The Economics of Food Rescue: Deriving the Value of Variable Food Donations

Honors Thesis

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Abstract

The emergence of food rescues in recent decades has filled a need to divert food waste from the landfill and distribute it for human consumption. This study aims to assign a dollar value to a year's worth of captured food waste by one food rescue in Colorado. Economic valuation of food waste has mainly been done from the supermarket's perspective. Other analyses of the value of food rescues are derived from the social value the resource itself provides, rather than the specific valuation of the goods it captures. This research provides a new and preliminary method to standardize food dollars across donor source types to create an approximate dollar value for food intake records. One food rescue in Northern Colorado was able to save $5.8 million worth of food from the landfill over one year by working with a variety of partners across the state. This method may provide a new means for food rescues to assign value when drafting reports for various stakeholders, and it may also offer a means of value estimation for communities looking to start a food rescue.

Introduction

The world produces enough food to nourish the entire population, and yet, one-fifth of that food is lost or wasted before it can be consumed (World Food Programme, 2024). There has long been inefficiency in the food system, leading to a gap between the food available and those who need it. The current food system can be described as a series of events: production, processing, distribution, retail, and consumption (UC Sustainable Agriculture Resource & Education Program, 2023). In the last few decades, food rescues have emerged as an innovative, community-level solution to this problem, working to capture waste at every level of the described food system. While the food gap is often discussed in terms of food insecurity, food rescues work with a different but coinciding mission in mind–capturing edible waste. Food rescues can be differentiated from food banks by a few additional factors; food banks are usually government-funded and contain fresher food; food rescues are more of a pre-dumpster-diving mission, focused more on eliminating waste than insecurity (N. Shaw, personal communication, March 5, 2026). Food rescues act as an intermediary to the current food system by working to "rescue" waste and redistribute that edible food for consumption. This process works to reduce global food waste at the community level.

In this study, social value is referred to as the valuation of the existence of a food rescue itself, while economic value is referred to as the actual valuation of goods taken in by a food rescue. Much of the current research on food rescue operations derives the social value of food rescue resources, measuring the degree to which food rescues can reduce waste and insecurity, allowing communities to manage food waste collectively (Warshawsky, 2015; Diprose and Lee, 2021). One study was able to calculate the social return on investment for a variety of food rescues in New Zealand to be 4.5:1 (Clare et al., 2023). This means that for every $1 investment that a government or an outside funding source provides to a food rescue, there is $4.5 of social value

felt by those using the resources. This dollar value estimate provides an insightful index for governments or corporate funding resources when choosing to support these missions. There is also a great amount of literature on food banks, which work to alleviate food insecurity, rather than solving the waste crisis as a priority (N. Shaw, personal communication, March 5, 2026). A traditional food bank has been shown to provide $40-60 of social value per visit for an average family, but this measure is mostly denoted by insights from the travel cost method (Byrne and Just, 2022).

While dollar values have been used to quantify social benefits of food rescues as community resources, few studies have drawn economic value estimates from these same missions. Food rescues capture the economic dollar value of specific goods that would have otherwise ended up in a landfill. Two studies have analyzed the economic value of rescued food from the perspective of an Italian supermarket (Cicatiello et al., 2017; Cicatiello et al., 2016). These studies were able to use the supermarket's register data to match exact prices to edible leftover food, offering a solid estimate for the economic worth derived from the donated food. Economic values have not yet been derived from the food rescue's perspective. Food rescues take their food from a variety of sources across the local area, including grocery stores, food service operations, farms, restaurants, and other charities and food rescues. During intake processes, dollar values are not usually provided to food rescues by their donors, and therefore, no standard estimate is made for this metric. By creating a standard metric to measure approximate economic dollar value across these sources, reporting can be broadened to show a total dollar value of food intake across many categories. These values can then be utilized to show greater detail on how source and category distribution help to stabilize variable food inflow throughout the year.

This paper aims to quantify the economic dollar value of a year's worth of food intake at Vindeket Foods, a food rescue located in Fort Collins, Colorado. Their recovery efforts have grown since the organization's founding in 2017, with recent yearly totals as high as 2.2 million pounds of food rescued in 2025 (Vindeket Foods, n.d.). That year, Vindeket sourced its food from 61 different sources across Fort Collins (Vindeket Data, 2025). Their operation serves as a great example showing how values may be derived across sources from the food rescue standpoint.

The primary research objective was to quantify the approximate dollar value of Vindeket's 2025 food intake from its 61 donors. Vindeket records each of its donations by date, donor, and pounds. Economic Valuation was created by using unit values calculated using the United States Department of Agriculture (USDA) dataset for food at home monthly area prices (FMAP) (U.S. Department of Agriculture, Economic Research Service, 2024). This was instrumental in providing the dollar valuation for Vindeket's intake records. This dataset allowed for the creation of a new column in Vindeket's records: "item worth". From there, the breakdown of donation amounts was characterized by months of the year, across food categories, and across donor types.

This allowed for a new means to evaluate a variety of monthly intake trends over one year using the created “item worth” metric.

By quantifying this value from a food rescue perspective, this study offers another method of quantifying economic value that stands apart from those already used in the few known studies tackling the economic valuation of food waste. This also shows that a food rescue perspective offers notable insights about diversifying donor source types for keeping a stable inflow of donated food. The created metric may be used as an additional means of quantifying impact for donors and potential donors to a food rescue. This metric may even serve as a resource to those communities looking to consider what kind of food rescue resource is right for their community, and how much economic value it may derive from what was previously going to the landfill.

Methods

In accomplishing the primary objective of quantifying the dollar value of Vineket’s food intake record, a series of steps was taken to create an unrecorded valuation, to the degree possible with reliance on the FMAP dataset. Vindeket’s donation intake records simply record the date, donor, pounds of food, and one of seven broad organization-denoted food categories. Personal volunteering experience at Vindeket Foods, as well as conversations with Vindeket’s founder, Nathan Shaw, allowed for a greater understanding of what kinds of food fall into each of Vindeket’s seven food categories (personal communication, March 16, 2026). These categories—bakery, beverage, dairy, grocery/shelf-stable, meat, prep, and produce—are mainly categorized by their method of storage at the food rescue. Recognizing that these categories can become very broad–especially in the case of grocery/shelf-stable and prep–these broad categories were easier to use in valuation methods for Vindeket itself rather than the FMAP categories. The FMAP dataset includes 87 ERS food purchase groups (EFPGs). These categories aim to classify every major type of food one might buy at a grocery store in the US, but notably include further breakdowns. For example, the “dark green vegetables” category spans four separate categories: fresh, fresh cut, frozen, and canned. When mapping these categories to Vindeket’s broad categories, “fresh” was mapped to “produce”, “fresh cut” was mapped to “prep”, “frozen” was mapped to “prep”, and “canned” was mapped to “grocery/shelf-stable”. This same mapping process was applied to every EFPG.

The FMAP listed unit prices for each of the 87 EFPGs for each month of 2018. These were found by dividing the total amount of purchase dollars for each EFPG by the total grams purchased (Sweitzer et al., 2024). These unit prices were listed twice: as a weighted value and an unweighted value. Weighted values were developed by the USDA, ERS, to better represent store sales, giving a greater weight to those items that may have been purchased more frequently (Sweitzer et al., 2024). However, food rescues receive the leftover, overstock, and unwanted food from stores, which often does not follow retail patterns. Thus, unweighted values were used in the valuation process. Because many EFPGs were fit into each of Vindeket’s categories, category

prices were found by taking the average unit price between every EFPG in each Vindeket category. These unit prices were in dollars/100 grams, which were converted to dollars/pound to match Vindeket's intake records. After completing this process, a price per Vindeket category per month in 2018 dollars was derived.

Vindeket's donation volumes were measured in 2025 dollars, but FMAP prices were collected in 2018 dollars. This required inflation of 2018 prices to express donation values in 2025 dollars. To do this, the government consumer price index (CPI) that tracks groceries, or "Food at Home" (FRED series CUSR0000SAF11), was utilized (U.S. Bureau of Labor Statistics, 2026). For each month of 2025, the FRED series was rebased to that month in 2018 = 100. For example, when computing January 2025 values, FRED was rebased to January 2018 = 100. The 2025 index values serve as an inflation scaling factor: for example, if the Food at Home index reads 128 in a given month of 2025, grocery prices are 28% higher than in January 2018, and the scaled price is (128/100) * FMAP price. The CPI values are missing for October 2025, so the median of September and November was used. The FRED series is seasonally adjusted, meaning the BLS has removed predictable, calendar-driven fluctuations from the raw index (citation). Retail food prices follow regular seasonal cycles tied to harvest schedules and holiday demand, so this adjustment smoothes this out.

The valuation creation process was applied to every record in Vindeket's 2025 intake dataset, which allowed the total donation volume to be calculated. This valuation could further be broken up by category, donor type, and month to show how the valuation was distributed. Categorical and graphical analysis of Vindeket's intake data was performed in R Studio, version 4.5.2.

Results

The total dollar valuation of food received by Vindeket in 2025 was calculated to be $5,856,817. This is the approximate valuation of food that was saved from the landfill by Vindeket's efforts in 2025.

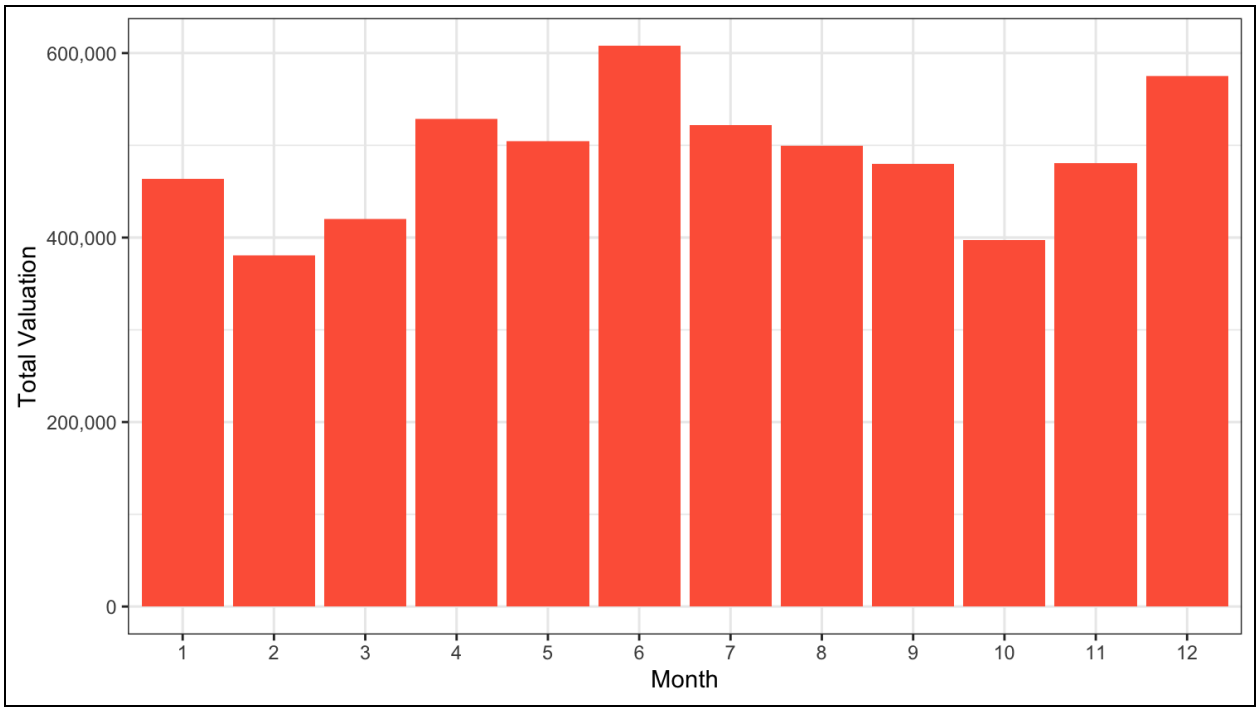

Figure 1: Total dollar valuation by month of food donations to Vindeket Foods in 2025.

The associated value of goods received by donors at Vindeket Foods varies from month to month (Figure 1). In 2025, spikes occurred in the months of June and December, with June's valuation reaching around $600,000. Lows occurred in the months of February and October, with valuation totals just under $400,000.

Vindeket Category	Average Price ($/lb)	Intake Valuation ($)
Bakery	$3.99	$1,074,156
Beverage	$2.20	$391,503
Dairy	$2.98	$1,132,413
Grocery / Shelf Stable	$3.70	$1,456,741
Meat	$6.12	$203,003
Prep	$3.70	$659,691
Produce	$1.85	$939,312

Table 1: Average prices and total valuation of donation intake in each category for Vindeket's 2025 intake records.

Average prices were calculated for each month of the year. Table 1 shows the average calculated price for each category. The highest price was for the meat category at $6.12, and the lowest price calculated was for the produce category at $1.85. The table also reports total valuation dollars for each food category in Vindeket's 2025 intake records. Vindeket received the most of the grocery/shelf-stable category, which was valued at $1.4 million. The category with the lowest total valuation was Meat at just over $203,000.

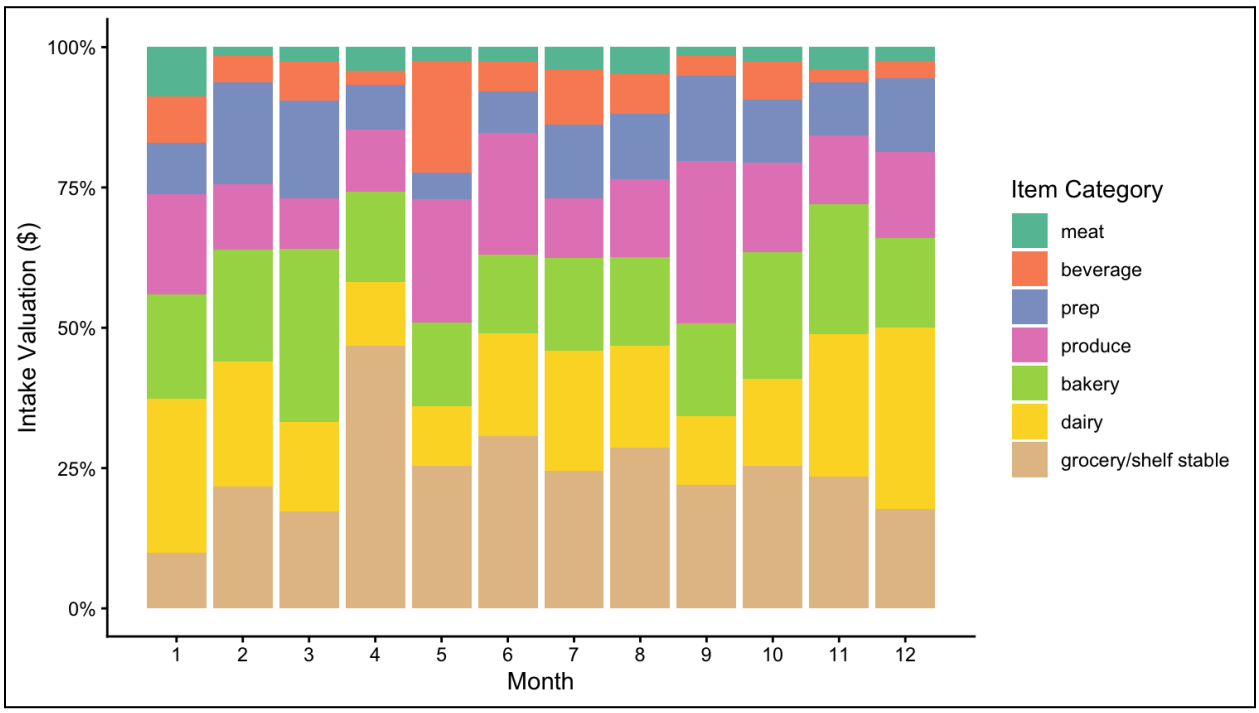

Figure 2: Item Category segmented intake valuation by month for Vindeket's 2025 intake. Item categories are arranged from the largest yearly valuation to the smallest (largest closest to the x-axis).

Categories of food intake vary from month to month (Figure 2). Table 1 denotes that grocery/shelf-stable is the category with the highest 2025 valuation, but this was not the case for every month of the year (Figure 2). The dairy and bakery categories often surpass the valuation of the grocery/shelf-stable category. Table 1 denotes the meat category as the smallest overall in terms of total valuation, but it can surpass smaller categories like beverage and prep in some months.

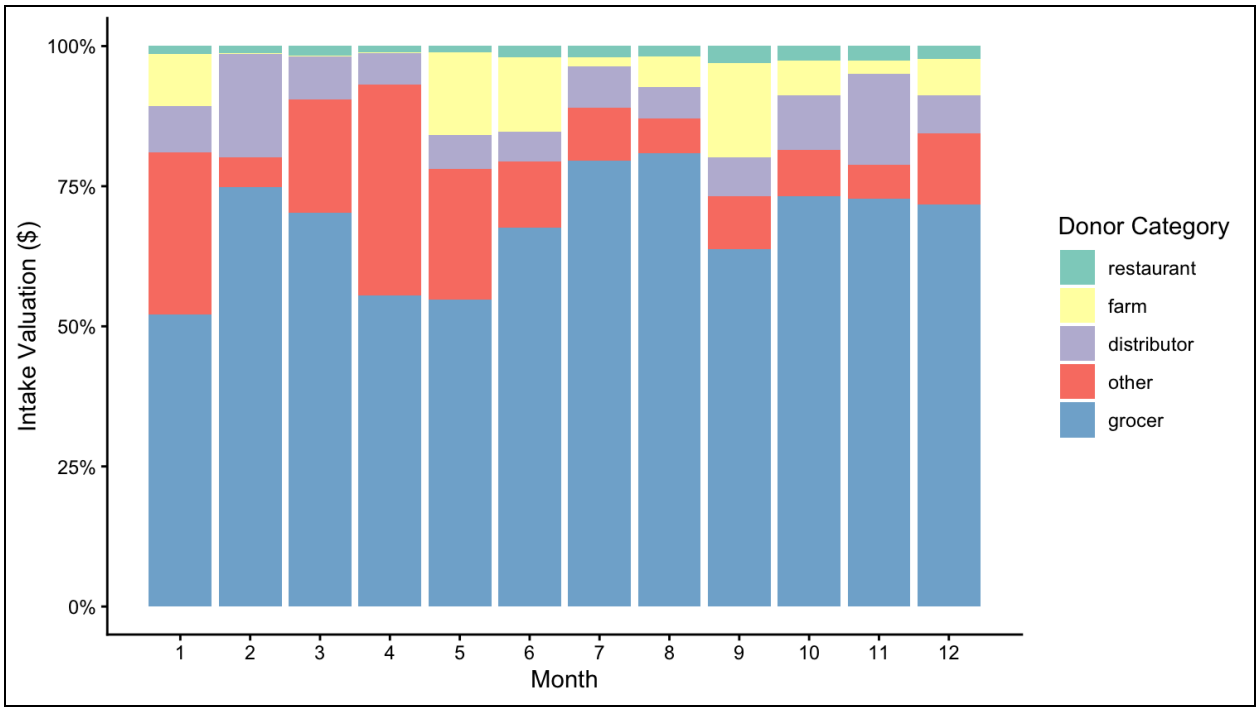

Figure 3: Donor category segmented intake valuation by month for Vindeket's 2025 intake. Donor categories are arranged from the largest yearly valuation to the smallest (largest closest to the x-axis).

Donations that are sourced from grocers make up the largest percentage of the monthly valuation for every month of 2025 (Figure 3). However, all other categories of donors can make up almost 50% of the monthly valuation in January, April, and May. The farm category spikes in some months and can be almost nonexistent in others.

Discussion

This study attempts to put a dollar value on all goods received by Vindeket Foods in 2025 from a wide variety of donors. Recognizing that the only "true" perfect value would need to be obtained with actual data from each of Vindeket's donors about how much they might each sell their items for, this study aims to get close without this level of communication. These valuations should not be taken at face value, but rather, they have been methodically crafted to incorporate data-backed averages for each category. The metric can be further used to quantify a food rescue's impact in terms other than pounds or social value.

It is important to note that not every item on the intake records makes it to the shelves and into the hands of shoppers at Vindeket. Donated food that enters Vindeket's receiving doors may be rejected by volunteer stockers for a variety of reasons–wilting or rotting, potential health risk, mold, or potential contamination, just to name a few (Tarasuk and Eakin, 2005). In conversation with Vindeket's director, Nathan Shaw, he listed his best guess at what percentage of each

category makes it from a truckload to the shelves for shoppers, and for every category but produce, this percentage was between 90-100% (personal communication, April 22, 2026). The only category he marked lower was produce, which likely relates to the nature of fresh produce to go bad in a shorter time period and in handling. Volunteers at Vindeket and other food rescues spend considerable energy separating rotting from edible produce (Tarasuk and Eakin, 2005). However, Shaw's estimates were not data-backed and thus not included in valuation estimation, but rather are intended to provide context to be considered with the data. Thus, food valuation done here reflects the total value of food saved from the landfill, rather than that received by community members.

The total 2025 valuation for Vindeket Foods' intake records is a seemingly large number, but it is not contextualized when stated alone. In 2024, the total yearly sales at an average US grocery store were valued at about $37 million (The Food Industry Association, 2025). This further constitutes Vindeket's 2025 total valuation as about 13% of the average sales of a US grocery store. Figure 1 shows that the valuation of food intake varied throughout the year, but more research would need to be done to analyze annual patterns. The item categories seemed to vary slightly through each month, but most categories could be expected to show out at a decent valuation each month of the year (Figure 2). The meat category could likely be expected to be small each month, but the beverage category showed up as quite variable in the graphical context (Figure 2). This may be due to categorization mistakes from miscommunication between those who complete intake records, as Shaw mentioned previously (personal communication, May 8, 2026).

When analyzing donor types, grocery stores undoubtedly dominate the valuation record, but food rescues should not be quick to discount the contributions from other sources (Figure 3). If grocery stores alone were allowed to donate waste to Vindeket, the food rescue would have been able to provide only around half of the amount of food it did to shoppers in January 2025 (Figure 3). Farms may be spiking due to seasonal harvest patterns, but this cannot be determined solely by the data shown here (Figure 3). More research could be done to further analyze the impact on forecasting the inflow of food and providing stability to food rescues from varying donor types. Additionally, further graphical analysis may be done with the data shown here, but it was limited due to time constraints.

Using FMAP and CPI data to create a valuation metric from food rescue poundage data adds new methodology to the food rescue and food waste research knowledge base. This provides a possible means of dollar valuation for those food rescues like Vindeket Foods that do not currently have a means of collecting economic parameters from their donors. As mentioned by Clare et al., Food rescues require donations of not only food to keep operations running, but also financial or charity gifts, and even sometimes government assistance to stay in operation (2023). They also explain that this "creates financial uncertainty and often requires them to demonstrate

the impacts of their work with limited resourcing". To those food rescues, like Vindeket, this valuation metric provides another means of demonstrating impact to the organization's stakeholders. While pounds provide an already useful metric to demonstrate weight and potentially visualize volume of food being saved from the landfill, dollar values may resonate more with some potential donors. Other donors are looking to show their dedication to helping the environment, which is done so here through lessening the carbon emissions resulting from food waste. In 2017, food loss and waste accounted for about half of CO2 emissions resulting from the food system (Zhu et al., 2023). This valuation method could even be expanded to those communities looking to start their own food rescue, whether it be as a means of improving their environmental impact or helping to alleviate local food insecurity. Even just starting with a small number of donors could generate benefits for a community, and this could be pre-measured with the methods listed here.

The category mapping process was not precise, but neither were intake records. In conversation, Shaw provided an example of the beverage category; of the volunteers and employees helping with intake, some will separate shelf-stable beverages into the beverage category, and some will roll it into the grocery/shelf-stable category (personal communication, May 8, 2026). These two categories may be imprecise as a result. This is just one example of a common intake mistake made by inconsistent knowledge of practices by volunteers. Food rescues like Vindeket often receive so much food at once, and their first goal after weighing donations is to move items to their proper mode of storage or refrigeration, not proper categorization (N. Shaw, personal communication, May 8, 2026). Aside from these imperfections, the category mapping process was made quite simple by the nature of EFPGs. EFPGs of one category are often further categorized into several categories by packaging details, like with the dark green vegetables example (fresh, fresh cut, frozen, and canned). This separation made it quite simple to categorize EFPGs into Vindeket's mostly storage-related categories. With every fruit or vegetable, the "fresh" denotation often maps to produce, and the "fresh cut" and "frozen" denotation always maps to prep. The "canned" categories of almost any item could be mapped to the grocery/shelf-stable category.

Methodology could be improved with more attention to donor source types, as well as more detailed recording processes. Food items were received mostly by grocery stores, but also by other sources like farms, food service distributors, restaurants, and other sources (Figure 3). At each of these places, the same food item may have been sold for a different price. For example, a bag of shredded lettuce at the grocery store will cost differently than a bulk bag of shredded lettuce from a large-scale distributor serving restaurants and food service operations. A chicken pot pie from a local bakery would likely be sold at a very different price than one in the freezer section at the grocery store. This raises the question of what kinds of values should be used when creating this value for food rescues. To capture value that corresponds to its respective donor type, further research would need to be done, with the possibility of adding certain weights to

certain donor types. Another possibility may be requiring certain information to be passed along by donors themselves. However, Shaw shared that donors often prefer to participate in donation with minimal effort on their side of the process, which would not support a greater sharing of this kind of information (personal communication, April 27, 2026).

Future research on Vindeket's impact on valuation could be quantified with the introduction of costs to the equation. If Vindeket wanted to complete a well-rounded cost-benefit analysis, a study would need to gather valuation from donors about what it takes for them to participate in food rescue. Current factors that influence Vindeket stakeholder willingness include pay of employees designated to waste transport, ease of pickup and dropoff processes, and a general lack of extra work for donors, to name a few (N. Shaw, personal communication, April 27, 2026). Cost-benefit analysis of food rescue operations could provide a detailed analysis to those communities looking to start their own food rescue operations, and would answer a variety of questions related to regular costs one might expect, as well as benefits. This kind of study could also be combined with previous research demonstrating social value that may be derived from food rescue missions (Clare et al., 2023; Byrne and Just, 2022; Warshawsky, 2015; Diprose and Lee, 2021). Food waste resulting from all sources listed exists all over the world, not just in Northern Colorado, and likewise, there is potential for towns without food rescues to help solve the waste crisis, and further, the carbon emissions and food insecurity crises.

Conclusion

This paper aims to outline a new method for food rescues to utilize when calculating the approximate dollar valuation of their food intake records. Here, FMAP and CPI data were used to calculate the total dollar valuation of rescued foods from Vindeket Foods in 2025 at $5,856,817. Valuation by month varies, as does valuation by food category and donor category. Vindeket captures the most value from grocery store waste, but this may differ for other food rescues, depending on their array of donors.

While not precise, this method uses national store-level purchasing data to give data-backed estimates of the valuation of food across source types at Vindeket Foods. This method may be used as an additional means of demonstrating impact to donors, potential donors, and any other stakeholders looking to understand more about the work of a food rescue, especially in numerical form. This method could be transferred to other food rescues under a similar goal, and potentially be used for those looking to start their own food rescue operation.

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Appendix

The following lists all R code that was used to manipulate data from Vindeket's 2025 food intake dataset (not public), the FMAP data from the U.S. Department of Agriculture, Economic Research Service, and the consumer price index data from the U.S. Bureau of Labor Statistics. This includes merging of all three datasets, formulas used to derive the values used in this study, and the creation of graphs and tables to visually display data.

```
# Load all packages necessary
 library(tidyverse)

## ── Attaching core tidyverse packages ──────────────────────────────────────── tidyverse 2.0.0 ──
 ## ✔ dplyr     1.2.0          ✔ readr   2.1.6
 ## ✔ forcats   1.0.1          ✔ stringr   1.6.0
 ## ✔ ggplot2   4.0.2          ✔ tibble  3.3.1
 ## ✔ lubridate 1.9.5          ✔ tidyr     1.3.2
 ## ✔ purrr     1.2.1
 ## ── Conflicts ────────────────────────────────────────────────────────── tidyverse_conflicts() ──
 ## ✖ dplyr::filter() masks stats::filter()
 ## ✖ dplyr::lag()   masks stats::lag()
 ## ℹ Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to become errors

library(ggplot2)
 library(lubridate)
 library(plotly)

##
 ## Attaching package: 'plotly'
 ##
 ## The following object is masked from 'package:ggplot2':
 ##
 ##     last_plot
 ##
 ## The following object is masked from 'package:stats':
 ##
 ##     filter
 ##
 ## The following object is masked from 'package:graphics':
 ##
 ##     layout

library(dplyr)
 library(tidyr)
 library(janitor)
```

```
##
 ## Attaching package: 'janitor'
 ##
 ## The following objects are masked from 'package:stats':
 ##
 ##     chisq.test, fisher.test

library(scales)

##
 ## Attaching package: 'scales'
 ##
 ## The following object is masked from 'package:purrr':
 ##
 ##     discard
 ##
 ## The following object is masked from 'package:readr':
 ##
 ##     col_factor

# Set the working directory
 setwd("/Users/malloryeisenreich/Honors Thesis")

 # Reading in 2025 Vindeket Foods Intake Data
 Vind2025 = read_csv("Vind25.csv")

## Rows: 2279 Columns: 26
 ## ── Column specification ────────────────────────────────────────────────────────────────────────────────────────────────────
 ## Delimiter: ","
 ## chr (14): date, item_type1, item_type2, item_type3, item_type4, item_type5, ...
 ## dbl (12): item_weight_lbs1, item_weight_lbs2, item_weight_lbs3, item_weight_...
 ##
 ## ℹ Use `spec()` to retrieve the full column specification for this data.
 ## ℹ Specify the column types or set `show_col_types = FALSE` to quiet this message.

# Pivoting item type and item weight data to long format
 Vind2025_long <- pivot_longer(
   Vind2025,
   cols = grep("^item_", names(Vind2025), value = TRUE),
   names_to = c(".value", "set"),
   names_pattern = "(item_type|item_weight_lbs)(\\d*)"
 ) %>%
   filter(!is.na(item_type)) %>%
   select(-set)

 # Removing unwanted item types (not helpful to my study) and updating long dataset
 remove <- c("Non-Food", "Pet Food", "Unknown")

 Vind2025_long <- Vind2025_long %>%
   filter(!item_type %in% remove) %>%
   rename(vindcat = item_type)

 # Creating month, day, and year columns
 Vind2025_long <- Vind2025_long %>%
   mutate(
             date  = mdy(date),
             year  = year(date),
             month = month(date),
             day   = day(date)
   )
```

```
# Reading in FMAP unit prices
FMAP_prices = read_csv("FMAP_unit_value_avgs.csv")

## Rows: 84 Columns: 4
## ── Column specification ────────────────────────────────────────────────────────────────────────────────────────────────────
## Delimiter: ","
## chr (1): vindcat
## dbl (3): month, avg_unit_value_mean_unwtd, avg_unit_value_mean_wtd
##
## ℹ Use `spec()` to retrieve the full column specification for this data.
## ℹ Specify the column types or set `show_col_types = FALSE` to quiet this message.

# Ensuring data frames are ready to be merged by forcing lowercase in "vindcat" column
library(stringr)

Vind2025_long <- Vind2025_long %>%
  mutate(vindcat = str_trim(str_to_lower(vindcat)))

# Merging data frames
vind2025_merge <- Vind2025_long %>%
  left_join(
    FMAP_prices,
            by = join_by(month, vindcat),
            relationship = "many-to-one"
  )

# Converting unit value avg columns to be in per pound instead of per 100g
vind2025_merge <- vind2025_merge %>%
  mutate(
            unwtd_avg_price_per_lb = avg_unit_value_mean_unwtd * 4.5359,
  )

# Reading in CPI table
cpi_2025 <- read_csv("cpi_2025.csv")

## Rows: 12 Columns: 8
## ── Column specification ────────────────────────────────────────────────────────────────────────────────────────────────────
## Delimiter: ","
## chr (2): date, month_abbr
## dbl (6): year, month, cpi_saf11_2018jan, cpi_saf11_2018jan_scaled, cpi_saf11...
##
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# Merging with CPI table
Vind2025_merge_cpi <- vind2025_merge %>%
  left_join(
    cpi_2025,
            by = join_by(month),
            relationship = "many-to-one"
  )

# Creating unit value column that's adjusted for inflation, using the CPI data
# from each month's corresponding 2018 base period
Vind2025_merge_cpi <- Vind2025_merge_cpi %>%
  mutate(
            unwtd_avg_price_per_lb_cpi = unwtd_avg_price_per_lb * cpi_saf11_mm_scaled
  )

# Creating an item worth column
Vind2025_merge_cpi <- Vind2025_merge_cpi %>%
  mutate(
```

```
        item_worth_unwtd = unwtd_avg_price_per_lb_cpi * item_weight_lbs
  )

 # Calculating the total worth of Vindeket's 2025 Food Intake
 total_worth <- sum(Vind2025_merge_cpi$item_worth_unwtd)

 # Visualizing Data

 # Visualizing donation valuation over the course of 2025

 # Recording total value of each month
 monthly_totals <- Vind2025_merge_cpi %>%
   select(c(month, item_worth_unwtd))

 # Bar chart of 2025 monthly donation value
 ggplot(monthly_totals, aes(x = factor(month), y = item_worth_unwtd)) +
   geom_col(fill = "tomato1") +
   scale_y_continuous(labels = label_comma()) +
   labs(x = "Month", y = "Total Valuation") +
   theme_bw()

# Category Breakdown

 # Creating table of Vindeket category totals and prices
 category_table <- Vind2025_merge_cpi %>%
   group_by(vindcat) %>%
   summarize(
        total_valuation = sum(item_worth_unwtd, na.rm = TRUE),
        avg_price_per_lb = mean(unwtd_avg_price_per_lb_cpi, na.rm = TRUE)
   ) %>%
   arrange(desc(total_valuation)) %>%
   adorn_totals("row")

 # Creating totals for each item category (vindcat)
 cat_yearly_breakdown <- Vind2025_merge_cpi %>%
   group_by(month, vindcat) %>%
   summarize(total_worth = sum(item_worth_unwtd, na.rm = TRUE), .groups = "drop")

 # Reordering data from highest item value to lowest
 cat_plot_data <- cat_yearly_breakdown %>%
   group_by(month) %>%
   mutate(pct = total_worth / sum(total_worth)) %>%
   ungroup() %>%
   mutate(vindcat = fct_reorder(vindcat, total_worth, .fun = sum, .aesc = TRUE))

 # Creating the bar chart
 ggplot(cat_plot_data, aes(x = month, y = total_worth, fill = vindcat)) +
   geom_bar(stat = "identity", position = "fill") +
   scale_x_continuous(breaks = 1:12) +
   scale_y_continuous(labels = label_percent()) +
   scale_fill_brewer(palette = "Set2") +
   theme_classic() +
   labs(
        x = "Month",
        y = "Intake Valuation ($)",
        fill = "Item Category"
   )

# Donor breakdown

 # Reading in donor category table and merging with all other data
 Donor_Types = read_csv(("Vindeket_donor_types.csv"))
```

```
## Rows: 5993 Columns: 2
## ── Column specification ────────────────────────────────────────────────────────
## Delimiter: ","
## chr (2): donor, donor_cat
##
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# Cleaning data (not necessary if Donor_Types data includes only one row per donor)
Donor_lookup_clean <- Donor_Types %>%
  distinct(donor, donor_cat)

# Merging data
Vind2025_merge_cpi <- Vind2025_merge_cpi %>%
  left_join(
    Donor_lookup_clean,
            by = "donor",
            relationship = "many-to-one" # This will now work perfectly
  )

# Creating bar chart of donor types in 2025 monthly valuation

# Creating totals for each donor category
totals_plot <- Vind2025_merge_cpi %>%
  group_by(month, donor_cat) %>%
  summarize(total_worth = sum(item_worth_unwtd, na.rm = TRUE), .groups = "drop")

# Reordering data from highest donor contribution to lowest
donor_plot_data <- totals_plot %>%
  group_by(month) %>%
  mutate(pct = total_worth / sum(total_worth)) %>%
  ungroup() %>%
  mutate(donor_cat = fct_reorder(donor_cat, total_worth, .fun = sum, .aesc = TRUE))

# Creating the bar chart
ggplot(donor_plot_data, aes(x = month, y = total_worth, fill = donor_cat)) +
  geom_bar(stat = "identity", position = "fill") +
  scale_x_continuous(breaks = 1:12) +
  scale_y_continuous(labels = label_percent()) +
  scale_fill_brewer(palette = "Set3") +
  theme_classic() +
  labs(
            x = "Month",
            y = "Intake Valuation ($)",
            fill = "Donor Category"
  )
```