Product and Metal Stocks Accumulation of China's Megacities
Patterns, Drivers, and Implications

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ABSTRACT

The rapid urbanization in China since the 1970s has led to an exponential growth of metal stocks (MS) in use in cities. A retrospect on the quantity, quality, and patterns of these MS is a prerequisite for projecting future metal demand, identifying urban mining potentials of metals, and informing sustainable urbanization strategies. Here, we deployed a bottom-up stock accounting method to estimate stocks of iron, copper, and aluminum embodied in 51 categories of products and infrastructure across ten Chinese megacities from 1980 to 2016. We found that the MS in Chinese megacities had reached a level of 2.6-6.3 t/cap (on average 3.7 t/cap for iron, 58 kg/cap for copper, and 151 kg/cap for aluminum) in 2016, which still remained behind the level of western cities or potential saturation level on the country level (e.g., approximately 13 t/cap for iron). Economic development was identified as the most powerful driver for MS growth based on an IPAT decomposition analysis, indicating further increase in MS as China’s
urbanization and economic growth continues in the next decades. The latecomer cities should therefore explore a wide range of strategies, from urban planning to economy structure to regulations, for a transition towards more “metal-efficient” urbanization pathways.
1. INTRODUCTION

The stock of metals in use, a material capital made and utilized by human beings, provides essential functions and services (e.g., housing, transportation, communication, production and manufacturing, household tasks, entertainment, and so on) to modern societies. Their formation and maintenance are crucial drivers of anthropogenic metal cycles, generating upstream metal demands and releasing scraps for recycling at the end of product lifetime\(^1\). Characterization of metal stocks (MSs) had a long history\(^4\), and started to attract extensive attention since the 1990s due largely to Baccini and Brunner’s efforts on bringing the concept of in-use material stock to wider audiences\(^5\).

MS are often seen as resource reservoirs for future collection and recovery (so called “urban mining”) and they are mostly formed in urban systems such as buildings, transportation, and facilities\(^6\). Therefore, a historical retrospect on the quantity, distribution, and patterns of MS in cities is an indispensable step to identify urban mining potentials and to project future metal demand\(^6\). Beyond the understanding of
the patterns of MS development, a further exploration on their socioeconomic drivers could help formulate sustainable urbanization strategies\textsuperscript{12,13}.

Previous studies on MS focused largely on the global or national level, and thus the quantity, quality, and patterns of these stocks were hitherto poorly understood at a city level\textsuperscript{14–16}. For example, iron stocks had been estimated for over 200 countries\textsuperscript{14}, but studies on the city level are relatively scarce. The global or national level metal stock estimation, based on a mass-balance top-down method\textsuperscript{3,14}, normally presents highly aggregated information and sometimes ignored the sector distribution about MS; on the contrary, city-level stocks are usually determined by means of bottom-up stock accounting\textsuperscript{6}, and thus could provide itemized accounts of MS and help inform governmental agencies and industry on future metal demand trends and recycling potentials at the city level.
The bottom-up stock accounting at the city level, however, is data and labor intensive. Such analysis is typically based on large amount of statistics and sometimes additionally with the assistance of Geographical Information System (GIS) tools and data. Table 1 shows a summary of the existing materials stock estimation literature at the city level categorized by their employed estimation methods.

These studies provided an overview of all or part of the materials stocks in case cities, but a few gaps remain unaddressed: (i) They were mostly static and did not cover the temporal dynamics of MS at the city level; (ii) They were mostly focused on single or several sectors and thus gave an incomprehensive picture of MS; (iii) Socioeconomic drivers of MS development and implications on sustainable urban transformation were seldom explored\(^6\); and (iv) There were only a few Chinese cities covered. China’s unprecedentedly rapid urbanization in the past decades is arguably the most massive demographic shifts the planet has ever seen. The massive population shift from rural to urban areas, together with extraordinary economic boom, has moved enormous amount
of metals from underground reserves to urban systems in order to provide functions and

services to urban residents\textsuperscript{13,17–20}. Thus, the understanding of metal stocks

accumulation in China’s megacities would have important implications for the world’s

other developing cities as well.

Here, we deployed a multi-year bottom-up accounting method to estimate product and

infrastructure stocks and three base metals embodied (i.e., iron, aluminum, and copper) in ten

selected Chinese megacities. We compiled an exhaustive inventory covering 51 categories of

products and infrastructure containing iron, aluminum, and copper, taking into account temporal

variations in metal intensities during 1980-2016. Drawing upon the historical patterns of city-

level product and metal stocks development, we further investigated the socioeconomic drivers

behind the metal stocks development and discussed their implications on sustainable metal

resource management and urbanization transformation in the future.

\begin{table}
\centering
\caption{Bottom-up stock accounting approach employed in previous city-level studies.}
\begin{tabular}{lllll}
\hline
Method & Material & Case city & Temporal scope & Sector Coverage & Reference \\
\hline
Statistics-based & Pb & Vienna (Austria) & 1991 & Overall city & 21 \\
Statistics-based & Cd, Cr, Cu, Pb, Hg, Ni, Zn & Stockholm (Sweden) & 1995 & Overall city & 22 \\
Statistics-based & Construction materials & Rio de Janeiro (Brazil) & 2010 & Residential buildings only & 23 \\
\hline
\end{tabular}
\end{table}
<table>
<thead>
<tr>
<th>Method</th>
<th>Metals</th>
<th>City/Country</th>
<th>Year</th>
<th>Time Period</th>
<th>Scope</th>
</tr>
</thead>
<tbody>
<tr>
<td>Statistics-</td>
<td>Cu, Al</td>
<td>Handan (China)</td>
<td>2005</td>
<td>Overall city</td>
<td></td>
</tr>
<tr>
<td>Statistics-</td>
<td>Cu</td>
<td>Nanjing (China)</td>
<td>2009</td>
<td>Overall city</td>
<td></td>
</tr>
<tr>
<td>Statistics-</td>
<td>Cu</td>
<td>Shanghai (China)</td>
<td>2012</td>
<td>Overall city</td>
<td></td>
</tr>
<tr>
<td>GIS-based</td>
<td>Iron, copper, aluminum</td>
<td>Norrköping (Sweden)</td>
<td>2010</td>
<td>Infrastructure</td>
<td></td>
</tr>
<tr>
<td>GIS-based</td>
<td>Copper</td>
<td>Linköping (Sweden)</td>
<td>2008</td>
<td>Power grids</td>
<td></td>
</tr>
<tr>
<td>GIS-based</td>
<td>Construction materials</td>
<td>Amsterdam (Netherlands)</td>
<td>2015</td>
<td>Buildings</td>
<td></td>
</tr>
<tr>
<td>GIS-based</td>
<td>Construction materials</td>
<td>Melbourne (Australia)</td>
<td>2015</td>
<td>Buildings</td>
<td></td>
</tr>
<tr>
<td>GIS-based</td>
<td>Construction materials</td>
<td>Esch-sur-Alzette (Luxembourg)</td>
<td>1860-2012</td>
<td>Buildings</td>
<td></td>
</tr>
<tr>
<td>GIS-based</td>
<td>Construction materials</td>
<td>Rhine-Main (Germany)</td>
<td>-</td>
<td>Non-residential buildings</td>
<td></td>
</tr>
<tr>
<td>GIS-based</td>
<td>Construction materials</td>
<td>Philadelphia (US)</td>
<td>2004-2012</td>
<td>Buildings</td>
<td></td>
</tr>
<tr>
<td>GIS-based and Statistics</td>
<td>Construction materials</td>
<td>All prefectures (Japan)</td>
<td>1965-2010</td>
<td>Buildings and infrastructure</td>
<td></td>
</tr>
<tr>
<td>GIS-based</td>
<td>Construction materials</td>
<td>Wakayama (Japan)</td>
<td>1855-2004</td>
<td>Buildings</td>
<td></td>
</tr>
<tr>
<td>GIS-based</td>
<td>Construction materials</td>
<td>Vienna (Austria)</td>
<td>1918-2013</td>
<td>Buildings</td>
<td></td>
</tr>
<tr>
<td>GIS-based</td>
<td>Cu, Zn</td>
<td>All cities in Australia</td>
<td>-</td>
<td>Overall city</td>
<td></td>
</tr>
</tbody>
</table>

2. METHODS AND MATERIALS

2.1. Case city selection and spatial boundary

Case cities were selected based on several criteria: population (more than 5 million), GDP ranking (mostly top 10 cities; details in Table S37 in the Supporting Information (SI-1)), and geographic zone distribution (Northeast, North, Northwest, Southwest, Middle, East, and South). As shown in Figure 1a, we have singled out ten megacities in
the end: Beijing (BJ), Shanghai (SH), Tianjin (TJ), Chongqing (CQ), Guangzhou (GZ), Shenzhen (SZ), Nanjing (NJ), Wuhan (WH), Chengdu (CD), and Shenyang (SY). Three major metals, namely iron, aluminum, and copper, were included in the analysis and the temporal scope was from 1980 (since China’s reform and opening-up policy) to 2016 (when the latest data are available).

Figure 1. (a) Selected Chinese megacities and their GDP and population in 2016 and (b) Conceptual visualization of spatial boundary of Chinese cities.
Spatial boundary is an important yet often overlooked issue for city-level resource and environmental analysis of Chinese cities, due to China’s special administrative and data reporting system. Typically, the Chinese administrative hierarchy consists of five levels in a descending order: (i) province (sheng)/municipality (zhixiashi)/autonomous region (zizhiqu), (ii) prefecture (dijishi)/autonomous prefecture (zizhizhou), (iii) county (xian)/district (qu), (iv) subdistrict (jiedao)/town (zhen)/township (xiang), and (v) residential committee (jumin weiyuanhui)/village (cun). Previous studies of material stocks for Chinese cities usually chose prefecture (i.e. 1+2 in Figure 1b) as the system boundary. Prefecture is an administrative division rather than an urbanized area, meaning that the prefecture usually includes rural areas (i.e., townships and villages). The rural areas possess substantial amounts of MS. In this work, we distinguished MS in urban areas from rural areas as much as possible in order to precisely determine MS in the case cities and make the results comparable with other efforts on MS estimation in the literature. Therefore, we used urban area (i.e., 1+2-3 in Figure 1b) as the spatial boundary, that is, the urban area in a prefecture excluding...
villages (Figure 1b). Although the administrative boundaries have changed in a few cases, they have no impact on the data collection because the data were always collected according to the changed boundaries.

2.2. Inventory compilation

We selected 51 categories of products and infrastructure containing iron, aluminum, and copper based on previous literature and our own assessment\textsuperscript{6,13}. The 51 categories are grouped into five broad categories: buildings, infrastructure, machinery, domestic appliances, and transportation equipment (Table 2). Whenever possible, we tried to collect data for the product categories based on our spatial boundary (1+2-3) defined above. However, data for some product categories are impossible to be disaggregated and thus include rural areas (1+2).

Table 2. Categorization and statistical scope of products containing iron, copper, and aluminum.
<table>
<thead>
<tr>
<th>Categories</th>
<th>Z(^{a)})</th>
<th>Fe(^{b)})</th>
<th>C</th>
<th>Al</th>
</tr>
</thead>
<tbody>
<tr>
<td>Buildings</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 Residential buildings</td>
<td>1+2-3</td>
<td>*</td>
<td>*</td>
<td></td>
</tr>
<tr>
<td>2 Non-residential buildings</td>
<td>1+2</td>
<td>*</td>
<td>*</td>
<td></td>
</tr>
<tr>
<td>Infrastructure</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3 Roads</td>
<td>1+2-3</td>
<td>*</td>
<td>*</td>
<td></td>
</tr>
<tr>
<td>4 Expressways</td>
<td>1+2</td>
<td>*</td>
<td>*</td>
<td></td>
</tr>
<tr>
<td>5 Urban roads</td>
<td>1+2-3</td>
<td>*</td>
<td>*</td>
<td></td>
</tr>
<tr>
<td>6 Bridges</td>
<td>1+2</td>
<td>*</td>
<td>*</td>
<td></td>
</tr>
<tr>
<td>8 Water supply pipelines</td>
<td>1+2-3</td>
<td>*</td>
<td>*</td>
<td></td>
</tr>
<tr>
<td>9 Sewerage pipelines</td>
<td>1+2-3</td>
<td>*</td>
<td>*</td>
<td></td>
</tr>
<tr>
<td>10 Gas distribution pipelines</td>
<td>1+2-3</td>
<td>*</td>
<td>*</td>
<td></td>
</tr>
<tr>
<td>11 Heat supply pipelines</td>
<td>1+2-3</td>
<td>*</td>
<td>*</td>
<td></td>
</tr>
<tr>
<td>12 Electricity generation</td>
<td>1+2</td>
<td>*</td>
<td>*</td>
<td></td>
</tr>
<tr>
<td>13 Electricity transmission</td>
<td>1+2</td>
<td>*</td>
<td>*</td>
<td></td>
</tr>
<tr>
<td>14 Street lamps</td>
<td>1+2-3</td>
<td>*</td>
<td>*</td>
<td></td>
</tr>
<tr>
<td>15 Water ports</td>
<td>1+2</td>
<td>*</td>
<td>*</td>
<td></td>
</tr>
<tr>
<td>16 Telecommunications</td>
<td>1+2-3</td>
<td>*</td>
<td>*</td>
<td></td>
</tr>
<tr>
<td>Machinery</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(Agricultural machinery)(^{c)})</td>
<td>3</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>17 Large and medium-sized tractors</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>18 Mini tractors</td>
<td>3</td>
<td>*</td>
<td>*</td>
<td></td>
</tr>
<tr>
<td>19 Motorized fishing vessels</td>
<td>3</td>
<td>*</td>
<td>*</td>
<td></td>
</tr>
<tr>
<td>20 Drainage and irrigation machinery</td>
<td>3</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>21 Pumps</td>
<td>3</td>
<td>*</td>
<td>*</td>
<td></td>
</tr>
<tr>
<td>22 Industrial machinery</td>
<td>1+2</td>
<td>*</td>
<td>*</td>
<td></td>
</tr>
<tr>
<td>Domestic appliances</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>23 Washing machines</td>
<td>1+2-3</td>
<td>*</td>
<td>*</td>
<td></td>
</tr>
<tr>
<td>24 Refrigerators</td>
<td>1+2-3</td>
<td>*</td>
<td>*</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Categories</th>
<th>Z(^{b)})</th>
<th>Fe(^{b)})</th>
<th>Cu</th>
<th>Al</th>
</tr>
</thead>
<tbody>
<tr>
<td>Buildings</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1+2-3 Microwave ovens</td>
<td></td>
<td>*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1+2-3 Air conditioners</td>
<td></td>
<td>*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1+2-3 Water heaters</td>
<td></td>
<td>*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Infrastructure</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1+2-3 Mobile phones</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1+2-3 Black and white TV sets</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1+2-3 Color TV sets</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>1+2-3 Video cameras</td>
<td></td>
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<tr>
<td>1+2-3 Computers</td>
<td></td>
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</tr>
<tr>
<td>1+2-3 Cameras</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1+2-3 Fitness equipment</td>
<td></td>
<td></td>
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<tr>
<td>1+2-3 Bicycles</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1+2-3 Smoke absorbers</td>
<td></td>
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<tr>
<td>1+2-3 Pianos</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1+2-3 Other instruments</td>
<td></td>
<td></td>
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<tr>
<td>1+2-3 Telephones</td>
<td></td>
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<tr>
<td>1+2-3 Electrical fans</td>
<td></td>
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<tr>
<td>1+2-3 Motor vehicles</td>
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</tr>
<tr>
<td>1+2-3 Motor vessels</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1+2-3 Motor vessels</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1+2-3 Barges</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1+2-3 Passenger coaches</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1+2-3 Freight cars</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1+2-3 Telecommunications</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

| Machinery                           |            |            |    |    |
| Transportation Equipment            |            |            |    |    |
| 1+2-3 Trucks                        |            |            |    |    |
| 1+2-3 Passenger cars                |            |            |    |    |
| 1+2-3 Other vehicles                |            |            |    |    |
| 1+2-3 Motor vehicles                |            |            |    |    |
| 1+2-3 Motor vessels                 |            |            |    |    |
| 1+2-3 Motor vessels                 |            |            |    |    |
| 1+2-3 Barges                        |            |            |    |    |
| 1+2-3 Passenger coaches             |            |            |    |    |
| 1+2-3 Freight cars                  |            |            |    |    |

Note: (a) Z means zones corresponding to administrative zone in Fig. 2b. (b) Fe refers to both iron and steel. (c) Agricultural machinery is excluded in the final stock.
accounting, but they were included in our product inventory for the estimation of industrial machinery.

Building sector is the major metal holder in which iron, copper, and aluminum are widely used. Iron makes up frame structures and is also used in plumbing, ventilation, and part of decoration. Copper is mainly used in plumbing and electricity wirings. Aluminum is mainly used in doors and windows. The building sector is categorized into residential and non-residential buildings. The non-residential buildings include commercial buildings, industrial buildings, and public buildings.

Infrastructure sector is one of the most significant iron containing reservoirs but uses relatively less copper and aluminum. Copper is only found in electricity and water supply pipelines. Aluminum exists in road signs and electricity wirings. Machinery stock in a previous study comprises both industrial and agricultural machinery stocks. We assumed that agricultural machinery only exists in villages. According to our definition of
system boundary, we therefore only considered industrial machinery for city-level metal stock estimation. We also included as many domestic appliances and transportation equipment as possible.

2.3. Bottom-up accounting method

Metal stocks $S(t)$ were calculated by bottom-up accounting method, that is, multiplying the quantity of products by their corresponding metal intensity.

$$S(t) = \sum_i \sum_j P_{ij}(t) \cdot m_{ij}(t)$$  (1)

Where, $P_{ij}(t)$ and $m_{ij}(t)$ refer to the quantity and metal intensity of products $i$ containing metal $j$ in use at time $t$, respectively.

MS in industrial machinery cannot be directly determined, because data of industrial machinery are not available in statistics. Assuming the metal content per power of agricultural machinery (of which data are available in statistics) applies to industrial machinery, the MS of industrial machinery $S_{\text{ind}}(t)$ were calculated by equation (2).
\[ S_{\text{ind}}(t) = TP_{\text{ind}} \cdot S_{\text{agri}}(t)/TP_{\text{agri}}(t) \]  

(2)

Where \( TP_{\text{ind}} \) and \( TP_{\text{agri}}(t) \) are total capacity (total power, KW) of industrial machinery and agriculture machinery at time \( t \). \( S_{\text{agri}}(t) \), determined by equation (1), is the agricultural machinery stocks at time \( t \).

Non-residential building stocks were determined based on equation (1). \( P_{i,j}(\tau) \) refers to floor area of non-residential buildings and was calculated by equations (3) and (4).

\[ P_{i,j}(t_0) = Pop(t_0) \times f(t_0) \quad t = t_0 \]  

(3)

\[ P_{i,j}(\tau) = P_{i,j}(t_0) + \sum_{t = t_0 + 1}^{\tau} F(t) \quad t > t_0 \]  

(4)

Where \( Pop(t_0) \) refers to population at time \( t_0 \), \( f(t_0) \) refers to non-residential floor area per capita in China at time \( t_0 \), \( P_{i,j}(t_0) \) is non-residential floor area of a city at time \( t_0 \), \( F(t) \) is non-residential floor area of building stock in a city at time \( t \). Here, \( t_0 \) is 1980 and the value of \( f(1980) \) was adopted from Huang's work\(^{44}\).
2.4. Data collection and uncertainty analysis

We collected the quantity of products from various official statistical yearbooks (e.g., Beijing Statistical Yearbook and so on45,46,55,56,47–54). We interpolated missing data points using linear or exponential regressions and chose regression functions that have a higher R² value (see detailed explanation in the SI). Metal intensities changed over time and were collected from either literature6,26,57,58 if available or estimated on informed assumptions. Aluminum intensities were referenced from two earlier studies (the Connecticut case58 and Liu’s study3) and thus were assumed to bear high uncertainties.

We assumed that the same metal intensities were applied to all the ten cities due to data availability. Detailed description on data sources and estimation process is available in the SI-2 Table S1-S12.

We used census population of urban residents (i.e., people who reside in a city for more than six months) and real GDP (converted from nominal GDP as detailed in the SI) to determine per capita GDP. Population density of a prefecture was determined by its
built-up area and urban residents. Data of urban residents and nominal GDP were collected from statistical yearbooks\textsuperscript{45–54}. Data of built-up area were from \textit{China City Statistical Yearbook 1999-2017}\textsuperscript{59}. We conducted Monte Carlo simulation to assess parameter uncertainties (produced by unrepeatable calculation for real data) in product quantity and metal intensity. We graded the uncertainties of each parameter as three levels: low, medium, and high. The uncertainty of product quantity collected directly from statistics was assumed to be low, those estimated by interpolation to be medium (e.g., non-residential buildings), and those estimated totally based on other data (e.g., industry machinery) to be high. The uncertainty of metal intensity collected directly from literatures was assumed to be low, those calculated by data in literatures to be medium, and those based on informed assumptions to be high. We performed the Monte Carlo simulation by 10,000 times, assuming uncertainties in product quantity and metal intensity are described by a normal distribution with coefficients of variation (CVs) (2\%, 5\%, and 10\% for the low,
medium, and high levels) as most previous studies did. A detailed description of data
treatment and uncertainty analysis is available in SI-2 (Table S1-S10 for product
quantity and Table S12 for metal densities).

Besides the Monte Carlo simulation, we also conducted a one-at-a-time sensitivity
analysis to test the robustness of MS results and to assess the impact of each parameter.
Here, we increased each parameter (i.e., product quantity and metal intensity) by 10%
and see what effect this change produces on the outputs. Hence, the impact of each
parameter on the MS could be easily compared. The formulas of sensitivity analysis are
available in SI-1 equation S4-S7.

In addition, we used Beijing, of which refined data are available, as a case to assess the
uncertainty inherent in the definition of spatial boundary and scope of population statistics.
2.5. Driving forces analysis

We employed the IPAT equation \( I = P \times A \times T \) to evaluate the effects of socioeconomic drivers on MS development. The IPAT equation has been extensively used to evaluate the impacts of drivers on CO\(_2\) emission, domestic material consumption, and ecological footprints\textsuperscript{61–64}. In the IPAT equation, three driving forces are assessed: population (P), affluence (A), and technology (T)\textsuperscript{65–67}. Specifically, population (P), affluence (A), and technology (T) are measured by urban residents, GDP per capita, and MS per GDP.

To quantify the contribution of the three driving forces to MS development, a logarithmic mean divisia index (LMDI) method was employed due to its path independence and its ability to handle zero value. The LMDI method has been widely used to quantify driving effects of energy consumption, CO\(_2\) emission and construction material stocks\textsuperscript{13,68}. The LMDI method could separate relative contribution of each driver to overall changes in MS (5)).
\[ \Delta I = \Delta P + \Delta A + \Delta T = \frac{I_c - I_t}{\ln(I_c) - \ln(I_t)} \times \ln \left( \frac{P_c}{P_t} \right) + \frac{I_c - I_t}{\ln(I_c) - \ln(I_t)} \times \ln \left( \frac{A_c}{A_t} \right) + \frac{I_c - I_t}{\ln(I_c) - \ln(I_t)} \times \ln \left( \frac{T_c}{T_t} \right) \] (5)

We further decomposed \( T(GDP) \) into five sub-sectors (i.e., \( T1(GDP) \), \( T2(GDP) \), \( T3(GDP) \), \( T4(GDP) \), and \( T5(GDP) \), respectively, for building (MS1), infrastructure (MS2), industrial machinery(MS3), domestic appliance (MS4), and transport equipment (MS5)), and decomposed \( \Delta T \) into technology of five sectors (i.e., \( \Delta T1 \): building, \( \Delta T2 \):infrastructure, \( \Delta T3 \): industrial machinery, \( \Delta T4 \):domestic appliance, and \( \Delta T5 \): transport equipment).

3. RESULTS AND DISCUSSION

3.1. Patterns of product stocks development

Figure 2 presents the temporal dynamics of 13 product stocks that we regard as most important or most typical (other product stocks are available in Figure S1 of SI-1). The development of product stocks reflects the ever-improving levels of urban citizens’ lifestyle in China. From a product perspective, we can observe certain patterns from the development of city-level product stocks.

- On a per capita basis, residential building stock and non-residential building stock continually increased during the recent decades and reached high levels (Figure 21).
China's current per capita levels of residential and non-residential building stocks are still lower than that of developed countries\(^6\), meaning that a steady growth is foreseen in China's construction sector. Recently, the residential buildings are no longer the biggest driver of China's construction boom. In several cities, the level of non-residential building stock started to surpass the residential building stock. For example, Nanjing's non-residential building stock has reached at a level of 48.3 m\(^2\)/cap while its per capita residential building stock is 28.4 m\(^2\)/cap in 2016.

- The per capita levels of road networks (including roads, expressway, and urban roads) in Chinese megacities have gradually saturated in the last few years (Figure 2b). The stagnation of urban roads development suggests that urban sprawl in China's megacities has plateaued out. The per capita levels of expressways started to catch up that of urban roads because expressways provided more efficient alternatives.

- The number of domestic appliances per 1,000 inhabitants (i.e., washing machines, refrigerators, microwave ovens, and air conditioners) has been relatively stable for
decades since the 1990s. Before that, the household size has been shrinking,
leading to a significant climb-up in all domestic appliances ownership (until
approximately one unit each per household). Due to breakneck economic growth
and urbanization in the past two decades, hundreds of millions of rural migrants
were headed to work in bigger cities. The majority of them has not settled down in
cities yet and thus has, so far, less decent living condition. This is perhaps one of
the major reasons behind the recent years' temporary slight decline of domestic
appliance ownership in the ten megacities (all who reside in a city for more than six
months were counted in our calculation for per capita levels).

Substitution between transport modes can be observed in all the ten megacities as
shown in Figure 2d. Bicycles and motor cycles, which were once the two most
popular transport modes in cities, were gradually replaced by passenger cars.
Recently, several first-tier cities (i.e., Beijing, Guangzhou, and Shenzhen) have
issued strict regulations on registration of new car plates, to tackle air pollution and
traffic congestion issues. A clear slow-down of passenger car ownership can be observed in these cities after 2000.
Figure 2. Development of in-use product stocks: buildings (a); road networks (b); domestic appliances (c); and transport equipment (d). BJ: Beijing; SH: Shanghai; TJ: Tianjin, CQ: Chongqing, NJ: Nanjing, GZ: Guangzhou, CD: Chengdu, SY: Shenyang, SZ: Shenzhen, WH: Wuhan.

It is worth mentioning that per capita product stock curves appear coarse (while stock curves derived from top-down approach are often smooth), due to the nature of multi-year bottom-up stock estimates, as shown in earlier studies as well\textsuperscript{2,13}. The scope and caliber of statistics often change over time (usually tends to become more comprehensive). One additional challenge for the scope of urban population statistics in a fast urbanizing China is the increasing migrants headed towards cities, since it took time for them to settle down and have decent living conditions.
3.2. Patterns of metal stocks development

Figure 3a shows the historical patterns of aggregate MS (summing up iron, copper, and aluminum stocks) since China’s reform and opening-up in the late 1970s. The past decades witnessed an enormous scale of metal accumulation in the ten case cities. The aggregate MS in case cities climbed up from a negligibly low level (0.2-5.3 Tg in 1980) to a significant level (23.3-72.3 Tg in 2014). The biggest boom occurred during the period 1994-2008, with a 200% increase of aggregate MS. Figure S2 in the SI-1 shows the patterns of iron, copper, and aluminum stocks in the ten case cities. Iron stock dominates (over 90%) in aggregate MS while copper and aluminum stocks only take up less 10%.

Figure 3b shows the composition of aggregate MS by sector. The proportion of MS in building sector increased from 19% to 42% during the period 1980-2016, while that of MS in machinery sector was gradually decreasing to 20% by 2016. This clearly showed that the residential and non-residential buildings gradually took the dominance over
industrial machinery from 1980 to 2016, as shown in Figure S3 (SI-1). The changing composition of metal stock reflects real estate boom and industrial transformation and upgrading in China’s megacities. For example, machinery stock of Beijing has constantly reduced since 2008 because of tightening environmental regulation and urban development strategy, and Shougang Group, a giant steelmaker, was moved out from Beijing in 2008\textsuperscript{70,71}. A detailed mapping of metal stock by sector for each city is available in Fig S4.

On the per capita basis (Figure 3c), the ten megacities experienced an apparent increase of MS from approximately 1 t/cap in 1980 to a level of 3 to 5 t/cap in 2016. An obvious heterogeneity of per capita metals stocks is also observed among cities. For example, Nanjing (the highest) has reached a level of above 6.2 t/capita in 2016 while Shenzhen (the lowest) was still below a level of 2.5 t/capita. Urban population density is one important factor behind these differences (Figure 3d): the denser cities (e.g., Shenzhen and Guangzhou) tend to have lower per capita MS than the less dense cities.
(e.g., Nanjing and Wuhan), indicating an important role of urban form and urban planning in MS growth. It was not surprising that Nanjing showed the highest metal stocks per capita among the ten case cities, due to its comparatively small population and large metal stock in machinery sector (Details in SI-1 Figure S4).
Figure 3. The patterns of metal stocks development by city (a), by sector (b), on a per capita level (c), and versus urban population density (d). (BJ: Beijing; SH: Shanghai; TJ: Tianjin; CQ: Chongqing; NJ: Nanjing; GZ: Guangzhou; CD: Chengdu; SY: Shenyang; SZ: Shenzhen; WH: Wuhan; BD: buildings; DA: domestic appliances; IF: infrastructures; MC: machinery; TE: transport equipment.)

Similar to the per capita stock curves, the TMS curves show also some fluctuations. On the one hand, the fluctuation was due to the nature of multi-year bottom-up stock estimates. On the other, a closer check showed that this was mainly caused by the estimation of industrial machinery stock (see Figure S4). Stocks of industrial machinery were determined by three parameters as Equation (2): agriculture machinery stocks, total power of industrial machinery, and total power of agriculture machinery. For agriculture machinery stocks, their statistical caliber is not always consistent due to the ever-changing statistical methods and samples.
Figure S5 (SI-1) shows uncertainties of our estimated MS. The relative uncertainties in
case cities range from 2% to 8% (uncertainties of total metal stock (TMS) and metal
stock per capita (MSP) are available in Figure S6). One additional source of
uncertainties arises from the inconsistency of product and population related data on
the city level, for example:

- Data of non-residential buildings, expressways, electricity facility, railways, and
  motor vehicles present products in-use in a prefecture, and thus include certain
  amounts of in-use products in rural areas. Non-residential buildings and motor
  vehicles are mainly distributed in urban areas, which would contribute merely a little
to the uncertainties. Expressways, electricity facility, and railways are not all
  geographically located within urban areas but are essential to urban inhabitants’
  basic needs.

- Population statistics in China have three scopes (Table S36): total population
  (TPOP; total number of people alive at a certain point of time within a given area),
  registered population with hukou/household registration (RPOP; persons who have
registered their permanent residence with the public security register authority of their habitual residence according to the Households Registration Regulations of China), and census population of urban residents (CPOP; persons actually living for more than half a year at a place). Statistics of living conditions (floor areas) are normally based on surveys of registered urban population (i.e., RPOP) only due to practical reasons. To include the buildings for migrants in cities, we used CPOP to adjust the RPOP-based per capita floor areas of building stocks.

To test the robustness of our results in the presence of data inconsistency, we conducted a sensitivity analysis on stock estimates of Beijing because data of Beijing allow us to distinguish metals stocks in its rural and urban areas. Figure S7 shows that TMS and MSP would decrease by 12-20% and 2-30%, respectively.

Additionally, Figure 4 shows the sensitivity analysis results for the average of the ten cities in the year of 1980, 2000, and 2016. Here only those subcategories whose
product quantity or iron intensity is larger than 1%, or copper intensity or aluminum intensity is larger than 0.05%, were presented. We found that generally, the impacts of product quantity and iron intensity were larger than copper intensity and aluminum intensity. Product quantity had the largest impact on TMS among the four parameters and iron intensity gradually became more significant than copper intensity and aluminum intensity. For subcategories, buildings (residential and non-residential buildings) turned out to have increasingly larger impact on TMS by time. The impact of product quantity and iron intensity of gas distribution pipelines also became significant while the aluminum intensity of electricity transmission became less impactful by time. Results of sensitivity analysis were slightly different among cities but generally showed a similar trend. Detailed sensitivity analysis result is available in Table S26-S35 of SI-2.
Figure 4. Sensitivity analysis for average ten cities aggregate four parameters (product quantity, iron intensity, copper intensity, and aluminum intensity).

When compared with previous studies (Table 3), our results indicate that there is plenty of room for further MS growth in Chinese cities. For example, the iron stock in New Haven (a much less dense city in eastern U.S. than the ten Chinese megacities) rose already to about 9 t/capita in 2000 and the saturation level of iron stock at the country level was hypothesized to be $13 \pm 2$ t/capita\textsuperscript{14}, but iron stocks in China’s megacities are
far from that yet. Therefore, a growing demand of metals would be foreseeable as these megacities continue to mature and many other smaller and younger cities (in western China) follow up in the future.

More specifically, an earlier estimation of the aluminum and iron stocks in Handan city (Hebei province, China) in 2005 appears less than that of our ten case megacities. This makes sense because Handan is a relatively small prefecture with lower population and GDP and the final products covered in the case of Handan are less complete than our list in this work. Another study on Beijing, Tianjin, and Shanghai’s iron stocks in building and infrastructure during 1978-2013 are close to results in our work. Iron stock per capita in Wakayama is similar to the case cities in this work but Wakayama, whose population in 2004 was only 3.73 million, was a small city in Japan comparing to Tokyo, Beijing, or Shanghai. Taipei seemed to have similar MSP to Chinese megacities but only building sector rather than all sectors was considered in the Taipei study. Moreover, total copper stocks in Shanghai and Nanjing from Zhang’s work are close to
our estimates on total copper stocks; but our estimates on the per capita level appears lower due to the different scope of population statistics we used\textsuperscript{26,43}. Table 3 also shows that both copper and aluminum stocks at the country level are lower than that at the city level, indicating that rural areas are less materialized than urban areas.

Table 3. MS comparisons between this work and previous studies

<table>
<thead>
<tr>
<th>Metal</th>
<th>City</th>
<th>Time</th>
<th>MS in the literature</th>
<th>Source</th>
<th>MS in this estimate (^{(a)})</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Tg</td>
<td>Kg/cap</td>
<td>Tg</td>
<td>Kg/cap</td>
</tr>
<tr>
<td>Iron</td>
<td>Handan (China)</td>
<td>2005</td>
<td>1333</td>
<td>25</td>
<td>1483-4420(^{(c)})</td>
</tr>
<tr>
<td></td>
<td>New Haven (US)</td>
<td>2000</td>
<td>9110</td>
<td>5</td>
<td>1079-4059(^{(c)})</td>
</tr>
<tr>
<td></td>
<td>Beijing (China)</td>
<td>1980-2013</td>
<td>1.8-40.7</td>
<td>13</td>
<td>5-48(^{(b)})</td>
</tr>
<tr>
<td></td>
<td>Tianjin (China)</td>
<td>1980-2013</td>
<td>1.5-37.0</td>
<td>2-36(^{(b)})</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Shanghai (China)</td>
<td>1980-2013</td>
<td>2.1-46.0</td>
<td>5-57(^{(b)})</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Vienna (Austria)</td>
<td>2013</td>
<td>3200</td>
<td>39</td>
<td>2411-6432(^{(c)})</td>
</tr>
<tr>
<td></td>
<td>Taipei (Taiwan, China)</td>
<td>2014</td>
<td>5750</td>
<td>27</td>
<td>2773-6989(^{(c)})</td>
</tr>
<tr>
<td></td>
<td>Wakayama (Japan)</td>
<td>2004</td>
<td>2082</td>
<td>38</td>
<td>1602-4620(^{(c)})</td>
</tr>
<tr>
<td>Copper</td>
<td>Shanghai (China)</td>
<td>2012</td>
<td>0.9</td>
<td>7</td>
<td>0.9 43</td>
</tr>
<tr>
<td></td>
<td>Nanjing (China)</td>
<td>2009</td>
<td>0.3</td>
<td>26</td>
<td>0.3 63</td>
</tr>
<tr>
<td></td>
<td>China</td>
<td>2006-2009</td>
<td>28.0-38.5</td>
<td>72</td>
<td>49-53 (^{(d)})</td>
</tr>
<tr>
<td></td>
<td>Vienna (Austria)</td>
<td>2013</td>
<td>31</td>
<td>39</td>
<td>31-97(^{(c)})</td>
</tr>
<tr>
<td>Aluminum</td>
<td>Handan (China)</td>
<td>2005</td>
<td>19.6</td>
<td>25</td>
<td>42-152(^{(c)})</td>
</tr>
<tr>
<td></td>
<td>China</td>
<td>2006-2009</td>
<td>41.2-66.6</td>
<td>72</td>
<td>95-109 (^{(d)})</td>
</tr>
<tr>
<td></td>
<td>Vienna (Austria)</td>
<td>2013</td>
<td>45</td>
<td>39</td>
<td>65-246(^{(c)})</td>
</tr>
</tbody>
</table>

Note: (a) is the accounting results of the ten case cities in the same time. (b) The range for MS is the minimum and maximum MS within the duration of certain city. (c)
The range for MSP is the minimum and maximum MSP of the ten cases cities in certain year; (d) represents the average values of the ten cities in the same time.

3.3. Drivers and implications

We divided historical patterns of MS development into three periods (i.e., 1980-1994, 1994-2008, and 2008-2016) based on turning points of MS growth. The two cut-off years are also of historical importance as well: China launched a series of reforms for a transition towards a full market economy in 1994 and the world economic crisis started in 2008.

Figure 5 shows the relative contribution of the three driving forces on MS development of the ten megacities. Throughout the three periods, affluence (measured as GDP per capita) acted as the main driver of MS development, while the contribution of population is relatively small. The biggest boom of MS growth, driven by significant increases in GDP per capita and population, happened in the second period. During the third period,
decreasing material intensities (measured by MS/GDP) dampened the increase in MS, meaning that China’s economic growth turned to be more “metal-efficient” or less dependent on “metal-intensive” industries.

As shown in Figure 5(d), buildings were not enough to meet the need for people’ living with GDP growth as $\Delta T_1$ was positive during 1980-1994. All sectors provided sufficient services in the second period because all values were negative. The latest six years, transport equipment did not provide sufficient services for the society and thus might further increase in the near future. Detailed technology decomposition results for each city are available in SI-1 Figure S8.
Figure 5. Relative influence of the three driving forces on metal stocks development in the ten megacities during 1980-1994 (a), 1994-2008 (b), and 2008-2016 (c). BJ: Beijing; SH: Shanghai; TJ: Tianjin; CQ: Chongqing; NJ: Nanjing; GZ: Guangzhou; CD: Chengdu; SY: Shenyang; SZ: Shenzhen; WH: Wuhan. (d) Technology decomposition results for average ten cities. $\Delta T_1$: building, $\Delta T_2$: infrastructure, $\Delta T_3$: industrial machinery, $\Delta T_4$: domestic appliance, $\Delta T_5$: transport equipment.
Figure 6 shows not only the heterogeneity but also commonness of the developmental trajectories of all Chinese cities. The ten case megacities (most in right and upside) were undergoing an exponential-like growth in affluence and urbanization rate during 1980-2016. Up to 2016, their affluence and urbanization rate have reached a considerably high level and thus are generally more urbanized and prosperous than most of other 268 cities in China (note that Shenzhen, as a Special Economic Zone of China, does not have any rural area so its urbanization rate has been 100% since 1980). The urbanization rate of over 80% of China’s cities still had not passed the 50% threshold in 2016. Although empirical data of the other 269 cities are lacking, we still could speculate that, if the MS in these latecomer cities are to catch up with the ten megacities, a significant increase in metal demand is foreseeable in the future. On the other hand, the MSP development patterns in some of the ten case megacities (e.g., Beijing, Shanghai, Tianjin, Guangzhou, and Shenzhen) demonstrate that economic development and urbanization do not necessarily lead to proportional MS growth. For example, the high affluence and urbanization of Beijing and Shanghai are sustained by
a low level of MSP (2.8 t/cap in 2016 for both cities). This may be due to the fact that, to address the serious environmental and resource problems, Beijing and Shanghai successively issued a series of regulations and guidelines on limiting the growth of vehicle registration, relocating heavy industries, and controlling the massive construction bubbles. These examples could inspire the latecomer cities to explore a wide range of strategies from urban planning to economy structure to regulations for more “metal-efficient” urbanization pathways in an increasingly resource and climate constrained future.

**Figure 6.** Metal stocks per capita, GDP per capita, and urbanization rate of the ten megacities and other Chinese cities. The urbanization rate refers to ‘1+2-3’, meaning
that the urban area excludes ‘village’. Bubble size represents MSP level (kg/cap) (No
MSP value is assigned to the other 268 cities due to lack of data). The temporal extent
of MSP, GDP per capita, and urbanization rate of the ten case megacities is 1980-2016.
The temporal extent of GDP per capita and urbanization rate of the other 268 cities is
2016.

The product and infrastructure stocks provide not only the physical environment of cities, but
also backbone of human activities and well-being in cities. These product and embodied metal
stocks drive metal cycles and thus future demand and associated energy use and emissions,
represent an extensive reservoir of secondary resources for “urban mining”, and entail temporal
and spatial lock-in effects for long-term socio-metabolic transition. Our analysis provides a first,
to our own knowledge, historical characterization of product and metal stocks of China’s
megacities. Such knowledge can be further used to inform sustainable metal management and
urban transformation of other Chinese cities and cities of similar status in other developing
countries.

ASSOCIATED CONTENT

Supporting Information
Method, data details, uncertainty analysis, and additional results (SI-1 and SI-2). This information is available free of charge via the Internet at http://pubs.acs.org/

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Notes

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