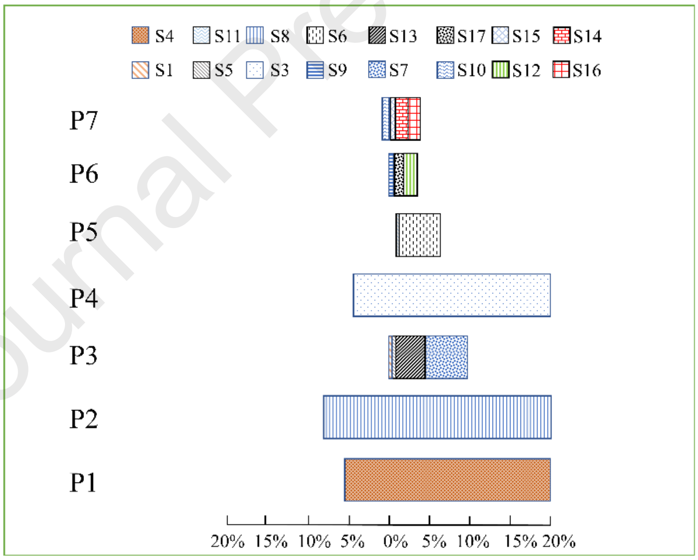
a) Beijing



b) Shanghai



c) Vienna



d) Malmö

Figure 4. The trophic structure of carbon emission among sectors in a) Beijing, b) Shanghai, c) Vienna, and d) Malmö in 2017.

Table 5. The trophic structure of carbon emission among 4 cities in 2017.

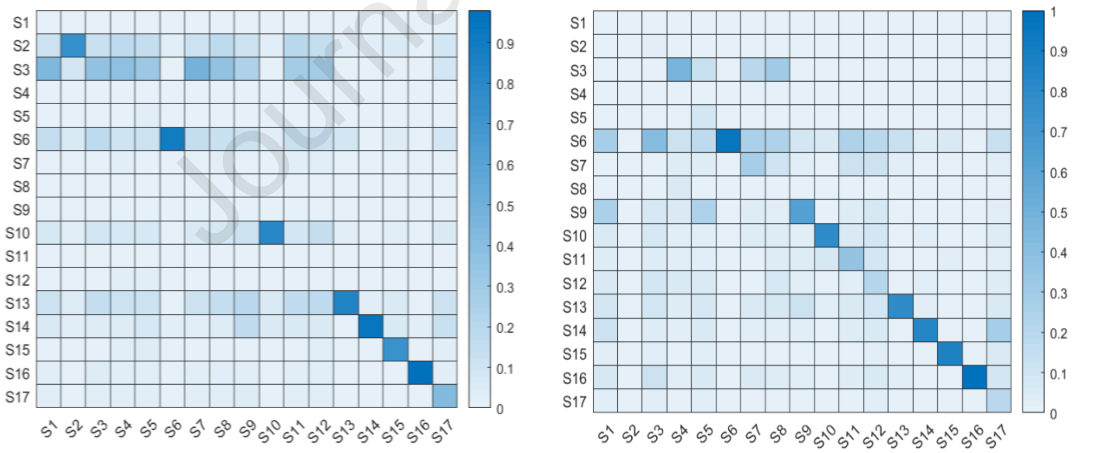
	Beijing	Shanghai	Malmö	Vienna
P1	S4	S4 S8	S4	S4
P2	S1	S1 S17	S8	S1 S2 S5 S8
P3	S8 S9	S2 S3 S6 S7 S9 S10 S11 S12 S13 S14 S15 S16	S1 S5 S7 S13	S3
P4	S11 S12		S3	S6 S9 S13
P5	S7		S6 S11	S7 S17
P6	S2 S3 S6 S10 S13 S14 S15 S16 S17		S9 S12 S17	S10 S15
P7			S10 S14 S15 S16	S12 S14 S16

3.5 Control and Dependence Relations

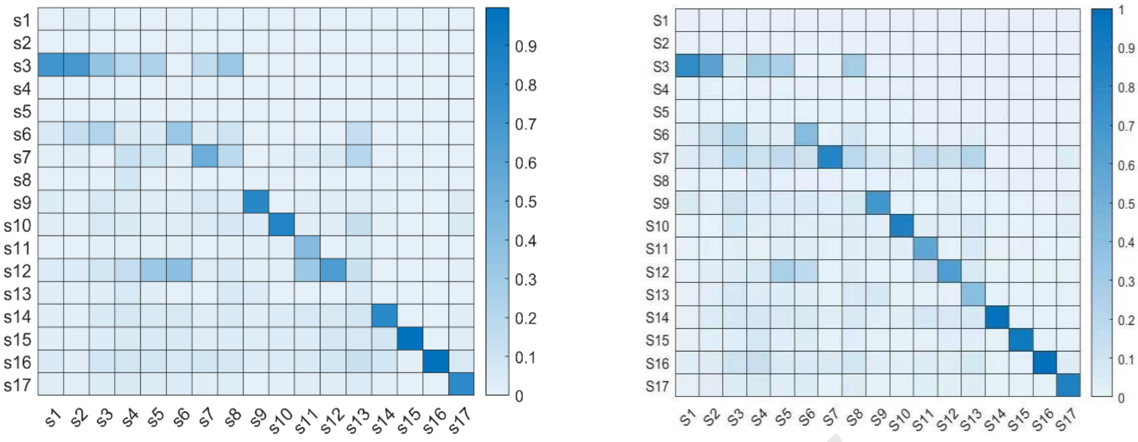
The control and dependence analyses reveal the whole network (direct and indirect) of influences between pairwise sectors (Fig. 5). The two approaches, control and dependence, run opposite each other with similar implications, so here only the results of the control analysis are given and discussed. Results show the strong self-implication that each node has on itself (the bright colors along the diagonal). This is particularly the case for S10, S13, S14, S15, S16 for all cities, which all represent service-oriented, higher “trophic-level” sectors. S2 self-loop is strong in Beijing and S6 is strong in both Chinese cities more so than in the European ones, indicative of the larger role of construction in the fast-growing Asian mega-cities. The European cities were higher in S17, revealing a higher activity of recreational services. In addition to the strong self-loops, it is useful to look at the pairwise interactions off the main diagonal for unexpected control relations. In most cases, these are primary flows, “lower in the food chain”, that have impact and control up to the higher levels, asserting a form of bottom-up control. This indicates that efforts to minimize carbon emissions at the lower levels will reverberate up having a positive impact throughout the web of interactions. As mentioned above, the main sectors terms of overall energy use and carbon emissions in Beijing are S3 (Manufacturing), S4 (Electricity), and S8 (transport). It is not surprising that S3 plays a strong role in the overall control, notably that it is strongly controlled by S1 (Agriculture), S4 (Electricity), S7 (Wholesale) and S8 (Transportation). Other sectors that show noticeable dependence are S6 (Construction), which is strongly controlled by S1 and S3 (Manufacturing); S13 (Professional, scientific), which is strongly controlled by S9 (Accommodation), S11 (Financial and insurance activities) and S12 (Real estate); and S14 (Public administration), which is strongly controlled by S9 (Accommodation) and S17 (Arts, entertainment).

In Shanghai (Fig. 5b) it can be seen that S1 (Agriculture) has a strong control over S6 (Construction) and S9 (Accommodation); S3 (Manufacturing) is strongly controlled by S4 (Electricity) and S8 (Transportation); S6 (Construction) and S9 (Accommodation) are strongly controlled by S1 (Agriculture); and similar to Beijing, S14 (Public administration) is strongly controlled by S17 (Arts, entertainment).

For Vienna, the analysis reveals that S3 (Manufacturing) is controlled by S1 (Agriculture) and S2 (Mining); S6 (Construction) is controlled by S3 (Manufacturing); and, S12 (Real estate) is controlled by S5 (Water supply) and S6 (Construction) (Fig. 5c).



a) Beijing b) Shanghai



c) Vienna d) Malmö

Figure 5. Control allocation of carbon emission among sectors in a) Beijing, b) Shanghai, c) Vienna, and d) Malmö in 2017.

Lastly, Malmö's sectoral control relationships include the following (Fig. 5d): S3 (Manufacturing) is controlled by S1 (Agriculture) and S2 (Mining); S6 (Construction) is controlled by S3 (Manufacturing); and, S12 (Real estate) is controlled by S5 (Water supply), S6 (Manufacturing) and S11 (Financial and insurance activities).

It is interesting to compare the control figures across cities, which shows in all cases, the S3 row has the most shading (although less noticeable in Shanghai) revealing that manufacturing emissions are influenced by the most other sectors. Row for S6 is important for all cities, but least so for Malmö, which likely has the smallest construction sector. S12 (Real estate) is important in the European cities, namely by S5 and S6, but not in China. And, row S13 stands out for Beijing as it does not for the others. This represents professional and administrative activities. While only Beijing and Vienna are capital cities in the study, the large role Beijing plays in the Chinese economy (and thus the related emissions) is evident by the number of sectors that influence it. The control analysis reveals subtle, yet present, direct and indirect influences propagated along the entire network of interactions.

3.6 ENA Analysis

Table 6 shows the ENA indices for four cities in 2017. The Total System Throughflow (TST) shows the overall carbon flux of the system. This is the most basic value that gives a sense of the scale of the overall emissions from direct and indirect pathways. As expected, given the discrepancy in size of the cities, the total system throughflow of Malmö (14,180.2 Mt) and Vienna (58,500.7 Mt) is less than Beijing (73,256.8 Mt) and Shanghai (154,987.8 Mt).

The Finn Cycling Index (FCI) represents the proportion of carbon emissions that cycle within a system rather than being lost outside the system. FCI in carbon metabolism reflects the ability of the system to retain and reuse carbon emissions (Jiao et al., 2020). A higher number corresponds to a higher degree of circularity, which reflects the city's movement toward a more circular economy. Results here shows greater cycling in the two European cities FCI index of Malmö (0.412) and Vienna (0.434), which is noticeably higher than those of Beijing (0.216) and Shanghai (0.194).

As we saw in Figure 4, none of the four cities demonstrate an ecologically healthy pyramid structure with sufficient within system production to support the higher consumer levels. The system structure index, STI, of the four cities is all less than 1, which indicates that the operation of the urban carbon metabolism system is not very ideal and needs to be improved particularly by adding more primary production into the cities. Otherwise, they remain dependent and reliant on external inputs to support higher level activities. Beijing and Shanghai have larger primary sectors and therefore values closer to zero, but still have too little production to support the entire system of flows. Malmö has the worst value of STI, as there is quite a bit of flow in the secondary and tertiary levels that is not supported from within the system. They are able to continue functioning because of the inputs that flow through the cities, but this shows they are dependent on external flows and not internally sustainable. Increasing the amount of primary sectors activities would lead to a more balanced and sustainable trophic structure.

Table 6. the ENA indexes for four cities in 2017

City/index	FCI (%)	TST (million tons)	STI (dimensionless)
Malmö	0.412	14180.2	−0.601
Vienna	0.434	58500.7	−0.336
Beijing	0.216	73256.8	−0.218
Shanghai	0.194	154987.8	−0.271

Note: FCI: Finn cycle index;TST: Total System Throughflow (carbon flux); STI: System structure index where STI < 0 shows an inverted pyramid where some of the higher trophic levels are greater than the lower ones.

3.7 Potential causes of uncertainty

The sectoral integration in IO may cause uncertainty. Though ENA identifies the most critical paths, it does not recognize the aggregated environmental impacts of given production processes (Lenzen, 2007). ENA has limitations in identifying critical paths in production chains for specific products such as lithium, iron, etc., since it discusses paths between sectors (e.g., Agriculture, Manufacturing) determined by IO. Also, the uncertainty due to the sectoral aggregation needs to be addressed in a future study. Aggregation can result in the impact of the combined sector being replaced by the average impact of several sectors. For example, aggregating sub-processes with high carbon emission dependencies may affect the results of the metabolic structure analysis. In addition, different kinds of aggregation such as NACE (Nomenclature of Economic Activities in the European Community) classification, result in nodes containing different production entities, which can affect the results. There is also some uncertainty due to the different statistical standards among Chinese and European cities. The EUROSTAT dataset (https://ec.europa.eu/eurostat) can be applied for comparison in future studies. Besides, in the ENA method, the boundary problem of the ecosystem is determined. The choice of different system boundaries may have a significant impact on the analysis results (Li et al., 2011). The system boundary can be defined to administrative borders, urban built-up area. Or both the anthropogenic and natural processes of the city's carbon missions should be taken into account, which also covered those metabolically linked activities that occur outside the administrative boundaries of the city (i.e., engaged in the exchange of carbon of the city). The results of carbon emissions accounting can vary due to the differing production entities included within the various system boundaries chosen.

To estimate IO tables for the cities for which they are not available from official statistics (i.e., Vienna and Malmö), we used a non-survey approach, FLQ. As argued by Buendía Azorín et al. (2022), it is a well-established and straightforward technique that makes uses of readily available data and often produces satisfactory results in estimating regional IO tables. However, as with other non-survey approaches, using FLQ to estimate sub-national IO tables causes some uncertainty (Pereira-López et al., 2022). First, it assumes that the production technology is the same across all regions of a country (Miller & Blair, 2022). However, the composition of inputs can differ significantly, especially in the case of large cities. For example, a different mix of power generation sources (coal, gas, hydropower, etc.) can be used on a city-level compared to the average national mix (Galychyn et al., 2022) – with the corresponding consequences for CO_2 emissions estimates. Second, the regional coefficients estimated with FLQ (as well as with other commonly used location quotients, such as simple location quotient (SLQ) or cross-industry location quotient (CILQ)) can never exceed the corresponding national counterparts, see equation (23). This can lead to a distorted representation of activities which transcend regional and national borders (for example, manufacturing sector in Vienna) as well as to underestimation of the share of regionally supplied inputs and underestimation of interregional purchases (Fujimoto, 2019; Pominova et al., 2021). These drawbacks can be partially addressed by the augmented FLQ (AFLQ) which allows the location quotient values to be greater than 1 and, therefore, regional coefficients to exceed the corresponding national ones (Flegg & Tohmo, 2013). However, it is argued that AFLQ generally does not yield more accurate results than FLQ (Flegg et al., 2021). Other options to improve the results can be application of estimation of SFLQ, i.e., industry-specific FLQ with distinct values of δ for different sectors (Kowalewski, 2015), or 2D-LQ (two-dimensional location quotient), a recently developed alternative to FLQ, (Martínez-Alpañez, 2023). However, the former method requires estimation of a regression, for which there is no available data for Malmö, and the latter requires estimation of two parameters instead of one (i.e., δ) in FLQ. Therefore, we used FLQ as a simpler and more established approach.

Second, the regional coefficients produced using FLQ are subject to uncertainty in the parameter δ (see equation (21)), which is generally unknown. Several methods have been suggested to specify δ based on either survey-based regional input-output tables or other regional data using regression models (Buendía Azorín et al., 2022). However, due to lack of such data, especially in the case of Malmö, we estimated δ using an approximation equation (22). (Jahn et al., 2020) suggest that in the absence of necessary regional data, the optimal range for $\delta = 0.3 \pm 0.1$. Future research is underway to explore the sensitivity of this parameter.

4. Conclusions

In this study, the carbon metabolism across sectors in Chinese and European cities was characterized and evaluated by direct and indirect interactions mediated by the complex connections and pathways in the urban network. By combining Input-Output (IO) and Ecological Network Analyses (ENA), properties of the carbon metabolism in terms of cycling, metabolic hierarchy, and control functions were unveiled. Both sectors and system properties were investigated through the traditional ENA framework, revealing some intrinsic characteristics of the urban carbon metabolism.

Based on IOA, the total carbon emissions for four cities, which included both direct and indirect emissions were as follows: Shanghai (774.94 Mt), Beijing (366.28 Mt), Vienna (84.21 Mt), and Malmö (12.00 Mt). The high carbon emissions of Shanghai and Beijing are related to the size of their economies, as the GDP of the four cities was \$501 billion, \$ 426 billion, \$ 116 billion, \$12 billion, respectively. When examining the total carbon emissions per capita, the highest was in Vienna at 44.83 tons, followed by

Malmö at 33.87 tons, Shanghai at 32.04 tons, and Beijing at 16.69 tons. However, it should be noted that the populations of Malmö (~0.25M) and Vienna (~2.5M) are much smaller than those of Beijing (~25M) and Shanghai (~25M), which may explain why the per capita emissions for the two European cities are higher. In addition, the European cities have a higher standard of living and longer dependence on carbon-based fuel resources.

From the perspective of sectoral carbon emission driven by final demands, the top three sectors with the largest carbon emissions in Beijing, Vienna, and Shanghai are S4 (Electricity), S8 (Transportation), and S3 (Manufacturing). In Beijing, S4 takes the largest share of total carbon emission, S8 takes the second largest and S3 takes the third. While in Shanghai, S3 and S8 swap 2^{nd} and 3^{rd} places. Thus, the key sector to reduce carbon emission for Beijing and Shanghai still should be electricity production sector. Suggestions For them, electricity sector should promote energy-saving upgrading of relevant coal power units, optimize grid dispatch to reduce power system losses, and accelerate the elimination of outdated generating units. In addition, arranging transport routes optimally and accelerating the construction of power grid infrastructure can help improve the efficiency of power utilization and achieve synergistic emission reduction between the transport and electricity sectors. In Vienna, the top three leading consumers of carbon emission are by S3, S4, S8. Vienna, like Beijing and Shanghai, needs to devise strategies to reduce emissions in the electricity and transportation sectors, but the first consideration should be the mitigation path for the manufacturing sector. Meanwhile, the results of the control analysis show that the Manufacturing in Vienna is majorly controlled by S1 (Agriculture) and S2 (Mining). Mitigating the carbon emissions via these two sectors are also identified as one of the keys to controlling these flows. In Malmö, the order is S8, S4, and S3, so the priority here should be on transportation sector, which has a surprising high proportion of the final demand for exports (both foreign and domestic).

Final demand takes several forms including outflow to the provinces, exports abroad, inventory increase, fixed capital formation, government consumption, urban household consumption, and rural household consumption. In 2017, the outflow to the province takes the largest share both in Shanghai and Beijing. While fixed capital formation, urban household consumption and government consumption only account for a relatively large contribution to certain sectors. Given the large role of both mega-cities in their national economy, it is not unexpected that domestic consumption is so high, but efforts at increasing regional or local production would put less pressure for demand on Beijing and Shanghai. Vienna and Malmö, being in relatively smaller countries in the European context, most of their final demand was for export abroad.

The city urban trophic structure was calculated and compared to natural ecosystems which show a dominant pyramid structure. The trophic structure of all four cities shows an irregular pyramid. Beijing and Shanghai have a larger share of emissions from ultimate consumers, indicating that the service and manufacturing industries have a large energy need while generating economic output. Vienna and Malmö, on the other hand, have a larger share of consumers at the lower levels. They have a relatively high share of emissions from the industrial sector, but perform part of the energy conversion function.

In the carbon emission systems of Beijing, Shanghai, Malmö and Vienna, most sectors are under the strong control of their own sectors, indicating that the industry itself is an important factor in controlling sector carbon emissions. The control matrix gives useful insight into all the pairwise combinations of sectors. However, given the importance of the manufacturing sector, we focus specifically there to learn that S3 (Manufacturing) is controlled by S1 (Agriculture) in Beijing, S2 (Mining) in Malmö, S4 (Electricity) in Shanghai, and S1 (Agriculture) and S2 (Mining) in Vienna. Thus, in the carbon emission policy design, the sectors' carbon emission reduction co-benefit and possible negative tradeoffs should be considered. The sector with high control index to others should be key to implement carbon emission reduction policy.

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Appendix

Table 1. Sector comparison of Beijing/Shanghai in 2017.

Aggregated 17 sectors	Original sectors	
Agriculture, forestry and fishing S1	Agriculture, forestry, animal husbandry and fishery	S1
Mining and quarrying S2	Coal mining and dressing	S2
	Petroleum and natural gas extraction	S3
	Metal ore mining	S4
	Non-metal minerals mining	S5
Manufacturing S3	Manufacture of food products and tobacco processing	S6
	Textiles	S7
	Wearing apparel, leather, fur, down and related products	S8
	Sawmills and furniture	S9
	Paper and products, printing and record medium reproduction	S10
	Petroleum processing, coking and nuclear fuel processing	S11
	Chemical industry	S12
	Nonmetallic mineral products	S13
	Metal smelting and pressing	S14
	Metal products	S15
	General purpose machinery	S16
	special purpose machinery	S17
	Transport equipment	S18
	electric equipment and machinery	S19
	electronic and telecommunication equipment	S20

	Instruments, meters, cultural and office machinery	S21
	other manufacturing products	S22
	Scrap and waste	S23
	Repair services for metal products, machinery and equipment	S24
Electricity, gas, steam and air conditioning supply S4	Electricity, steam and hot water production and supply	S25
	Gas production and supply	S26
Water supply; sewerage, waste management and remediation activities S5	Water production and supply	S27
Construction S6	Construction	S28
Wholesale and retail trade; repair of motor vehicles and motorcycles S7	Wholesale and retail trade services	S29
Transportation and storage S8	Transport, storage and post services	S30
Accommodation and food service activities S9	Accommodation and food serving services	S31
Information and communication S10	Telecommunication, computer services and software	S32
Financial and insurance activities S11	Finance and insurance	S33
Real estate activities S12	Real estate	S34
	Rental and business services	S35
Professional, scientific and technical activities S13 administrative and support service activities	Scientific research	S36
Public administration and defense; compulsory social security S14	Water resources, environment and public facilities management	S37
	Public management and social organization	S42
Education S15	Educational services	S39

Human health and social work activities S16	Health, social security and welfare	S40
Arts, entertainment and recreation other service activities S17	Cultural, sporting and recreational services	S41
	Residential services and other social services	S38

Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: