Supplementary Information

Social and environmental analysis of food waste abatement via the Peer-to-Peer Sharing Economy

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Supplementary figures

Supplementary Figure 1: Social network of food exchanges*.* Interconnected social network representing food exchanges via OLIO. Nodes (dots) represent users and lines represent exchanges. Node size is proportional to the number of overall exchanges users engaged. Node color represents the share of items supplied out of overall exchanges from green (net supplier) to purple (net collector).

Supplementary Tables

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Table S1a. Avoided food waste and associated GHG emissions, Full OLIO network

Table S1b. Estimated retail value of all foods exchanged, Full OLIO network

Table S2a. Collection rates by category and supplier's Food Waste Hero status (# of listings)

Table S2b. Collection rates by category and supplier's Food Waste Hero status (percent)

Notice that since listings often contain more than one food item, the number of exchanges (i.e. network edges) can be larger than the number of listing collected. The cost benefit analysis is calculated according to the number of exchanges. in the greater London area.

Table S3a. Avoided food waste, Greater London area

Table 3b. Added GHG emissions from road travel (tons CO₂eq), Greater London

Table S3c. Avoided vs. added emissions Greater London (tons of CO₂eq avoided)

Table S3d. Number of exchanges (i.e. edges) by supplier user group and food category, Greater London area

The sensitivity analysis followed the same steps as the main analysis using different GHG emissions coefficients. For environmental benefits resulting from avoided food waste, we chose a lower value for GHG reductions e_{waste} 2.1tCO₂eq/ton food waste, as reported by the European Commission (2011) for the whole EU. For environmental costs associated with added road travel, we chose higher emissions factors - e_{car} = 240 gCO₂eq/passenger-km, as reported by European Environment Agency (2018) for the average passenger vehicle in the EU, and e_{bus} =120 gCO₂eq/passenger-km, as reported for a regular bus outside of London by Hill et al. (2018). Since no uncertainty was reported for these coefficients, we used Monte Carlo analysis (10⁴) to estimate them (assuming a normal distribution with a coefficient of variation of 10%).

Table 4a. Sensitivity analysis, Cost benefit (tons of CO₂eq reduced)

Table 4b. Sensitivity analysis, Added GHG emissions from road travel (tons CO₂eq)

Table S4c. Sensitivity analysis, Added GHG emissions from road travel (tons CO₂eq)

The calculation of the carbon opportunity cost was preformed by assigning values for COC from Searchinger et al, 2018 to each food group and calculating a weighted average for COC/kg of food waste based on the relative share of each food group in the overall composition of UK food waste (as detailed by WRAP, 2012).

Table 5. Carbon Opportunity Cost

Table S5b. from waste weight to production

Table S6. Food category definitions and weights based on empirical samples

[1] In groups where the empirical samples are N<50 we report statistics of the fitted lognormal distributions from which weights were drawn.

For groups where the empirical samples are N>50 we report mean, mode, and SD of empirical distribution from which weights were drawn (in grams).

[2] This group of samples by food waste heroes had only a few items. Therefore, we assumed its distribution is identical to that of regular users.

Table S7a. Monte Carlo results by user type and food category, weights and GHG emissions

Table S8a. UK exchanges by Income Decile (where 1 is most deprived 10% of LSOAs)

	collectors												
			$\mathfrak z$	3	4	5.	6		8	9	10	Total	
suppliers	$\mathbf{1}$	2,178	2,506	1,542	1,146	517	543	340	386	219	488	9,865	
	$\overline{2}$	3,047	4,858	3,580	1,954	2,001	1,223	941	878	348	801	19,631	
	3	1,286	2,515	3,540	1,716	1,774	1,003	620	714	388	631	14,187	
	4	1,516	2,424	1,923	2,852	1,128	898	812	577	452	785	13,367	
	5	581	878	951	594	1,303	645	547	575	254	697	7,025	
	6	548	991	941	802	751	954	483	388	320	400	6,578	
	7	462	764	1,202	773	836	1,009	1,259	765	490	837	8,397	
	8	271	396	657	389	609	435	366	493	215	318	4,149	
	9	207	306	468	263	659	507	385	335	592	556	4,278	
	10	348	537	1,041	650	672	640	814	496	393	2,255	7,846	
	Total	10,444	16,175	15,845	11,139	10,250	7,857	6,567	5,607	3,671	7,768	95,323	

Table S8b. UK exchanges by Education Decile (where 1 is most deprived 10% of LSOAs)

Supplementary notes

Supplementary Note 1. Introduction

OLIO is a UK based food sharing startup founded in 2015 by Tessa Clarke and Sasha Celestial One. The platform can be accessed via Web browsers [\(https://olioex.com/\)](https://olioex.com/) or dedicated smartphone apps and is freely available through the Apple and Samsung application stores. At the time of writing the platform had over 700,000 registered users worldwide. While the main focus is on food, the platform also has sections for sharing furniture, clothes etc. In addition to regular users, offering whatever food waste they have in their houses, OLIO also operates a network of individual volunteers, called 'food waste heroes', who collect food surplus from local businesses such as delis and bakeries, and offers them for collection via the network. OLIO's business model is to charge local businesses for certifying that they are 'zero-food waste' operators. Critically, while the startup is a for-profit enterprise, users are free to post or collect as many items as they wish, and all exchanges facilitated via the platform are currently free of charge.

Supplementary Note 2. Classification into food categories

We developed the classification scheme using an iterative and inductive process. Each of the 53,463 OLIO postings that comprised the training set was first manually categorized by one of four researchers. These categories were not predetermined; the researchers were free to create categories as needed. Efforts were made to select food categories that appeared to be mutually exclusive and sufficiently encompassing, which required a degree of iteration even within the first pass. The nature of the data posed some challenges for effective categorization. For one, information about each posting was exclusively in open text fields, which means there was no standard format in terms of text structure or content. Furthermore, the international scope of OLIO's user base means that there were many food products and slang terms used that were unfamiliar to the researchers.

Nevertheless, this initial pass through the data set resulted in 448 unique tags, which were then harmonized and condensed to 19 categories by a single researcher. After identifying systemic errors and inconsistencies, some of which stemmed from the open field format of the listings and others which stemmed from differences of the three initial coders, a second pass by a single researcher adjusted and reduced the categories down to 15. This scheme was used to train the classifier and test accuracy of the algorithm. Based on results from this test, a final scheme of 13 food categories (see Supplementary Table 6 in the SI excel) and 3 non-food categories (supplements, pet foods and NA) was imposed on the training set. This is the classification used in this paper

Supplementary Note 3. Sensitivity analysis- Environmental cost benefit

The sensitivity analysis followed the same steps as the main analysis differing only in the GHG emissions coefficients used for calculations. For environmental benefits resulting from avoided food waste, we chose a lower value for GHG reductions, $e_{\text{waste}} = 2.1 \text{tCO}_2$ eq/ton for food waste, as reported by the European Commission (2011) for the whole EU. For environmental costs associated with added road travel, we chose higher emissions factors - e_{car} = 240

gCO₂eq/passenger-km, as reported by European Environment Agency (2018) for the average passenger vehicle in the EU, and e_{bus} =120 gCO₂eq/passenger-km, as reported for a regular bus outside of London by Hill et al. (2018). Since no uncertainty was reported for these coefficients, we used Monte Carlo analysis (10⁴) to estimate them (assuming a normal distribution with a coefficient of variation of 10%). Result for sensitivity analysis are presented in the supplementary information (see Supplementary Tables 4a-c in the SI excel).