

Saving Food from Waste or Advance Selling? An Empirical Analysis of Too Good To Go Offering in Rome

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Abstract

Food waste is one of the greatest challenge to sustainability in developed and developing countries. In the former, food waste is concentrated in the final part of the chain. Too Good To Go is a digital platform aimed to prevent food waste, where consumers can buy magic boxes from different outlets containing food products that are approaching their end-of-life. However, the mechanism of the platform enable the outlets to publish their offering much in advance of the pick-up time, raising the question whether the food sold on the platform is effectively a leftover or a planned production. Our empirical study gathers data from over 1200 outlets in Rome on the Too Good To Go platform.

Keywords: food waste; web scraping; Too Good To Go; empirical analysis

1 Introduction

“As much as half of all food grown is lost or wasted before and after it reaches the consumer” (Lundqvist, De Fraiture, & Molden, 2008). In the past decades, food loss and waste have drawn more attention from the academic research field to policy-making governments, and business sectors. Food waste underlines the loss of food at any point of the Food Supply Chain (FSC), from production and processing to retail and final consumption (Parfitt, Barthel, & Macnaughton, 2010). Comparing to developing countries, where food waste occurs mainly during the earlier stages of the FSC, it usually occurs in the final stages of the FSC in developed countries where the cultural, social, or economic decisions made by the producers and final consumers play a big role (Dorward, 2012). In Europe, 42% of food produced in the FSC goes to food waste at the final consumption stage, without considering the agricultural phase (Monier et al., 2010).

Food waste not only represents an economic cost for households and food providers (food growers, manufacturers, distributors, retailers, and hospitality stakeholders), but it also has equally profound impact on environmental and social factors. Taking the final consumers as an example, the economic impact by food waste is interpreted as the cost for households. The cost of an average UK household is estimated as £420 a year, and in Italy, an average Italian household “wastes” approximately €454 a year (Segrè & Falasconi, 2011). From the environmental aspect, the amount of food waste can be transformed into Greenhouse Gas (GHG) emissions (Venkat, 2011; WRAP, 2008, 2009) or water wastage (Lundqvist et al., 2008). According to WRAP, the average carbon footprint of avoidable household food waste reaches approximately 330kg CO₂ equivalent per person per year, which equals one-third of the CO₂ emissions from the electricity use per person in the UK (WRAP, 2011a, 2011b). The average annual amount of food waste generated in developed countries (220 million tons) is almost as high as the total net food production of Sub-Saharan Africa (Gustavsson, Cederberg, & Sonesson, 2011). The social impacts of food waste, which especially occurs in developed countries, are obvious.

Numerous initiatives have been implemented in the EU countries in the last few years, sharing the same goal of halving food waste by 2025 by the European Commission (Secondi, Principato, & Laureti, 2015). Most research efforts in this field inspire new prevention methods with the collaboration of stakeholders, as well as awareness campaigns directly addressing to key agents at the final consumption stages like families, school children, and restaurants (Monier et al., 2010). Recent studies indicate that consumer awareness concerning the consequences of food waste is significantly correlated with food waste behavior. Consumers do not waste food carelessly, instead, food habits as well as socially determined factors impact consumers' wastage of food in the UK (Evans, 2011; Watson & Meah, 2012). On the contrary, consumers are playing a crucial role in food waste because their perceptions and purchasing behaviors influence the decision-making of stakeholders (retailers, restaurants, and so on) at the final stages of FSC (Stuart, 2009). Current studies indicate that reducing food waste by consumers is positively associated with initiatives that provide simple and practical suggestions to avoid food waste, and raise the awareness towards food waste with various communication tools (Aschemann-Witzel, De Hooge, Amani, Bech-Larsen, & Oostindjer, 2015; Secondi et al., 2015).

Too Good To Go (TGTG) is a digital platform that allows consumers to order meals in the form of Magic Boxes (MB) with unknown content which otherwise would be disposed as food waste. In their 2021 report, they claim 52,554,009 meals were saved in the year – a figure equivalent to feeding the entire population of South Korea (Too Good To Go, 2021). However, in previous studies it already emerged the use of TGTG by restaurant managers as a way to increase turnover for the restaurant (Vo-Thanh et al., 2021), even if the impact on profitability was not clearly identified.

2 Data

We set up a regular scraping job to recover data from TGTG leveraging the open source `tgtg-python` library¹. The routine was collecting data from TGTG four times a day (8:00, 12:00, 18:00, and 22:00), recovering information about all outlet offering MB within 10km from an arbitrary place in the center of Rome². For the present work we collected 91,799 observations from 1,285 outlets from July 4th 2022 to July 24th 2022 included.

Each observation includes the type of MB, how many of those MB are available at that moment in the outlet, deadline for purchase, time window for collection, price, value, and other information on the outlet. As we can see in Figure 1, the two dominant types of MB are Meal and Baked Goods.

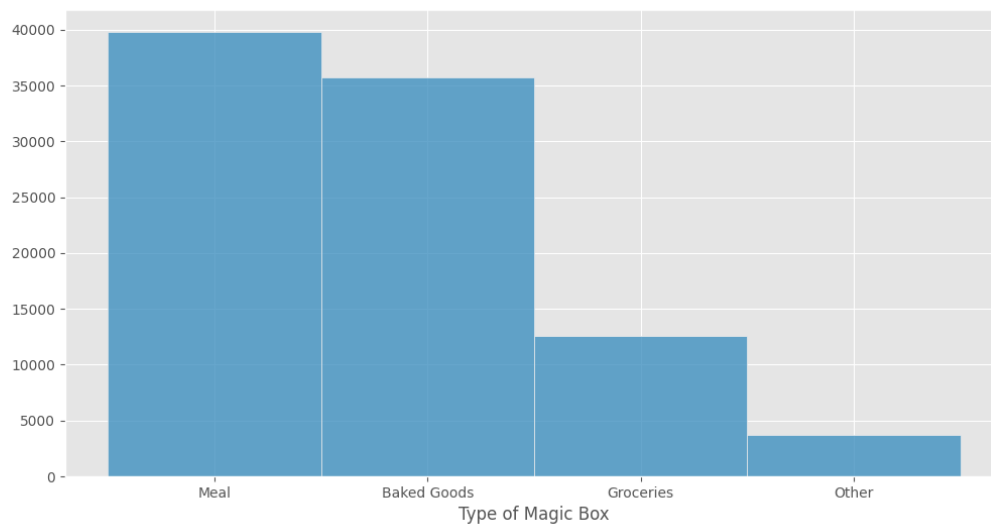


Figure 1: Distribution of Magic Boxes by type.

Figure 2, instead, provide some initial insights about the number of MB available in each listing. We can clearly see a cluster of outliers offering about 100 MB in a single listing, while the median and 75th percentile are respectively 2 and 3 MB per listing. Such a skewed distribution deserves a more in-depth analysis before moving further, as extreme values may distort subsequent elaborations.

¹Full code for the `tgtg-python` library available at <https://github.com/ahivert/tgtg-python>.

²Specifically, the center was set at the following coordinates: 41.896940N, 12.504330E.

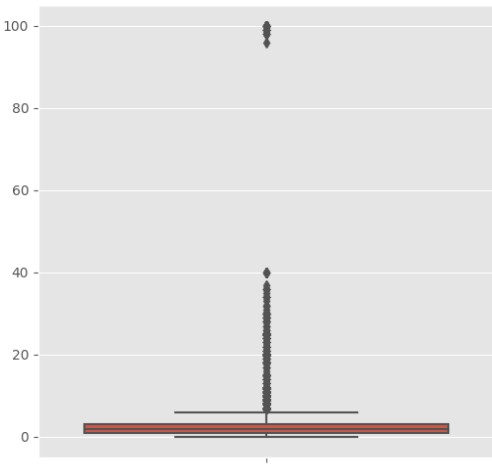


Figure 2: Number of Magic Boxes available in each listing. All observations.

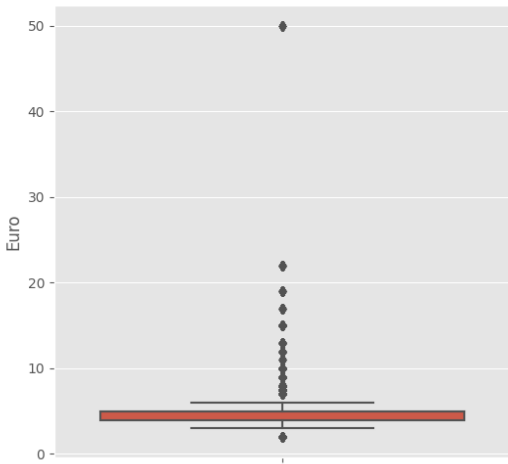


Figure 3: Price per Magic Box. All observations.

A more granular analysis showed that all 81 observations with 96 to 100 MB per listing belong to the same outlet, and the outlet does not have any observation outside this range. Therefore, we considered appropriate to remove this outlet from our sample, as it is clearly displaying a distinct pattern in terms of MB offered.

In terms of pricing, we can see in Figure 3 that some observations stand out, with a price of EUR 49.99, while the median and 75th percentile are both EUR 4.99. All those 24 observations belong to a wine shop offering a MB composed by wine bottles. Also in this case we believe it is appropriate to exclude those observations from further elaborations. The rest of the analysis and discussion will take into account only data not belonging to those two outlets, therefore our clean dataset is comprised by 91,694 observations over 1283 outlets.

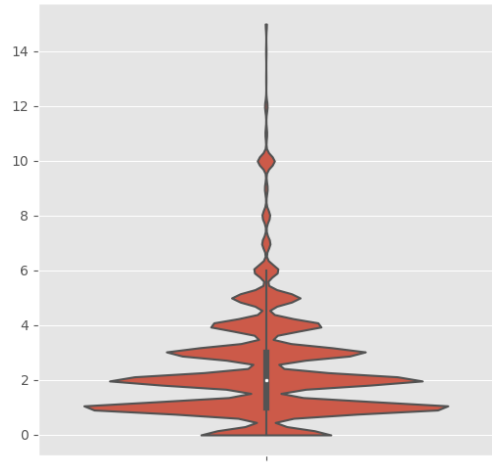


Figure 4: Number of Magic Boxes available in each listing. Clean data until 99th percentile.

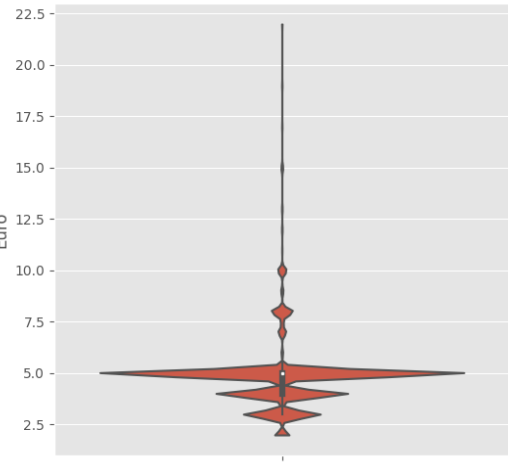


Figure 5: Price per Magic Box. Clean data until 99th percentile.

Figures 4 and 5 provide some more insights on the distribution of the cleaned dataset. We can see that most listings offers less than 5 MB, and prices are concentrated at or below EUR 4.99 per MB. Even though there is still a long tail in the upper side of the distribution for both metrics, heterogeneity seems to have been reduced

to an acceptable level³.

Another point of interest is the distribution of hours left to purchase MB in a listing. In Figure 6 we can see a clear pattern emerging. Listing sampled at 8:00 have a mean time left at about 11 hours, and this value decrease for the two following sampling time. This seems reasonable, as with the passing of time there will be less time left to purchase the MB in the listings. However, already at 18:00 we can see a cluster of listings with over 20 hours left. Those are new listings for MB to be collected the following day. This becomes more apparent for listings sampled at 22:00, where a vast majority is up for collection the following day.

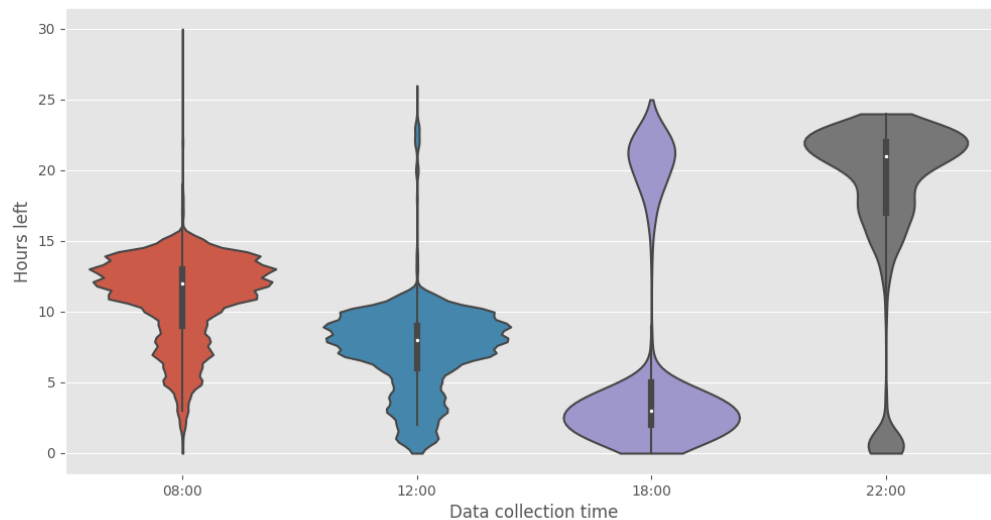


Figure 6: Distribution of listings by time left and sampling time. Violins' area is proportional to the number of listings.

From a weekly seasonality, in Figure 7 we can also note that on Saturdays there seems to be a lack of listings with long ordering time, and somehow less listings in general. On Sundays, instead, listings for collection on the following day seems prevalent, and there seems to be less listings for collection on the same day. This evidence may be related with outlets' opening schedules.

³Data displayed in Figure 4 and 5 has been capped to 99th percentile for better visualization. Cutoff values for visualization are 15 available MB per listing and EUR 21.99 per MB.

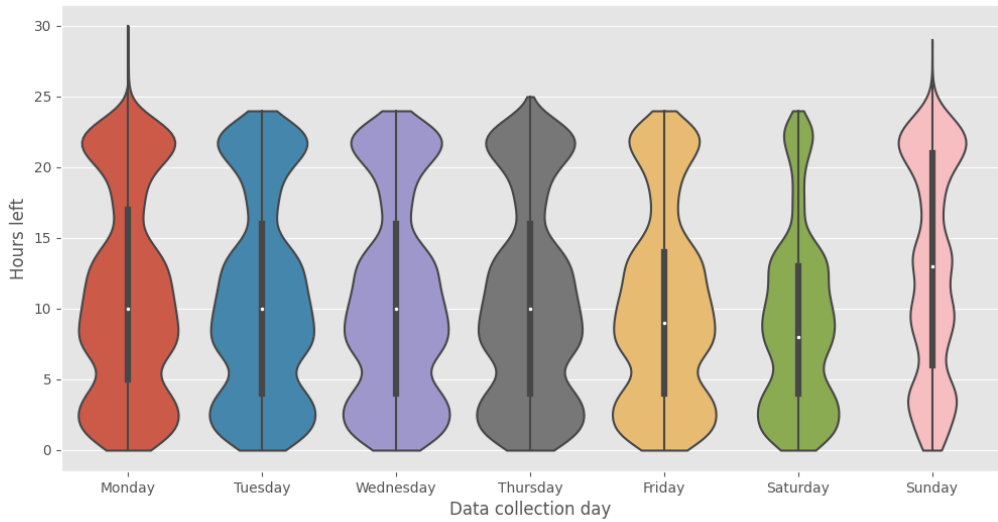


Figure 7: Distribution of listings by time left and sampling day. Violins’ area is proportional to the number of listings.

In terms of items available, Figure 8 shows how the number of listing with zero availability progressively increases from 8:00 to 18:00, and then drops at 22:00. This visualization also shows more clearly that the last sampling time of the day also has a reduced number of listings compared to the others.

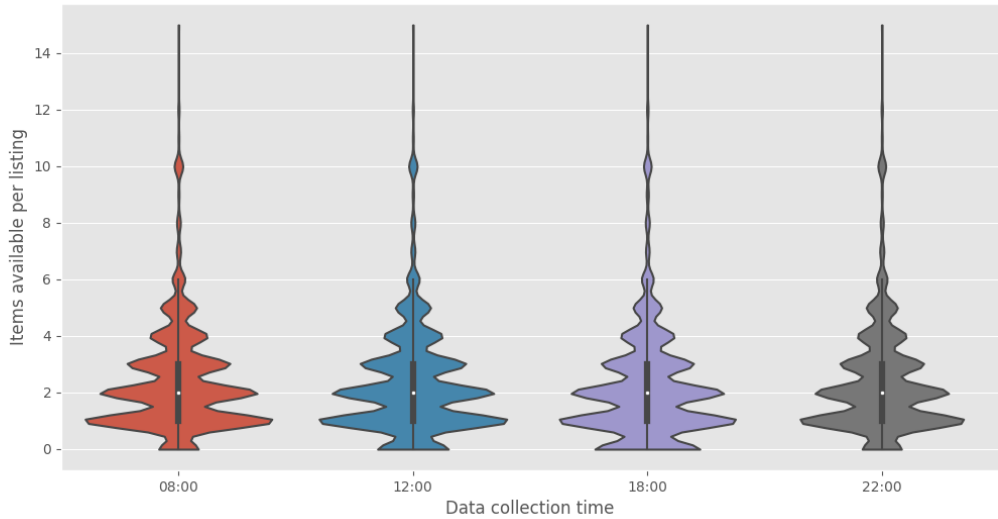


Figure 8: Distribution of items available by sampling time. Violins’ area is proportional to the number of listings. Clean data until 99th percentile.

Also in this case, we can not that on Saturdays and Sundays the number of available items progressively drops compared to weekdays (Figure 9). On Saturdays there seems to be an higher number of listing with zero availability compared to other days.

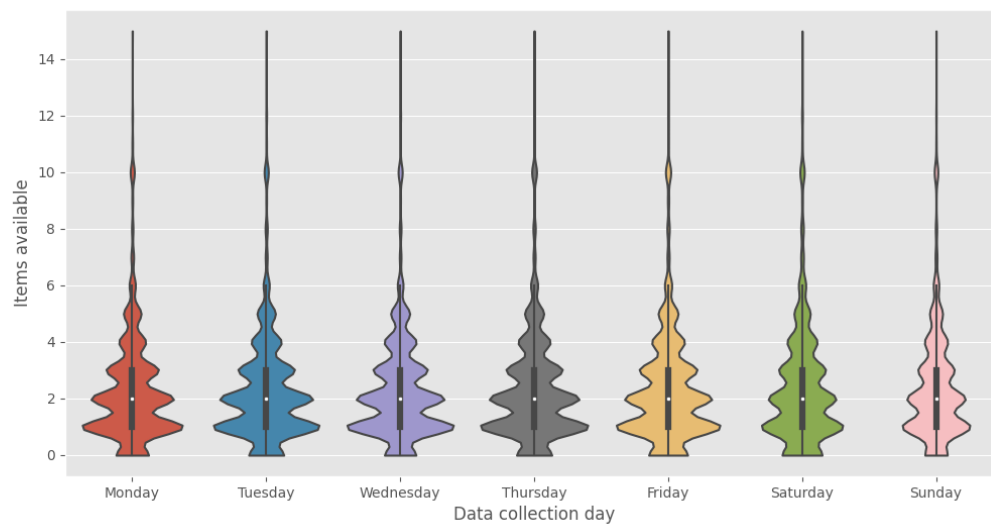


Figure 9: Distribution of items available by sampling day. Violins' area is proportional to the number of listings. Clean data until 99th percentile.

3 Conclusions

This is a work-in-progress release of our research, aimed to open the discussion and prepare our next steps. We welcome comments, suggestions, and potential further insights on the phenomena we are studying.

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