Waste Electronics in the United States: Future Trends and Economical Potential

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Supplementary Information

S1 Summary of Uncertainties and Key Assumptions

This section summarizes the key source of uncertainties and assumptions used in this study. All of the uncertainties and assumptions are also discussed in the different sections of the supplementary information and in the main text when they are applied to the corresponding analysis. In all, the key assumptions and sources of uncertainties of this study are summarized as follows.

1. This study includes most of the mid to small size consumer electronics. Large equipment such as fridges and ovens are not included in this study. Due to this assumption, we expect that the overall amount of waste electronics will be higher than what is predicted in this study.

2. The life span, average mass of different brands within the same type of waste electronics are not modelled.

3. Refurbished electronics are not modelled in this study.

4. The content involves approximations of electronics whose composition cannot be found in previous literature. When UN number is not available, the content is estimated based on authors' best knowledge.

S2 MFA Analysis

S2.1 Determining MFA Parameters

As described in the Methods Section of the Main text, we used the Weibull distribution in the Material Flow Analysis (MFA) to model the life span of the waste electronics. Figure S1 shows the decision tree used to estimate the Weibull distribution parameters for each electronics. The Weibull distribution parameters used in this study are summarized in Supplementary table. Since most published data has focused on conventional waste electronics such as TVs, phones, etc, there were multiple sources of the Weibull distribution parameters available for these waste electronics, namely the first 20 of the 96 electronics shown in the supplementary table. For these electronics, we combined the available data from recent literature.[1-4]

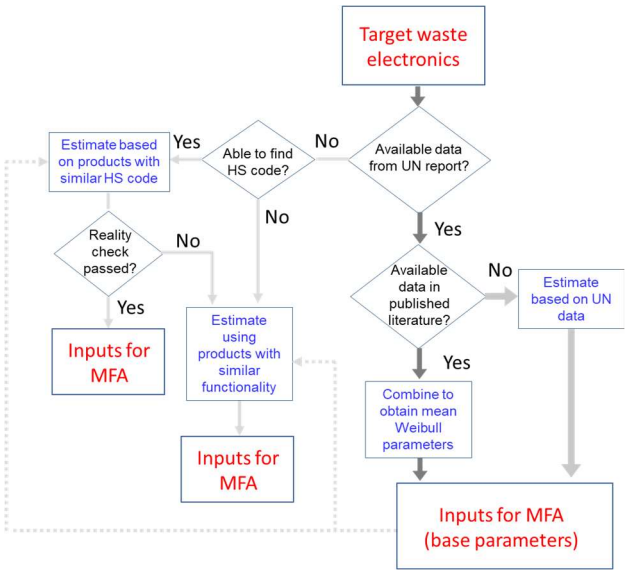

Figure S1 Decision tree for estimating the Weibull parameters and average mass for various waste electronics in this study. Darker arrows represent more ideal scenarios. Dashed arrows denote when the parameters are estimated by comparing with other types of electronics.

Note that CTA stopped tracking the sales percentages of certain electronics, for example the stand alone caller ID devices, satellite ratios, and VCR decks. For these electronics, the sales data after the last reported year were not modelled and assumed to be zero. Although the reported sales number of these electronics are small when CTA stopped tracking them, these electronics are still purchasable in the market, mostly as refurbished devices, which are not included in the MFA in this study. On the other hand, electronics that did not diminish in sales, but CTA stopped tracking before 2021,were extrapolated for different growth scenarios based the last reported year, as described in Supplementary Section S2.

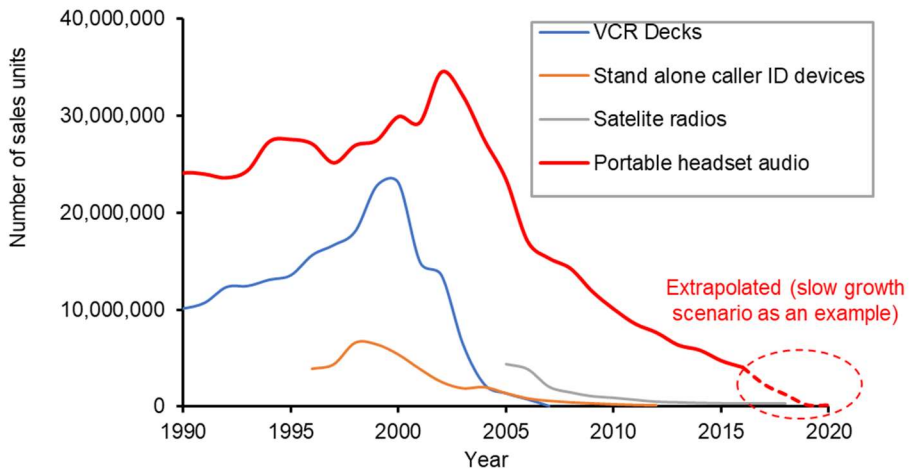

Figure S2 Example data for electronics that CTA stopped tracking when sales number is close to zero (blue, orange, and gray) versus electronics that CTA stopped tracking but required extrapolation (red). Data for solid line supplied by CTA.

S2.2 Growth Scenarios and Compositions

As discussed in the main text, the MFA in this study was conducted based on historical sales data from various sources. Since most of state-of-the-art historical sales data was recorded up to 2021, reasonable predictions must be made to predict the historical sales data up to 2031, in order to further determine the range of product and resource availabilities from the waste electronics.

Based on the rapid-changing nature of the electronics sales market driven by technology innovation, product development, and robustness of consumer demand, the past previous three and five year data was used to make the prediction. Three interpolation methods were used to predict the future sales of electronics based on the most-recent three or five year historical sales data. The first two were linear interpolation using the latest three-year data and five-year historical sales data. The third scenario was second-degree polynomial function interpretation using five-year historical sales data. If the predicted sales number was negative, then it was replaced by zero.

Note that for several conventional electronics whose sales number are diminishing, the fast growth approximation (2nd degree polynomial) predicted that the sales number will increase after reaching the lowest point. For these electronics, namely DVD, Blu-ray, family radio services, satellite radios, DVRs, home theater-in-a-box, and standard wireless phones. The fast growth scenario was manually reduced to avoid unreasonable increase predicted by the model. After the sales data reaches the minimum point, the minimum value was used for the following years. Similarly, sales data of the prior year was used if the

model predicts a negative value of the waste electronics. These adjustments led to negligible change in terms PCB and gold content used for the geospatial analysis in the following sections.

Sales data for each of the electronics was predicted using all three models. Using the 2031 prediction for each model, model with the highest value was selected as the "fast growth scenario", vice versa.

Besides the growth scenario, another key factor in the MFA of this study was the composition for both PCB and gold within the waste electronics. The process of assigning the PCB and gold composition in the waste electronics was similar as what was used for the Weibull parameters and maximum year as described previously in Section S2.1.

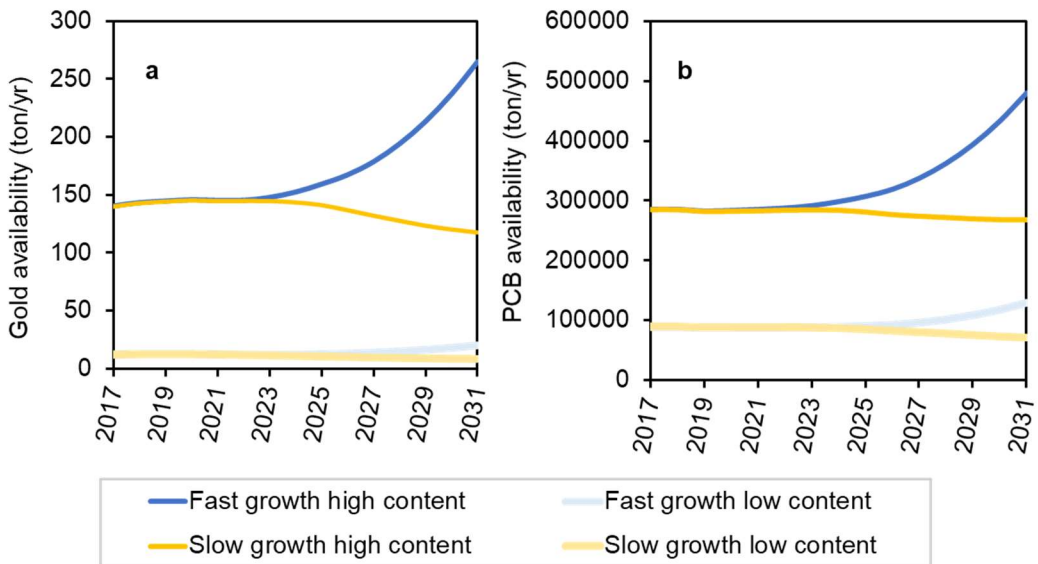

Figure S3 MFA results under different growth and composition scenarios from waste electronics for (a) gold availability (b) PCB availability

Lastly, as there are uncertainties associated with the PCB/metal composition within the waste electronics, which also contribute to the range of temporal distributions in Figure 1 (c and d) of the main text. Four possible scenarios are plotted to quantify the effect of electronics growth and PCB/metal composition. The separate results of the four scenarios are plotted in Figure S2. The individual relative impacts (RI) of the growth scenario and composition, as plotted in Figures 1 (c and d), are defined using the following equations:

$$RI\ (composition - upper) = \frac{A_{fast-high} - A_{fast-low}}{2} \quad \text{(S1)}$$

$$RI\ (composition - lower) = \frac{A_{slow-high} - A_{slow-low}}{2} \quad \text{(S2)}$$

$$RI\ (growth - upper) = \frac{A_{fast-high} - A_{slow-hig}}{2} \quad \text{(S3)}$$

$$RI\ (growth - lower) = \frac{A_{fast-low} - A_{slow-low}}{2} \quad \text{(S4)}$$

$$RI\ (composition) = \frac{RI\ (composition-upper) + RI\ (composition-lower)}{Total\ amount} \quad \text{(S5)}$$

$$RI\ (growth) = \frac{RI\ (growth-upper)+RI\ (growth-growth)}{Total\ amount} \quad \text{(S6)}$$

where upper and lower represent the RI above or below the median of the four scenarios, respectively. The average value of different scenarios are denoted by the center line in Figures 1 (c) and (d) in the main text, and the RIs are denoted by the areas above or below the average. Note that the RI parameters defined to help visualize the relative influence of the growth scenario and composition in Figure 1 of the main text, and the values change dynamically with the year.

S3 Geospatial modeling

S3.1 Spatial Distribution of Waste Electronics Production

As discussed in the main text, the geospatial modelling centered around the population distribution in the U.S. and representative possession data of electronics in each region. Plotting and analysis of the geospatial data were performed using open-source python packages such as GeoPandas, Pandas, and Matplotlib.[5-8]

The population in each zip code was obtained from the 2016, 5-year American Community Survey as reported by Whyte 2018[9], and the possession data of electronics for each geographical region was obtained from the residential energy consumption survey by the United States Energy Information Administration (USEIA)[10]. The shape file used for plotting the zip code map and calculating the area was obtained from the U.S. Census Bureau.[11] Since the possession data and population by zip code were for 2015 and 2016, they were combined to give an estimation of waste electronics generated per capita in 2016.

First, the total number of possession for the reported electronics were calculated using Equation S7.

$$n_{i,k} = \sum_{j=0}^{j_{max}} j \cdot \dot{n}_{i,j,k} \quad \text{(S7)}$$

Where $n_{i,k}$ was the total number of possessions for electronics i in region k. i in (1-5) represents each of the surveyed electronics (smartphones, TVs and screens, Cellphones, Desktop Computers, and Laptops), respectively. j was the number of possessions per household, and $\dot{n}_{i,j,k}$ was the number of household with the possessions of j number of electronics type i in region k. The total number of surveyed electronics in each geographical region (n_k) was calculated via the sum of number of electronics possessed (n_i calculated in Equation S7).

$$n_k = \sum_{i=1}^{5} n_{i,k} \quad \text{(S8)}$$

The weighted percentage of electronics generated in region k (φ_k) within the total electronics generated in the nation were represented by the total allocation of the five surveyed electronics (i=1-5) estimated using equation (S9), where k from 1 to 13 represents the 13 geographical regions included in the survey (Table S1).

$$\varphi_k = \frac{n_k}{\sum_{k=1}^{10} n_k} \quad \text{(S9)}$$

In this study, we assumed that all of the waste electronics generated were allocated using the weight percentage determined from the five representative electronics discussed above. The total allocated electronics generated in each geographical region (m'_k) was calculated using Equation S10.

$$m'_k = \varphi_k \cdot m_{nation} \quad \text{(S10)}$$

where m_{nation} was the national-level waste electronics generated for each growth scenario discussed in Supplementary Section S1.

The average kg per capita (ρ'_{zip}) was calculated via Equation S11,

$$\rho'_{zip} = \frac{m'_k}{P_k} \quad \text{(S11)}$$

where P_k was the population of each geographical region. For each zip code, its kg/capita waste electronics generated was calculated as the average value of the geographical region it covered, which was listed in Table S1 using the fast growth scenario as an example.

Table S1 Example of kg/capita waste electronics generated in different geographical regions and zip codes.

	Percent allocation (φ_k)	**kg/capita per region** (for 2021 as plotted in Figure 3a)	**Estimated first number of Zip code**	**Average kg/capita per zip code** (ρ'_{zip}) (for 2021 as plotted in Figure 3a)
New England	7.0%	7.4	0	6.2
Middle Atlantic	13.2%	5.0		
Middle Atlantic	14.9%	5.0	1	5.0
South Atlantic	6.8%	4.7	2	4.7
South Atlantic	19.6%	4.7	3	4.5
East South Central	5.4%	4.4		
East North Central	11.1%	5.0	4	5.0
West North Central	7.0%	4.9	5	4.9
West North Central	15.0%	4.9	6	4.9
East North Central	7.0%	5.0		
West South Central	13.2%	4.3	7	4.3
Mountain	14.9%	4.4	8	4.4
Pacific	6.8%	4.4	9	4.4

In this study, we assumed that the average kg per capita (ρ'_{zip}) values for all the zip codes with the same first number were identical. For example, all zip codes with the first number "0" generated 6.2 kg waste electronics per capita

We also assumed that the population-dependence between 2016 to 2021 of ρ'_{zip} was not studied, as there was only 2% change between U.S. population from 2016 to 2021.[9, 12, 13] Next, to calculate the waste electronics production density (ρ_{zip}) plotted in Figure 3a in the main text, the average kg per capita value listed in Table 1 was multiplied by the population of the zip code, then divided by its area (A_{zip}) as obtained from the shapefile from U.S. Census Bureau, as shown in Equation S12 below.

$$\rho_{zip} = \frac{\rho'_{zip} \cdot P_{zip}}{A_{zip}} \quad \text{(S12)}$$

The production per km taken to its one fourth power before plotting to offer the most straight-forward visualization of the values. For mapping, $(\rho_{zip})^{1/4}$ was used plotted the color map to help visualize the difference of production density Figure 3a. One-forth power was determined suitable because logarithmic scale could not be used due to many values were close to zero, which lead to errors when plotting using the geospatial packages.

S3.2 Distribution and Scales of Mines and Refineries

The mine plants where different metals are produced were identified from the online spatial data at USGS.[14] Since the source data containing the active mines in the U.S. was from 2003, we tried to cross-reference them with those listed in other online sources and provide the qualitative mapping in Figure 1f. As mentioned in the Methods Section of the main text, the addresses of the nation-wide certified recycler data was provided by SERI based on their certified recycler lists across the U.S.[15] For the following productivity and profitability analyses, the geospatial data of the gold mines were used. Since there was limited up-to-date productivity data of the mines, the mines were first sorted based on the states they were located, and state-level gold productivity was then used for the productivity and profitability analyses, as described below.

The gold production in the United States was around 226 metric tons across 12 different states in 2019, as measured by the United States Geological Survey (USGS).[16] State data are extracted instead of the detailed mine plants. The twelve states with gold production are listed in Table S2. Among the twelve states, Nevada and Alaska occupy the largest gold production, with annual production rate at 173 and 20.6 metric tons per year in 2018, respectively.[17] For California and Arizona, the productions were estimated from other business and company reports, which showed reasonable agreement compared with USGS data.[17-19] Since there were limited up-to-date data available, for gold distribution among the rest of the states, we assumed that the remaining production was uniformly distributed among these states, which was plotted in Figure 4b of the main text.

Table S2 States with gold mines and the corresponding production. Data extracted from the USGS 2018 Minerals Yearbook. Data extracted from References [17-19]

State	Production (ton/yr)
Arizona	2.6
Massachusetts	2.5
South Carolina	2.5
Utah	2.5
Colorado	2.5
Idaho	2.5
Montana	2.5
South Dakota	2.5
Washington	2.5
California	4.2
Nevada	173.0
Alaska	20.6

For the representative refineries that included waste electronics as part of the feedstock, information was gathered from major electronics product companies whose metal source were publicly available.[20, 21] The representative refineries selected that made to these supplier lists indicated that they had the capability of extracting metals from waste electronics that meet the quality for electronics manufacturing. From the list, the refineries for gold underwent Google searches to select the ones that identified waste electronics/electronics scraps as part of their feedstocks, which were listed in Table S3 below.

Table S3 List of representative refineries that takes waste electronics. Data extracted from lists in References[20, 21], with feed stream information obtained from company websites.

	Name of Plant	**Location**
1	Materion	California
2	Asashi refining	Utah
3	Kennecott	Utah
4	CJ Environmental	Massachusetts
5	Dillon Gage Reinery	Texas
6	Sims Lifecycle Services	Illinois
7	Sabin Metal Corporation	New York
8	Metalor	Massachusetts
9	Geib Refining Corporation	Rhode Island
10	Advanced Chemical Company	Rhode Island
11	Abington Reldan Metals	Pennsylvania
12	Garfield Refining	Pennsylvania

S3.3 Economic Potential Analysis

The spatial distribution and the scales of virgin refineries are discussed in the previous Section S2 and the main text. From these distributions the profitability and productivity of potentially integrating waste electronics into virgin gold production can be analyzed. For the productivity and profitability analyses, one key assumption made was that the PCB and gold allocations for each region (φ_k) were the same as the electronics. Thus, Equation S13 were used to calculate the distribution of resources (ρ'_{k_r} in ton/capita) in each region.

$$\rho'_{k\_r} = \frac{\varphi_k \cdot m_{nation\_r}}{P_k} \quad \text{(S13)}$$

The ton/capita resource in each zip code (ρ'_{zip_r}) was averaged using the same method as described in column 4 of Table S1, which could then be fed into the productivity and profitability analysis.

First, the center point of each zip code was extracted from the shape data for all the distance-related calculations. And the total mass or resource (gold or PCB) was calculated using Equation S14, where P_{2031} was the total predicted national population of the U.S. in 2031. P_{2016} was the recorded historical population of the U.S. in 2016. Since the population in each zip code was available only for 2016 (P_{zip_2016}), in this analysis we assumed that the population growth pattern in each zip code was the same as the entire country.

$$m_{zip\_3} = \rho'_{zip\_r} \cdot P_{zip\_2016} \cdot \frac{P_{2031}}{P_{2016}} \quad \text{(S14)}$$

Second, for each zip code area, the distances between its center point and all of the states with virgin gold mining plants were calculated. The zip code areas were then categorized based on the state closest to it, as shown in Figure 3c. For each state with virgin gold refinery, its allocated zip code areas were sorted based on the distance from shortest to longest. Then, the mass of potential recoverable gold from waste electronics was accumulatively added within all of the sorted zip codes, which was colored in light blue in Figure 3. For each mining plant, if the sum of all the allocated zip codes was still less than 0.25x or 1x of capacity (legend of Figure 3 in the main text), indicating that the mining plant had excess capacity beyond handling what was allocated based on the closest-distance assumption, then the region was plotted in dark blue.

If the embedded gold within the waste electronics generated of a certain zip code is beyond the productivity of its nearest facility, we assumed that the waste electronics would be handled by the next closest facility with the largest excess productivity, which were Nevada in Figures 3(d to g), South Dakota in Figures 3(h to j), and Massachusetts in Figure 3k. Once the target transportation destination is selected, the straight-line distances between the zip codes and the destination were calculated. In this study, we assumed that the transportation burden (i.e., cost, energy, emissions) increase with longer distance. Zip codes with longer distance to their destinations were represented using darker red color for heavier transportation burden. Thus, in this study, the transportation burden was a theoretical measurement to show how the penalty when transporting the waste electronics to its nearest facility with excess productivity.

For the analysis of metal refineries listed in Table S3, the same procedure was followed for sorting the gold productivity by virgin plants, except with geospatial information of the refineries listed in Table S3. We assume their base-case gold productivity 0.8 metric tons per year. Previous techno-economic analysis show that approximately 20,000 metric tons per year of PCB is required to make profit for both virgin integration, and electro-chemical plants targeting specifically for waste electronics. Using the average gold content (10^{-2} to 10^{-1} wt %) in PCBs [1, 22] from previous tear down studies, the 20,000 metric tons per year requirement of PCB is equivalent to 4 to 20 metric tons of gold per year.[23, 24] But since these refineries have existing infrastructures for metal refining and extraction, they would theoretically require less PCB feed to make profit. Therefore, 0.8 tons are assumed as the future competitive case for these refineries, which is roughly one third of the current average virgin productivity of 2.5 metric tons for each state other than Nevada and Alaska. The overlap of refineries and virgin plants means that the virgin plant is already including waste electronics as part of the feedstock. For these cases (Kennecott and CJ Environmental) [25, 26], the virgin productivity is used for the analysis in Figure 3 of the main text.

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Supplementary dataset: Complete list of the waste electronics studied

360 Cameras
5G Home Gateways
5G Smartphones
Action Camcorders
Aftermarket Advanced Driver Assistance Systems (ADAS)
Aftermarket Autosound Equipment
Aftermarket Computer Monitors
Aftermarket Vehicle Security
Analog Color TV
Analog Handheld LCD Color TV
Analog Handheld LCD Monochrome TV
Analog Projection TV
Augmented Reality Headset/Eyewear
Blu-ray Players
Cable Set-Top Boxes
Camcorders
Car CD Players
Compact Audio Systems
Connected Health Monitoring Devices
Connected Switches, Dimmers and Outlets
Connected Thermostats
Corded Phones
Cordless Phones
DIY Installed Home Security Solutions
Dash Cameras
Desktop 3D Printers
Desktop PCs
Digital Cameras
Digital Direct-View TV
Digital Photo Frames
Digital Storage
Digital Video Recorders (DVRs)
Digital and Non-Digital Memo Recorders
Digital-to-Analog Converter Boxes
Drones
E-readers
E-toys
Electric Scooters
Family Radio Service Devices
Fax Machines
Fitness Activity Trackers
Front Projection
Home Gaming Consoles
Home Robots
Home Theater-in-a-Box
Home and Clock Radios
LCD TV
Laptop/Notebook PCs
Laserdisc Players
Mobile Video Devices
Modems/Broadband Gateways
Monochrome TV
OLED TV
Other Smart Home Systems/Sensors
Pagers
Personal Digital Assistants (PDAs)
Personal Word processors
Pet Tech
Plasma Flat Panel
Portable CD Equipment
Portable Gaming Consoles
Portable Headset Audio
Portable Media Player Speaker Docks
Portable Media Players
Portable Navigation Devices
Portable Wireless Speakers
Printers
Rack Audio Systems
Radio/Tape Players or Recorders
Rear View Cameras
Satellite Radios
Satellite Set-Top Boxes
Smart Door Locks
Smart Doorbells
Smart Home Security and Monitoring Systems
Smart Light Bulbs (Including Kits)
Smart Smoke Detectors and CO Detectors
Smart speakers
Smartphones
Smartwatches
Soundbars
Sports Technology
Stand Alone Caller ID Devices
Standalone Wi-Fi Routers

Standard DVD Players
Standard Wireless Telephones
Streaming Media Players
Tablet PCs
Turntables
VCR Decks
Virtual Reality Headset/Eyewear
VoIP Adapters
Wired Earbuds
Wired Headphones
Wireless Earbuds
Wireless Headphones