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Retail food environment and household food waste: An empirical study

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A B S T R A C T

We examine the relationship between the retail food environment for individual households and household food waste. Conceptually the relationship is ambiguous and depends on how store access interacts with frequency, size, and the composition of food purchases. We use FoodAPS data to estimate the relationship between store proximity and household food waste. We measure this relationship for different retail food store formats and also investigate heterogeneity and mediating factors. We find that a 1% increase in the distance to the nearest small food store is associated with 0.02% more food waste among all households. A 1% increase in the distance to the nearest large food store – such as supermarkets and grocery stores – is associated with 0.05% more food waste among households in poverty, with larger associations among households without cars. We find that shopping frequency and size do not mediate the relationship between large food store proximity and food waste, but we find differences over the amount of fresh foods purchased on the average shopping trip. Among households that purchase large amounts of fresh foods per trip, greater distance to a large food store is substantially associated with more food waste. Our results contribute to policy discussions surrounding food waste as well as food access.

Worldwide about 30% of food produced is not consumed, resulting in significant waste (FAO, 2013). Mitigating food waste may reduce greenhouse gas emissions (Cattaneo et al., 2021) and may also increase food security (FAO, 2013). In the United States, retail and household food waste accounts for the majority of foods wasted (USDA, 2020). At the household level, shopping behaviors such as the frequency of grocery shopping and food storage practices may influence food waste (Davenport et al., 2019; Dobernig and Schanes, 2019; Ellison et al., 2022). These shopping behaviors may in turn be affected by the household's retail food environment, or geographic access to retail food stores (Gustat et al., 2014).

Conceptually, the influence of the retail food environment on household food waste is ambiguous. On the one hand, greater proximity to stores would decrease the household's transportation costs (time and monetary) of grocery shopping and, at least weakly, increase the number of times the household visits a store. Easier access to stores may incentivize households to purchase more produce, leading to an increase in food waste – if households do not consume produce fast enough – or a decrease in food waste – if households purchase small amounts of produce each time that they then consume quickly (Lee, 2018). On the other hand, households that shop more frequently have been found to purchase more temptation foods, which are often shelf-stable (Rudi and Çakır, 2017) and thus less likely to be wasted.

This paper empirically estimates the relationship between household retail food environment, as measured by proximity to retail food stores, and household food waste. We use the National Household Food Acquisition and Purchase Survey (FoodAPS) dataset, which is the first survey to collect comprehensive data about food purchases and acquisitions from grocery stores, other food retailers, and eating establishments. Importantly, Yu and Jaenicke (2020) show how to use FoodAPS data to quantify food waste among respondent households. We combine this measure of food waste with the detailed information provided by the FoodAPS on each household's geographic proximity to retail food stores of different formats to conduct the estimation.

Previous empirical work on the relationship between the retail food environment and food waste have come to conflicting conclusions. Yu

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and Jaenicke (2020) and Smith and Landry (2021a) use novel methods to estimate food waste and both measure determinants of household food waste. Both papers find that greater distance to the household's primary grocery store is associated with less food waste. In contrast, Lee (2018) shows that shorter travel time to the household's primary food retailer is associated with less food waste in a dense urban environment. Similarly, a higher number of food retail establishments in a county is associated with lower county-level food waste (Landry et al., 2018).

With the exception of Landry et al. (2018), all of the previous studies measure the association between food waste and the distance (or travel time) to a single primary store (e.g., Yu and Jaenicke, 2020; Smith and Landry, 2021a; Lee, 2018). In contrast, we use household proximity to stores – as captured by the distance to the nearest super store, large food store, and small food store – to measure geographic access to food stores. This difference is important, because in our data on average only 40 percent of weekly food expenditures and 32 percent of shopping trips were at the household's primary store. Thus, while the primary store may not be the closest store (ver Ploeg et al., 2015), much of the household's shopping may be done at closer stores. In terms of food waste, it is not clear whether food purchased at the primary store or food purchased at other stores contribute more. Our focus on the household's proximity to a range of stores rather than on a single primary store allows us to examine the influence of the household's options on their food waste behavior.

In examining food waste and store proximity (instead of household choice of a primary store) our paper is closest to Landry et al. (2018). Landry et al. estimate the relationship between the municipal solid waste in Mississippi counties and the number of food-at-home retailers in the county. They find a negative relationship between the number of food-at-home retail establishments and municipal food waste. We build on Landry et al.'s work by measuring store density relative to individual households and using a novel and reasonable approximation of food waste. Specifically, we use food waste data derived from restricted-access FoodAPS (more details in the data section). Since we have household-level data, we are furthermore able to investigate heterogeneity and mediating factors contributing to household-level food waste.

Our results indicate that greater distance to the nearest small food store and large food store – but not to a super store– is associated with an increase in food waste. We find that, on average, a 1% increase in the distance to the nearest small food store increases food waste by 0.02% among all households. Among households in poverty, we find that a 1% increase in the distance to the nearest large food store – such as a supermarket or grocery store – is associated with 0.05% more food waste. This relationship is larger for further disadvantaged households: among households in poverty without a car, a 1% increase in the distance to the nearest large food store is associated with a 0.08% increase in food waste. The frequency of shopping and size of the shopping basket does not mediate the relationship between food waste and large food store proximity. The composition of the shopping basket does, however. Among households that purchase a substantial amount of fresh foods from large food stores, greater distance is associated with much more food waste.

These results contribute to two distinct policy discussions. First, policies to reduce food waste often focus on inducing voluntary action (Stancu and Lähteenmäki, 2022). In particular, public awareness campaigns have been suggested to educate consumers on food waste mitigation strategies. Since disadvantaged households waste more food when large food stores are further away, the impact of these campaigns may be smaller among disadvantaged populations further from a store. Campaigns may therefore require targeted messaging for these households, or policymakers would need to improve food access before launching educational campaigns.

Our paper also contributes to the discussion surrounding policies to improve access to food. Building more physical food stores is expensive and has been found to have very limited impacts on food insecurity and nutrition (e.g. Allcott et al., 2019; Cummins et al., 2014). Our results suggest that these impacts may be underestimated if households are able to decrease their food waste in response to a store opening, though it is unclear if adding benefits from food waste would significantly improve the cost-benefit analysis of physical stores. Alternative ways to improve food access, however, may be cheaper and may also decrease household food waste. For example, improving public transportation, making mobile markets more widely-available, or increasing access to online shopping may allow households more flexible food management strategies that would lead to less food waste.

The paper proceeds as follows. We discuss the data and our measures of food waste and store proximity in the next section. Following this we introduce our empirical specification. Main results come next, followed by a discussion of how our results are different for policy-relevant subsamples and of potential mediating factors. We conclude with implications for food policy.

1. Data

Our primary data source is the public-use data files of FoodAPS, which was collected by the United States Department of Agriculture (USDA) over 2012–2013 and released in 2015. In addition to collecting detailed sociodemographic information on U.S. households, FoodAPS collected information on food purchases/acquisitions and shopping behaviors.

To obtain information of food purchased or otherwise acquired, FoodAPS household members at least 11 years old reported all food acquisitions by scanning the barcodes of packaged foods, submitting receipts from stores and restaurants, and filling out daily food manuals for a one-week period. Eating events both at home as well as away from home were included. The primary respondent reported food events for children under 11 years of age. Households were asked to report a description of every food item acquired, including weight (grams), package size (ounces, pounds, and count), cost, and which shopping trip it was acquired in.[1] Although food-at-home expenditures may be underreported in FoodAPS by 9 percent (Hu et al., 2020), underreporting of the amounts of food acquisitions is unknown. We sum the number of grams obtained in each shopping trip ("trip size") and measure the average trip size per household. We also measure each household's trip frequency as the total number of shopping trips to each food retail store in the reference week.

1.1. Food waste

We supplement public-use FoodAPS data with food waste data derived from restricted-access FoodAPS. Our measure of food waste comes from Yu and Jaenicke (2020), who model household food consumption as a production process and estimate food waste as inefficiency in this process using stochastic production frontier methods. They regard food acquisitions as inputs and the energy requirement of household members as the output in the production process.

Specifically, for households indexed by h, the baseline model in Yu and Jaenicke (2020) estimates the following production equation:

$$ln(BMR_h) = Translog\left(x_{1,h}, x_{2,h} \cdots x_{I,h}\right) + v_h - u_h \quad (1)$$

where $BMR_h = \sum_m BMR_{m,h}$ is the sum of the Basal Metabolic Rates (BMR) for all household members m in household h. The BMR represents the caloric energy needed to maintain body functioning and is calculated by the revised Harris-Benedict equation using a person's weight, height,

[1] Since the focus of this paper is retail food stores, we use the term "shopping trip" to refer to food acquisition events. In FoodAPS, these events need not be traditional grocery shopping trips.

age, and sex (Roza and Shizgal, 1984).[2] We assume that during the one-week FoodAPS survey period, household members are maintaining balanced states of energy intake and that any deviation from their calculated energy requirements is random. The first term on the right-hand side is a production technology described by a translog function, where $x_{1,h}, x_{2,h} \cdots x_{I,h}$ are the quantities of food inputs from I food categories.[3] The v_h term follows a zero-mean normal distribution and the u_h term follows a half-normal distribution whose value is non-negative.[4]

The key to the estimation procedure is the u_h term, called the output-oriented inefficiency. It describes the portion of output that should be produced (but is not) if the production is fully efficient. With the half-normal distributional assumption on u_h, we can perform a maximum likelihood estimation and recover a predicted value of the output inefficiency $\widehat{u_h}$ for each household in the sample. The next step is to transform the output-oriented inefficiency to an input-oriented inefficiency term for each household. Following a long literature on economic inefficiency, we refer to input-oriented inefficiency as "food waste." [5]Yu and Jaenicke (2020) use the following transformation to solve for the percentage food waste $\widehat{\delta_h}$, given the estimated $\widehat{u_h}$:

$$Translog\left((1-\widehat{\delta_h})x_{1,h}, (1-\widehat{\delta_h})x_{2,h} \cdots (1-\widehat{\delta_h})x_{I,h}\right) = Translog(x_{1,h}, x_{2,h} \cdots x_{I,h}) - \widehat{u_h}$$

This equation can be solved using the quadratic formula since the translog function is quadratic (see footnote 3). The intuition is that if the inputs are wasted at the rate of $\widehat{\delta_h}$, then the resulting inefficiency in terms of the output is $\widehat{u_h}$. The closed-form solution of $\widehat{\delta_h}$ can be found in Eq. (8) of Yu and Jaenicke (2020) and Eq. (9) in Smith and Landry (2021a).

There are two issues relating to the food waste measure that are worth noting. First, unless the production function is linearly homogeneous, $\widehat{\delta_h}$ is typically different from $\widehat{u_h}$ (Smith and Landry, 2021a). This means that the marginal productivity varies at different levels of inputs. Hence, given a fixed $\widehat{u_h}$, the food waste measure $\widehat{\delta_h}$ depends on the values of $x_{1,h}, x_{2,h} \cdots x_{I,h}$. Conceptually, store proximity can thus influence food waste through purchase decisions of $x_{1,h}, x_{2,h} \cdots x_{I,h}$. , which would in turn be determined by shopping frequency, how much is purchased on each shopping trip, and the specific mix of foods purchased on each trip.

Second, as the stochastic frontier literature points out, the output and input inefficiencies are relative measures. In other words, the most efficient household in the *sample* is assumed to produce "zero waste", and food waste of all other households is measured against this most efficient household. However, it is possible that food waste could be systematically underestimated if the most efficient household in the sample does not exhibit a zero-waste production (Smith and Landry, 2021b). Thus Smith and Landry (2021b) suggest caution regarding interpreting food inefficiency as food waste. Smith and Landry (2021a) investigate this and find a very high correlation between food waste defined as input inefficiency and actual food waste in their data (correlation coefficient of 0.949). Given the high correlation between food waste and food inefficiency, as well as the long tradition of interpreting inefficiency as waste, we interpret our measure of food input inefficiency as food waste. We note that with the data available to us, we are unable to correct the systematic underestimation of food waste measurement, and note that, though addressing this issue is an important subject for future work, it is beyond the scope of this paper.

1.2. Store proximity

Importantly, FoodAPS also reports household proximity to a range of food retail stores of different formats. These measures were derived by geocoding FoodAPS household addresses and all stores authorized to accept Supplemental Nutrition Assistance Program (SNAP) benefits. Most, though not all, food stores are authorized to accept SNAP benefits. Caspi et al. (2015) document that almost 80% of a sample of small urban stores accept SNAP; the percentage of larger food stores accepting SNAP is likely much higher. FoodAPS categorizes stores into five formats (super stores, supermarkets, grocery stores, combination stores, and convenience stores). For tractability we collapse this classification into three formats. *Super stores* are large retailers that sell food and a wide variety of non-food items. *Large food stores* sell an array of food options and limited non-food times, including supermarkets and grocery stores. *Small food stores* sell a limited variety of foods and include convenience stores and combination stores such as pharmacies, and dollar stores. We use the distance (in miles) between the household and the nearest SNAP store of each format to measure store proximity.

1.3. Sociodemographic measures

FoodAPS also provides a range of sociodemographic variables in addition to proximity to food stores. *Household Poverty Ratio* is the household income as a percentage of the federal poverty guidelines. *Rural* designates whether a household lives in a rural Census tract (as defined by the Census Bureau). *Food Secure* is an indicator for whether the household is food secure. *Male* is an indicator for whether the primary respondent is male. *Employed* is an indicator for whether the primary respondent has a full-time job. *Household size* is a variable for the number of individuals in the household (not including household guests). *Children* is an indicator for the presence of individuals under 18, and *Children under 5* is an indicator for the presence of children under 5. *Black*, *white*, and *Hispanic* are variables for the percentage of the household that identifies as non-Hispanic black, non-Hispanic white, and Hispanic. *High school plus* is the percentage of the adults (18 years old and over) with at least a high school education. *Car* is an indicator for whether the household owns a car. *SNAP* is an indicator for whether the household is currently participating in SNAP. *Primary store proportion* is the proportion of weekly shopping trips that were at the household's self-reported primary store. *Month* is a variable that indicates the month in which the food acquisition data collection week began. *Day of month* is a variable indicating the day of the month (ranging from 1 to 31) for the first day of the food acquisition data collection week.

[2] The calculation of BMR is a linear approximation and Yu and Jaenicke (2020) assume that the error from this approximation resides in the white noise term v_h. For example, the BMR measure does not include the caloric energy needed by physical activities, which are assumed to be random and contained in the error v_h. In practice, omitting physical activities might lead to small biases in the food waste estimates, depending on its correlation with the output inefficiency term. Yu and Jaenicke (2020) estimated two additional models that account for physical activities and examined the consequence of omitting physical activities. Their tests indicate a small upward bias in food waste (about 1–3%), but this bias does not influence the relative differences in food waste between households. They also estimate models that use calorie contents of food purchases instead of quantities as inputs and find major results unchanged. Note that this approach considers food that is diverted for other uses, e.g., feeding pets, as food waste. Lastly, it is assumed that during the one-week survey period, inventory replenishment of storable food is random. Thus, error from households purchasing less than their energy needs in the data collection week is contained in the v_h white noise term and does not enter into the food waste calculation (which comes from the u_h term).

[3] The translog function is formulated as: $Translog(x_{1,h}, x_{2,h} \cdots x_{I,h}) = \lambda_0 + \sum_i \lambda_i lnx_{i,h} + \sum_i \sum_{j \le i} \lambda_{i,j} lnx_{i,h} lnx_{j,h}$.

[4] These two distributional assumptions are commonly used in the stochastic frontier literature.

[5] The idea of interpreting economic inefficiency as waste dates back at least to Harberger (1964) in his seminal study of deadweight loss. Diewert (1983) calculates the loss of productive activity and terms it as a waste measurement. In the recent efficiency analysis literature, technical efficiency refers to "the ability to avoid waste, either by producing as much output as technology and input usage allow or by using as little input as required…" (Fried et al. 2008, p. 20).

Table 1
FoodAPS sample summary statistics.

Variable	Distance to nearest SNAP store (miles) <0.25	0.25–0.5	0.5–1	1+
Household poverty ratio	0.72	1.06	1.15	1.12
	(0.04)	(0.04)	(0.05)	(0.06)
Rural	0.10	0.17	0.28	0.81
	(0.03)	(0.03)	(0.04)	(0.05)
Male primary respondent	0.29	0.35	0.24	0.28
	(0.02)	(0.03)	(0.04)	(0.02)
Primary respondent employed	0.53	0.56	0.55	0.50
	(0.03)	(0.03)	(0.03)	(0.04)
Household size	2.52	2.60	2.61	2.47
	(0.10)	(0.10)	(0.10)	(0.10)
Household has children	0.34	0.36	0.37	0.29
	(0.03)	(0.03)	(0.03)	(0.03)
Household has children < 5	0.16	0.13	0.15	0.09
	(0.02)	(0.02)	(0.02)	(0.02)
% black household members	0.17	0.12	0.08	0.03
	(0.03)	(0.02)	(0.02)	(0.01)
% white household members	0.52	0.66	0.79	0.92
	(0.04)	(0.03)	(0.03)	(0.02)
% Hispanic household members	0.22	0.12	0.09	0.03
	(0.04)	(0.03)	(0.02)	(0.01)
Household owns a car	0.78	0.93	0.97	0.96
	(0.03)	(0.01)	(0.01)	(0.01)
% adults with at least high school education	0.87	0.92	0.92	0.93
	(0.02)	(0.01)	(0.02)	(0.01)
Proportion of trips to primary store	0.42	0.39	0.42	0.43
	(0.02)	(0.03)	(0.04)	(0.03)
Day of month	16.60	16.05	14.63	15.53
	(0.34)	(0.40)	(0.74)	(0.41)
Month	7.65	7.64	7.78	7.65
	(0.10)	(0.14)	(0.24)	(0.20)
Food waste (% of food acquisitions)	0.36	0.39	0.39	0.40
	(0.01)	(0.01)	(0.01)	(0.01)
Observations	1070	777	524	695

Notes: Observations weighted by FoodAPS sampling weights, linearized standard errors that take sampling design into account in parentheses. Children are any household member under 18 years old. *Day of month* is the day of the month (1–31) on which the food acquisition data collection week began. *Month* is the month (1–12) in which the food acquisition data collection week began.

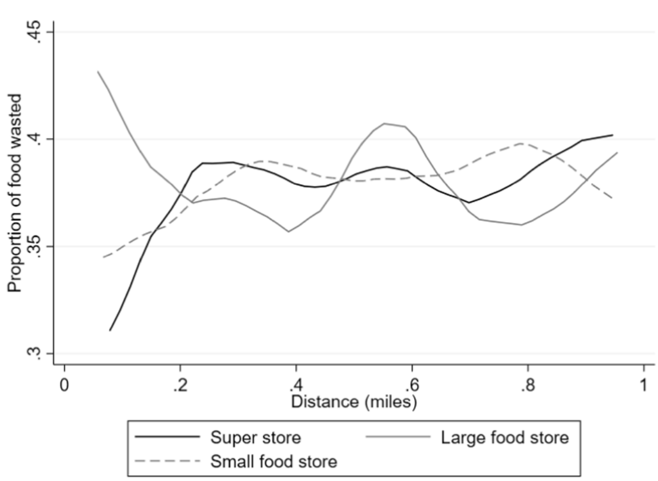

Fig. 1. Food waste over distance to the nearest store. *Note:* This figure displays local polynomial regressions of the proportion of food wasted over distance to the nearest super store, large food store, and small food store.

1.4. Sample definition and summary statistics

Of the 4,826 households in the full FoodAPS data, we are able to calculate food waste for 3,657 households. We further exclude any households that have zero acquisitions, extremely large acquisition quantities (over 100 kg), or missing store proximity measures. We also exclude households that do not yield a percentage food waste estimate when we transform the output inefficiency $\widehat{u_h}$ to the input inefficiency $\widehat{\delta}_h$.[6] Our final sample consists of 3,066 households.

Table 1 describes our sample over distance to the nearest SNAP store (of any format). In general, households close to a store have lower ratios of income to poverty. Approximately one third of our sample has children in the household. Households closer to SNAP stores are more likely to be black and less likely to own a car. Regardless of distance to the nearest SNAP store, around 40% of weekly shopping trips are to the household's self-reported primary store. Households are estimated to waste between 36% and 40% of weekly food acquisitions.

Fig. 1 shows how food waste changes as households get closer to the nearest super store, large food store, and small food store within 1 mile of each format. In general, Fig. 1 shows that as households get closer to a super store or small food store, they waste less food. As households get closer to the nearest super store food waste drops by 8 percentage points (from 40% to 32%), with most of this drop occurring among households within 0.2 miles of a super store. In contrast, households within 0.2 miles of a large food store waste more food.

2. Empirical Strategy

We model the log of household $h's$ food waste $ln(FW_h)$ as a function of proximity to each retail food store format and other controls:[7]

$$ln(FW_h) = \sum_{f=1}^{3} \left(\alpha_f \ln(Dist)_{hf}\right) + \theta X_h + \varepsilon_h \quad (2)$$

where $Dist_{hf}$ is the distance (in miles) between household h and the nearest store of format f and X_h are sociodemographic controls explained in the Data section. We use FoodAPS sampling weights, and standard errors are calculated using Taylor linearization taking into account clustering by FoodAPS strata and clustering by primary sampling unit (Kreuter and Valliant, 2007). We do not make causal claims in this paper because of the possibility that household location relative to stores is correlated with unobserved reasons for food waste. In the appendix we provide a more detailed discussion of the potential sources of endogeneity.

[6] The transformation from output inefficiency to input inefficiency involves using the quadratic formula to solve for the input-oriented inefficiency (see equation (8) in Yu and Jaenicke (2020)). In our sample, 200 households have no real-valued solutions to this calculation, likely due to their large output-inefficiency measure estimated from the stochastic frontier analysis. These households are excluded. Note that as in Yu and Jaenicke (2020), the output-oriented inefficiency is assumed to be half-normal and hence, not bounded from above.

[7] Note that we do not perform a "two-step" analysis of the output-oriented inefficiency here. A "two-step" analysis in the standard stochastic frontier analysis would involve estimating the output inefficiency as the first step and then regress it on some contextual variables that are believed to influence the output inefficiency. This type of analysis likely generates biased estimates because these contextual variables can correlate with the inputs and lead to an omitted variable issue at the first stage (Wang and Schmidt 2002; Alvarez et al. 2006). This could lead to biased estimates of the output-oriented inefficiency. Our analysis, on the other hand, is based on the input-oriented inefficiency (i.e., food waste), which is derived from the output inefficiency *and* food purchases (see Eq. (8) of Yu and Jaenicke, 2020). We assume that store proximity affects food waste through food purchases, not the output inefficiency. In fact, it makes little economic sense to include proximity variables when estimating the output efficiency at the first stage since store proximity does not have a direct impact on the household production process that only takes place *after* the shoppers go home. Rather, proximity directly influences food purchase decisions, which in turn, affect food waste. Hence, as long as the estimated output-oriented inefficiency is not biased, the implied input-oriented inefficiency is unbiased.

Table 2
The relationship between the distance to the nearest store and the natural log of food waste.

	Full	> poverty	< poverty Full	< poverty No car	< poverty Food insecure
ln(Dist. to super store)	−0.005	−0.005	0.006	−0.062	0.027
	(0.013)	(0.011)	(0.031)	(0.048)	(0.028)
ln(Dist. to large food store)	−0.010	−0.014	0.047*	0.082*	0.058*
	(0.009)	(0.009)	(0.028)	(0.040)	(0.031)
ln(Dist. to small food store)	0.021*	0.017	0.005	−0.010	−0.071**
	(0.011)	(0.012)	(0.018)	(0.027)	(0.030)
Observations	3066	2433	633	189	298

Notes: Standard errors in parentheses. The first column uses the full sample, the second column uses only individuals over 100% of poverty ("> poverty"), the third column uses all individuals under 100% of poverty ("< poverty"), the fourth column restricts the sample to below-poverty-line households without cars, and the fifth column restricts the sample to food insecure below-poverty-line households. Regressions also control for the household poverty ratio, rural status, whether the primary respondent is male, whether the primary respondent is employed full time, the household size, whether the household has children younger than 18, whether the household has children younger than 5, whether the household is food secure, the % of the household that is black, the % of the household that is white, the % of the household that is Hispanic, whether the household owns a car, the % of the adults in the household with at least a high school education, the proportion of weekly spending at the self-reported primary store, the day of the month on which the food acquisition data collection week began, and the month. Standard errors account for complex survey design. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

3. Empirical findings

3.1. Main estimates

Table 2 displays our main results for the full sample and four policy-relevant subsamples. The subsamples that we examine are households above 100% of the federal poverty line, all households below 100% of the federal poverty line, households below 100 percent of poverty without a car, and food insecure households below 100% of poverty.

In the full sample, the further away small food stores are, the more households waste food. A 1% increase in the distance to the nearest small food store is associated with a 0.02% increase in food waste. This result appears to be driven by households above poverty, though the relationship among households above poverty is statistically insignificant – the coefficient for all households under 100 percent of poverty is much smaller and in low-income food insecure households distance to small food stores actually decreases food waste. Among households in poverty, an increase in the distance to a large food store by 1% is associated with an increase in food waste of almost 0.05%. To help interpret these results, Table A1 in the appendix shows the proportion of the low-income sample that is in different distance bandwidths of each store format.

This is most pronounced for food insecure households and for households without a car. An increase in the distance to a large food store by 1% is associated with an increase in food waste among households in poverty without a car by over 0.08%. This estimate implies that households in poverty without a car with a large food store 1.5 miles away waste 16% more food than similar households that have a large food store 0.5 mile away. A 16% reduction in food waste is equivalent to food waste dropping from 40% of food acquisitions (the mean food waste among households with stores 1 mile away in Table 1) to 33.6%.

3.2. Mechanisms

The previous subsection presented the relationship between store

Table 3
The relationship between store distance and the natural log of food waste among car owners, over frequency of shopping at each store format.

Variable	# trips
Super stores	
ln(Dist. to super store)	0.003
	(0.045)
ln(Dist. to super store) × 1–2 trips	0.010
	(0.046)
ln(Dist. to super store) × 3 or more trips	−0.017
	(0.089)
Large food stores	
ln(Dist. to large food store)	0.064**
	(0.030)
ln(Dist. to large food store) × 1–2 trips	−0.019
	(0.044)
ln(Dist. to large food store) × 3 or more trips	−0.043
	(0.057)
Small food stores	
ln(Dist. to small food store)	−0.018
	(0.018)
ln(Dist. to small food store) × 1–2 trips	0.050**
	(0.025)
ln(Dist. to small food store) × 3 or more trips	0.042
	(0.064)
Observations	633

Notes: Standard errors in parentheses. The sample is restricted to households below 100% of the poverty line. Distance is interacted with indicators for whether the household took 1–2 trips or 3 or more trips to the specific store format. Regressions also control for the household poverty ratio, rural status, whether the primary respondent is male, whether the primary respondent is employed full time, the household size, whether the household has children younger than 18, whether the household has children younger than 5, whether the household is food secure, the % of the household that is black, the % of the household that is white, the % of the household that is Hispanic, whether the household owns a car, the % of the adults in the household with at least a high school education, the proportion of weekly spending at the self-reported primary store, the day of the month on which the food acquisition data collection week began, and the month. Standard errors account for complex survey design. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

proximity and food waste for the full sample and policy-relevant subsamples. Our finding that large food store proximity matters a great deal for households without a car suggests that the influence of store proximity on food waste may be mediated by shopping behavior such as trip frequency, the size of the shopping basket (in grams), or the composition of the shopping basket. There are many potential dimensions over which shopping basket composition could be measured; we focus on the grams of fresh foods (fruit, vegetables, meat, and seafood) obtained on an average shopping trip since fresh foods may expire quickly and may be a significant source of food waste.

We investigate the possibility of these mediating factors by supplementing the model given in Eq. (2) with interactions between $\ln(Dist)_{hf}$ and indicators for different levels of household h's trip frequency to store format f, average shopping basket size at format f, and average amount of fresh fruit and vegetables purchased at format f. To measure the influence of trip frequency, we interact $\ln(Dist)_{hf}$ with two mutually-exclusive indicators: whether household h went to store format f once or twice in the reference week, and whether household h went to store format f three or more times.[8] Interaction coefficients are interpreted relative to the omitted category of never visiting the store format in the data collection week. The series of interactions allow us to measure the

[8] Appendix Tables A2 and A3 show relevant percentiles of the distribution of average shopping trip size and average amount of fresh foods for each store format.

Table 4
The relationship between store distance and the natural log of food waste among households without car, over average trip size and amount of fresh foods purchased.

Variable	Avg. size	Avg. fresh foods
Super stores		
ln(Dist. to super store)	0.004	0.025
	(0.043)	(0.031)
ln(Dist. to super store) × I(0 < X > 75th pct)	0.028	−0.041
	(0.054)	(0.036)
ln(Dist. to super store) × I(75th < X > 95th pct)	−0.022	−0.056
	(0.064)	(0.057)
ln(Dist. to super store) × I(X > 95th pct)	−0.084	0.094
	(0.085)	(0.090)
Large food stores		
ln(Dist. to large food store)	0.057*	0.055**
	(0.030)	(0.026)
ln(Dist. to large food store) × I(0 < X > 75th pct)	−0.045	0.066
	(0.038)	(0.068)
ln(Dist. to large food store) × I(75th < X > 95th pct)	0.034	−0.110***
	(0.057)	(0.039)
ln(Dist. to large food store) × I(X > 95th pct)	0.011	0.227**
	(0.077)	(0.089)
Small food stores		
ln(Dist. to small food store)	−0.007	0.008
	(0.018)	(0.018)
ln(Dist. to small food store) × I(0 < X > 75th pct)	0.084	
	(0.050)	
ln(Dist. to small food store) × I(75th < X > 95th pct)	0.023	
	(0.023)	
ln(Dist. to small food store) × I(X > 95th pct)	0.019	
	(0.053)	
ln(Dist. to small food store) × I(any fresh food)		−0.002
		(0.103)
Observations	633	633

Notes: Standard errors in parentheses. The sample is restricted to households below 100% of the poverty line. Each column shows the results of one regression of the natural log of food waste on distance to each store format and interactions between this distance measure and indicators for different levels the average size of trips to that store format in grams (first column), and the average amount of fresh foods (vegetables, fruit, meat, and seafood) purchased per trip to that store format in grams (second column). Distance is interacted with indicators for whether the average trip size or average amount of produce is greater than zero but less than the variable's 50th percentile (inclusive) [I(0 < X > 50th pct)], greater than the 50th but less than the 95th percentile (inclusive) [I(50 < X > 95th pct)], or greater than the 95th percentile [I(X > 95th pct)]. In the regressions for the average trip amount, for small food stores the interactions are compared to all below-median observations. In the regression with the average amount of produce, for small food stores [I(X > 95th pct)] is an indicator for whether any produce was purchased at small food stores. Regressions also control for the household poverty ratio, rural status, whether the primary respondent is male, whether the primary respondent is employed full time, the household size, whether the household has children younger than 18, whether the household has children younger than 5, whether the household is food secure, the % of the household that is black, the % of the household that is white, the % of the household that is Hispanic, whether the household owns a car, the % of the adults in the household with at least a high school education, the proportion of weekly spending at the self-reported primary store, the day of the month on which the food acquisition data collection week began, and the month. Standard errors account for complex survey design. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

extensive and intensive margins in one model, and also allow us to capture nonlinearities in the mediating relationship of trip frequency.

We measure the mediating influence of average trip size using a series of mutually-exclusive store format-specific indicators: whether household h's average trip size to store format f is >0 but less than the median trip size to format f, whether the trip size is between the median trip size but below the 95th percentile trip size, and whether the trip size is greater than the 95th percentile trip size. Similar to the trip frequency model, these indicators are interacted with $\ln(Dist)_{hf}$. The mediating relationship of the average amount of fresh foods is measured using comparable indicators to trip size that are defined over the distribution of the average amount of fresh foods purchased from format f. Given the larger relationship among households in poverty, we estimate these models using the poverty subsample.

Table 3 shows the results for frequency. Households that shop more often at super stores and large food stores have the same relationship with store distance as households that did not shop at these formats in the reference week. There is some indication that distance to small food stores matters more for households that shop more frequently at small food stores. Relative to households that do not shop at small food stores, greater distance to small food stores is associated with more food waste among households that shop more frequently at small food stores.

Table 4 shows the results for average shopping trip size (column 1) and average amount of fresh foods purchased per trip (column 2). We note that due to the low amount of fresh produce purchased at small food stores we only interact small food store proximity with a single indicator for whether any fresh food was purchased from small food stores. While greater distance to large food stores is associated with more food waste, we find no statistically-significant differences in this relationship between households that purchase different amounts at large food stores. Fresh food purchasing, however, may matter. Among households that purchase no fresh foods from large food stores, greater distance is associated with more food waste. Among households that purchase a moderate amount of fresh foods from large food stores, however, greater distance is associated with *less* food waste. This relationship again changes at the top distribution of fresh food purchasing: greater distance to large food stores increases food waste among households that purchase a very large amount of fresh foods from large food stores (above the 95th percentile).

In sum, our investigation of mechanisms underlying the relationship between food waste and store proximity among low-income households reveals a few possibilities. In general we find surprisingly little difference in the relationship between food waste and store proximity among households that shop at differing frequencies and for different basket sizes. The only exception is that distance to small food stores increases food waste among households shopping occasionally at small food stores. On the other hand, we find that the composition of foods at large food stores may matter a great deal. Households purchasing a moderate amount of fresh foods per trip experience less food waste when the store is further away. Among low-income households purchasing a large amount of fresh food, however, greater distance to the large food store is related to much greater food waste.

4. Discussion

Using a detailed sample of households and their food acquisition records, we examine the relationship between household food waste and proximity to super stores, large food stores, and small food stores. We examine heterogeneity in the overall relationship, and also investigate potential mechanisms. Proximity to super stores has no significant relationship with household food waste. Proximity to small food stores may matter differently for different households – among all households greater distance to small food stores is associated with more food waste, but food insecure households waste more food if they are closer to the small food store. Greater distance to the nearest large food store, however, is associated with more food waste among households below the poverty line. This relationship is largest for further disadvantaged subsamples: households without a car and food insecure households.

We also test whether our results are driven by three types of consumer shopping behavior that directly relate to food management and food waste – shopping frequency, the amount of food purchased during trips, and the amount of fresh food purchased during trips. We find little difference in the relationships between food waste and store proximity between low-income households that shop more frequently or purchase more food per trip.

On the other hand, we find that the amount of fresh food purchased may mediate the relationship between large food store proximity and food waste among low-income households. Low-income households that purchase a moderate amount of fresh foods per trip have less food waste when the large food store is further away. One possible explanation for this is that when the large food store is close by these households visit the store more frequently, and on each trip they purchase more fresh food than they are able to consume. When the store is further away, they visit less frequently and thus have less fresh food to consume. Among low-income households that purchase a large amount of fresh food per trip, greater distance to the large food store is associated with more food waste. One possible explanation is that these households – in contrast to households purchasing only a moderate amount of food waste – consume a greater proportion of the fresh food they obtain on each trip. Being closer to the large food store allows them to purchase only what they need and thus waste less food. These possibilities highlight the complicated interplay between the composition of the shopping basket, household characteristics, and shopping frequency that underlie the relationship between store access and food waste. Our findings suggest that future research seeking to understand this interplay could focus on the impact that store access has on the frequency that households purchase fresh foods.

Our study provides the first set of empirical evidence showing the role of food access for individual households – rather than a single primary store or county-level store density – in determining household food waste. Conceptually, with better access to food retail stores, household food waste could either increase due to more purchases of perishable food or decrease because of more frequent shopping trips and flexibility in food choices. Our results resolve this conceptual ambiguity by empirically estimating the relationship between store proximity and food waste.

This paper builds upon the latest measurement of consumer food waste as well as detailed and intuitive measures of store proximity. Our approach has several limitations that might be addressed in future research. First, our paper necessarily depends on an approximation of food waste obtained using stochastic frontier methods. As noted in our Data section, this measure requires assumptions such as the functional form of errors in the household energy production process.

A second limitation of our paper is that beyond fresh fruits and vegetables we do not investigate in detail the mediating link of consumer food choices on food waste. Existing studies show that both food access and store formats have significant effects on food choices (Volpe et al., 2013; Chenarides and Jaenicke, 2019) and that the frequency of shopping is associated with the healthfulness of food purchases (Rudi and Çakır, 2017). Understanding how household diet responds to better food access will be useful in explaining the changes in food waste.

Third, we do not distinguish food waste generated on at-home and away-from-home occasions. Instead, we have a single percentage food waste measure that includes food waste from both types of occasions. It is therefore possible that we estimate a lower bound on the relationship of store proximity with food waste for households whose members mostly eat at home.

Finally, as explained in our Empirical Strategy section, we do not estimate the causal impact of store proximity on food waste. Other studies that estimate the causal impact of store proximity use either time-varying measures (Allcott et al., 2019; Arcidiacono et al., 2020) or combine time-varying measures with detailed geospatial data (Cuffey and Beatty, 2022) to minimize concerns regarding unobservables. These measures are not available for us through FoodAPS, but developing plausibly-causal estimates of the impact of store proximity – and other environmental factors – represents an area for future work.

5. Policy implications

Mitigating food waste can have important environmental and efficiency implications, and food waste from households and retailers represents the largest source of food waste (USDA, 2020). Food waste disposal taxes and subsidies have been suggested as policies to mitigate food waste (Katare et al., 2017), but such policies are politically difficult and also very likely to be regressive (Landry and Smith, 2019). Inducing voluntary action on the part of households is a primary lever for policy to influence food waste (Stancu and Lähteenmäki, 2022). Information campaigns to educate consumers about food waste mitigation strategies – such as just-in-time shopping (Ellison et al., 2022) – is one way to induce household action. Our results suggest that broad education campaigns that do not address underlying access to large food stores may be less useful for food insecure households, households without cars, or households that purchase large amounts of fresh foods. Educational campaigns therefore would need to be tailored for these populations, and policymakers may need to consider material incentives to reduce food waste among these households.

Our findings also add another layer to the policy discussion surrounding food access, which often focuses on nutrition and food insecurity (e.g. Allcott et al., 2019; Mayer et al., 2014). We add to this policy discussion by finding that better access to large food stores is associated with less household food waste. This suggests that the benefits to society of improving food access may be broader than improved nutrition and health, and thus the welfare implications of household food access are currently underestimated. Policies to improve access to food have traditionally focused on increasing the number of brick-and-mortar stores, and research on these policies have found very limited impacts on health and nutrition (e.g. Allcott et al., 2019; Cummins et al., 2014). If improving access to food stores reduces food waste, the benefits of improving the availability of brick-and-mortar stores may be broader than currently understood.

Beyond physical access to stores, implementing or supporting food recovery programs could be another potential policy to mitigate food waste and improve food security. Food recovery programs involve the systematic collection of surplus food from households and the subsequent distribution of these resources to individuals experiencing food insecurity. By engaging in this coordinated effort, communities can simultaneously address two pressing issues: reducing food waste and alleviating food insecurity. Furthermore, these programs may foster a culture of sustainable consumption and responsible resource management, encouraging households to be more mindful of their food usage patterns.

Our results further suggest an additional benefit to society from improving transportation options for low-income households to access larger food stores as well as promoting the provision of fresh produce in small food stores. In our sample, 83% of low-income households are located at least 0.5 miles away from a superstore and 65% reside at least 0.5 miles from a large food store (Table A1). Conversely, 62% of low-income households live within 0.5 miles of small food stores, which may include convenience stores, corner shops, or discount stores. Given the considerable distances between low-income households and larger food stores, improved transportation policies could facilitate access to these retail outlets. These transportation policies may include shuttle services, discounted public transportation fares, or the promotion of grocery delivery services. Second, small food stores, which are in closer proximity to a majority of low-income households, typically offer a limited selection of fresh food items. To enable low-income households to implement just-in-time shopping patterns that may reduce food waste (Ellison et al., 2022), policy could encourage smaller stores to stock fresh produce.

Given the cost involved in building physical stores or improving transportation access, however, recent attention has been given to more flexible ways to improve access to foods. Alternatives to building brick-and-mortar stores include operating mobile markets (Horning and Porter, 2020). Online grocery shopping may also improve access to foods without the need to build physical stores (Brandt et al., 2019). Customers can either order directly from a retailer and have groceries delivered through traditional logistics firms such as FedEx and UPS, or can connect with a personal shopper through on-demand grocery delivery services such as DoorDash and Instacart. Until recently the ability of low-income consumers to use online shopping was constrained because food assistance benefits could not be redeemed online. Starting in 2019, the USDA therefore implemented the Online Purchasing Pilot, which allowed customers to use SNAP benefits to purchase groceries online through select retailers (USDA, 2021). Online shopping may reduce household food waste by reducing impulse purchases (Huyghe et al., 2017) and allowing households to purchase groceries more frequently without the need to travel to a store. Additionally, online purchases may include fewer fresh foods (Pitts et al., 2018), which could reduce food waste but has more ambiguous health implications. On the other hand, customers are more likely to purchase bulk items online (Pitts et al., 2018), which could increase food waste. Incorporating food waste into measurements of the impact of diverse ways to improve food access would allow policymakers to compare the full effect of each alternative.

CRediT authorship contribution statement

Joel Cuffey: Conceptualization, Methodology, Formal analysis, Data curation, Writing – original draft. **Wenying Li:** Conceptualization, Methodology, Formal analysis, Data curation, Writing – review & editing. **Yang Yu:** Conceptualization, Methodology, Data curation, Writing – original draft. **Ruiqing Miao:** Conceptualization, Methodology, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

Potential sources of endogeneity

The causal interpretation of our coefficients of interest α_f faces three potential threats, which suggest that an associative interpretation of our results may be most appropriate. Household location relative to stores could be due to either households' or stores' location choices. The reasons for this sorting could be closely related with household food waste. First, stores may locate near households – or households locate near stores – specifically to reduce food waste. In this case, our outcome (food waste) would influence our variables of interest (store proximity), resulting in reverse causality. We believe that reverse causality is not a significant concern, since it is unlikely that households locate near stores explicitly to reduce food waste and also unlikely that stores locate near households primarily due to those households' food waste.

The second threat to identifying the impact of store proximity is the possibility that households move near stores, or stores locate near households, for other reasons that are correlated with the food waste in those households. Smith and Landry (2021a), for example, document the association between education and food waste. If less-educated households with higher food waste are also more likely to live closer to stores, we would find a positive relationship between store proximity and food waste. While we control for many observables (e.g., education level) that plausibly separately influence food waste, we cannot rule out that unobservables may also be related to both food waste and store proximity.

The third threat to a causal interpretation of our estimate is the possibility that systematic measurement error in either store location or household food waste may result in a spurious relationship between the two. FoodAPS distances are generated from geocoded addresses, so we do not believe measurement error in store location relative to households is a serious concern. If measurement error in food waste is correlated with the household's location relative to stores, our estimates may be biased. For instance, if food waste in the most efficient household depends on store proximity, any underestimation of food waste would be correlated with store proximity. Without the ability to directly observe food waste, we cannot rule this possibility out. Measurement error may also come from self-reported height/weight or self-reported food acquisitions. We cannot rule out the possibility that households close to a food retail store are more (or less) likely to systematically misreport height/weight, or systematically misreport food acquisitions. For example, if households close to a food retail store visit the store more often and buy smaller baskets of items, it is possible that these households are more likely to forget to report all of the store trips than households further from a store.

Table A1
Percentage of low-income households at different distances from store formats.

Format	<0.25 mi	0.25 mi-0.5 mi	0.5 mi-1 mi	1–2 mi	2 + mi
Super store	3	14	27	22	34
Large food store	16	19	27	15	22
Small food store	41	21	20	7	12

Table A2
Distribution of average trip size (in grams) to each store format.

Format	Median	75th percentile	95th percentile
Super store	3255.4	9561.7	26126.8
Large food store	1102.6	6502.4	20358.1
Small food store	0	452.2	6513.2

Note: This table describes the average trips size in the full sample of 3,066 respondents to each of the store formats. The average trip size is defined as the average number of grams purchased in trips to stores of that format. A value of 0 indicates no trips to the relevant store format. The first column shows the median average trip size, the second column shows the 75th percentile average trip size, and the third column shows the 95th percentile average trip size.

Table A3
Distribution of average amount of fresh foods (fresh vegetables, fresh fruit, fresh meat, and fresh seafood) in a shopping trip (in grams) to each store format.

Format	Median	75th percentile	95th percentile	99th percentile
Super store	0	723.5	3175.1	6570.6
Large food store	0	453.6	2404.4	5331.2
Small food store	0	0	0	1605.7

Note: This table describes the average amount of fresh foods in a shopping trip in the full sample of 3,066 respondents to each of the store formats. The average amount of fresh foods is defined as the average number of grams of fresh foods purchased in trips to stores of that format. A value of 0 indicates no fresh foods purchased at the relevant store format. The first column shows the median average amount of fresh foods, the second column shows the 75th percentile average amount of fresh foods, the third column shows the 95th percentile average amount of fresh foods, and the 99th percentile shows the 99th percentile amount of fresh foods. The analysis in the main text does not include the 99th percentile. Only 135 respondents have non-zero fresh food purchases from small food stores, of which only 26 are low-income respondents.

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