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ANALYSIS

The effect of food prices on fruit and vegetable food waste in private households☆

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ABSTRACT

Despite numerous studies on private households' food waste behaviour, the effect of food prices on food waste generation is still not well understood. This study provides empirical estimates on the effect of food prices on avoidable fresh fruit and vegetable food waste. This is the first time that results of this kind, based on an extensive and recent dataset, are being presented. We used data on the waste of 35 fresh fruit and vegetable food items documented in food waste diaries by 6696 different households observed in 2016/17 and 2020 in Germany. We applied a mixed-effects model to account for the crossed data structure between observed food items and participating households. After controlling for time and seasonality effects as well as for household-specific characteristics, we find a 10 % higher food price to be associated with 1 % less waste of fresh fruit and vegetables. In an extended version of our mixed-effects model, we disentangled this effect for two kinds of price variation and their association with food waste: We distinguish *price differences between* food items and *price changes within* food items over time. We find a significant and severe negative effect of price differences between fresh fruit and vegetable food items: A 10 %-price difference *between* two food items is associated with 7 % less food waste for the more expensive food item. In contrast, we do not identify any relevant effect of price changes within a food item over time on food waste. We discuss potential implications for policy proposals like a reduction of the value-added tax rate for fruits and vegetables.

1. Introduction

Halving per capita food waste (FW) by 2030 is a declared target (12.3) within the United Nations' Sustainable Development Goals (SDGs) (UN, 2015). In view of the increasing nutritional needs of a growing world population, resource scarcity and climate change, the objective of reducing FW is undisputed. Loss or waste of food can occur at various stages of the food value chain (Bellemare et al., 2017). The majority of FW in more affluent countries is generated in private households, of which fresh fruit and vegetables (FAV) are the main component in terms of weight (Caldeira et al., 2019; Priefer et al., 2016; Ananda et al., 2022). A distinction is usually made between avoidable (edible) and unavoidable (inedible) FW (Roodhuyzen et al., 2017).

In the last few years, there has been an enormous increase in research on FW (Principato et al., 2021). A major stream of the existing literature deals with the quantification of FW amounts (Xue et al., 2017). In Germany per capita FW in households is estimated to be 56 kg per year (Hübsch, 2021). Another central stream of FW literature examines influencing factors, which are considered diverse and complex (Aschemann-Witzel et al., 2015; Quested et al., 2013). In these studies, however, little attention has been paid to the influence of food prices on FW. Hamilton and Richards (2019) addressed this gap by developing a theoretical model to evaluate policies that alter the (relative) market prices of fresh and processed foods, focusing on the impact of such policies on household FW. In their framework, household FW results from utility-maximizing consumer decisions regarding both food purchases and utilization, taking into account (relative) food prices and the opportunity costs associated with food utilization efforts. The model distinguishes between processed and fresh food products and their respective prices. In their definition, FW refers to the unconsumed portion of fresh food, based on the assumption that only fresh foods are subject to household-level waste due to the effort required for their utilization. Based on their theoretical assumptions, Hamilton and Richards (2019) argue that a change in the (relative) price influences not

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only the optimal purchase quantities of fresh and processed foods, but also the optimal food utilization rate of fresh food. They conclude that the relationship between food prices and household FW is ambiguous, depending on the fresh food price elasticity of household demand: For households with sufficiently price elastic fresh food demand, increasing fresh food prices would lead to an increase in FW.

However, empirical evidence on the relationship between food prices and FW remains sparse. Some empirical studies have investigated related aspects, such as the relation of price-reduced suboptimal foods and FW (e.g., Aschemann-Witzel et al., 2015), the role of consumer price orientation or sensitivity and FW (Aschemann-Witzel et al., 2015; Veselá et al., 2023) or the effect of retail price *promotions* on household FW (Tsalis et al., 2021). However, the effect of "regular", non-promotional food prices on FW appears to be an empirically understudied aspect. This is notable, given that the assumption that food prices affect FW generation seems reasonable, considering the widely acknowledged role of price in consumer decision-making (Cattaneo et al., 2021; Parfitt et al., 2010; de Gorter et al., 2021).

Empirical evidence on the food price - FW relationship is particularly important when it comes to policy or market environments and instruments that influence food prices or aim to reduce FW. For example, a proposal to promote FAV consumption for healthier diets by removing value-added taxes (VAT) on fresh FAV (0 % rate)[1] is being discussed in Germany (Daniel, 2023). However, despite the suspected positive effects on health, the FW effects of a policy of this kind remain unclear because evidence in the existing literature on the food price - FW relationship appears inconclusive.

According to a qualitative study by van Geffen et al. (2016), participants in several European countries mentioned that low food prices contribute to consumer FW. In Germany, some even assessed food prices in this context as being "too cheap". Thus, it could be hypothesised that a further VAT reduction on FAV might have negative side effects in terms of more FW. However, barely any quantitative research has been conducted on the effect of food prices on FW.

Estimates of the food price elasticity of demand for wasting food input calories have been reported by Landry and Smith (2019), and range from −1.35 to −1.5. They applied a household production model of FW and proxy FW by using the difference between observational data on food stock usage and consumption by US households in 1977. In view of changing economic conditions and societal trends, these estimates may now be outdated. Aureli et al. (2021) refer to more recent FW data from 2018, but do not estimate the food price elasticities of FW. Instead, they applied principal component analysis to several food groups and found a negative correlation of 0.5 between wasted amounts of a food group and its average price per kilogram. In contrast, two other related studies with hypothetical experimental settings did not find a statistically significant effect of varying (hypothetical) prices of a certain food item on the decision to waste that food item (Dusoruth and Peterson, 2020; Ellison and Lusk, 2018).

Hence, the results of these quantitative studies appear inconclusive regarding the potential effect of food prices on FW. We aim to address this research gap by estimating the effect of food prices on avoidable FW for FAV based on recorded acts of FW in German households in 2016/17 and 2020. The use of a recent data set and a sample of 6696 households distinguishes our work from the few previous quantitative studies that have investigated the effect of prices on FW. We address the crossed data structure of the FW observations between both households and food items by applying mixed-effects (ME) models. In an extended model-version, we combine the ME model with a within-between (WB) model to disentangle the estimated price effect into two kinds of price variation and their association with FW. We distinguish *price differences between* food items and *price changes within* food items over time which is a distinctive feature of this study. Our work is the first to present results of this kind and constitutes a starting point for subsequent empirical analyses on the effect of food prices on FW which may have relevant implications for policy.

The remaining sections of this paper are structured as follows*:* Section 2 introduces the data and methods used, Section 3 presents and discusses descriptive and empirical results, and Section 4 concludes with a summary of the main findings.

2. Material and methods

2.1. Data collection and sample

We used data from the survey "Systematic monitoring of food waste from private households in Germany", which was commissioned by the German Federal Ministry of Food and Agriculture (BMEL) and carried out by GfK SE (Hübsch, 2021; Hübsch and Adlwarth, 2017).[2] A first wave was conducted in 2016/2017 and a second wave in 2020, each comprising 12 months (24 months overall). Different households from all over Germany were selected from the GfK survey panel (Consumer Scope). Within the survey, the "household managers", defined as the household members primarily responsible for managing the household, including food purchasing, preparation, and waste were asked to respond to the survey. This involved maintaining FW diaries for two weeks (14 days) within a designated month. The months were assigned to achieve a balanced distribution across the calendar year, aiming for a roughly equal number of respondents in each month. Some of the households participated in both, others in only one of the two waves (unbalanced panel). With the help of a code number system, the respondents assigned the documented FW to a predefined food item (e.g., apple), and an assignment was made as to whether the FW was avoidable or unavoidable. In addition, the participants were asked to report the corresponding FW amount. The weight of the wasted food items could either be measured or estimated with the help of a data sheet. Alternatively, households could report the number of units of wasted food items, which were then transferred into grams by GfK SE using conversion tables.

Various methods for measuring waste are used in the literature, all of which have different advantages and disadvantages (Hermanussen and Loy, 2024). In order to collect data on FW at household level, FW diaries are commonly used (Xue et al., 2017). Nevertheless, one has to be aware that inaccuracies can occur with such self-reported data due to measurement errors, social desirability or observational bias including behavioural changes among respondents due to participation in the study, which is also known as the"Hawthrone effect" (Podsakoff et al., 2003; Xue et al., 2017). More information on the study design and data collection, as well as results of this survey, can be found in Hübsch and Adlwarth (2017) and Hübsch (2021).

The complete original dataset compromised 505,166 observations of FW acts from 9849 different households for 116 predefined food items. Firstly, since we were only interested in the price effect on *avoidable* waste, we excluded all observations of FW acts that were classified as *unavoidable* FW. Unfortunately, the dataset initially contained no information about purchased food quantities or about the food prices of purchased and/or wasted foods. Thus, we are unable to assess whether a household that did not report any avoidable FW purchased a certain food item in the first place. However, we argue that we are interested in the overall price effect on fresh FAV FW, regardless of the extent to which the price affects FW directly or indirectly via the food purchasing channel.

[1] Following a reform of the EU VAT Directive, which will come into force in 2025, it is possible to remove VAT (i.e. 0 % rate) on certain goods including food items in the EU (Scholle, 2022).

[2] We are grateful to the Thünen Institute for Market Analysis, in particular to Dr. Thomas Schmidt, for making the data available to us and for the efforts to clarify all our questions.

To proxy the price of wasted food items, we used monthly price data for 2016, 2017 and 2020 from the consumer price index of the Agricultural Market Information company (AMI), which provides continuously monitored price levels of several food items in the German retail sector (AMI, 2024). The price data we used refer to conventional food items and are a weighted monthly average across all German regions and all types of retail stores. As much as possible we assigned fresh FAV food items used in the FW data from GfK SE to the fresh FAV food items used in the AMI consumer price index (see Appendix Table A.1).

We cannot use more specific prices, since we are unable to determine where and at what price the food items were purchased. It is also possible that some of these items were unmarketed FAV, such as self-cultivated produce, for which no market price was directly paid.[3] However, the majority of the FAV in our dataset, including (sub-)tropical varieties (see Appendix Table A.1), cannot be grown (year-round) in the temperate German climate. Moreover, 88 % of the households in our sample are located in urban areas ($\geq$ 20,000 inhabitants), where growing substantial amounts of FAV in private gardens is relatively uncommon due to space constraints.[4] In addition, we assume that even for unmarketed, homegrown FAV, households may still associate them with the prevailing market price as a reference, reflecting the price they would have otherwise paid in a supermarket. Therefore, we assume that self-cultivated FAV account for at most a very small share of the items in our dataset and do not substantially affect our results.

Moreover, using these price proxies instead of the actual prices paid by the reporting households offers the advantage that we circumvent one possible source of price endogeneity: It is plausible to assume that low-quality FAV food items are offered for a lower price (Millichamp and Gallegos, 2013) and, at the same time, are more likely to be wasted due to their lower quality. As we are not able to control for the unobserved food quality level, such a relation could lead to omitted variable bias (Antonakis et al., 2010). Inspired by Hausman et al. (1994), who used food prices at neighboring locations as instruments to address price endogeneity, we use the average food price across regions. The use of these average prices in our statistical analyses should ensure that a possible link between food prices, food quality and FW does not bias our statistical estimation results with respect to the effect of food prices on FW. We decided to focus on FAV for a number of reasons. We assumed that the FW data documented in the two-week FW diaries are least prone to observational bias for *perishable* food items such as fresh FAV. Moreover, FAV represent the main component in terms of weight of FW, and would be directly affected by the proposed 0 % VAT rate (see Section 1). Finally, we also found that FAV had the most straightforward assignment between GfK FW data and the AMI price data. Accordingly, we excluded all observations referring to food items from other food categories than fresh FAV.

In addition, we excluded all FAV food items for which a clear assignment between FW data from GfK SE and consumer price index data from AMI was not possible. For some food items ($n = 5$) the allocation of prices was based on approximately equal and not exactly the same food item designations (see Appendix Table A.1). However, a robustness check showed that excluding corresponding food items from the analyses did not lead to essentially different results (see Appendix Table A.2).

Thus, we were ultimately left with 35 fresh FAV food items in the dataset. Accordingly, this would give 35 food items, each with 24 monthly price observations, resulting in a total of 35*24 = 840 food-time combinations with corresponding food prices. However, for some of these food items, AMI price data were not available for all 24 months under observation (e.g., for seasonal food items). Thus, the FW observations for corresponding food items in corresponding months without price data (missing values) could not be considered in the statistical analysis. In all, we observed 746 food-time combinations with corresponding different food prices. Given that our main interest is on the food price effect on FW and we have monthly food prices per food item for each wave, we used these 746 food-time combinations, which are nested in the 35 food items, as an additional grouping layer for the FW observations (see Fig. 1).

Subsequently, for each wave we aggregated the recorded avoidable FW amounts in grams per household and food item, which made the FW data compatible with the monthly price data provided by AMI. Thus, in our final dataset one observation of a FW act corresponds to the reported overall FW amount for a specific food item within a certain household, within a month or, more precisely, within the two-week observation period within this month. Ultimately, we were left with a final dataset of 20,204 FW observations from 6696 different households for 35 fresh FAV food items. Given the two different waves in which data were collected, the dataset contains 8357 different household *observations* with 746 food-time combinations. Fig. 1 illustrates the data processing and the resulting data structure using the example (in light grey and italics) of 125 g of wasted apple in July 2020 by household 508.

The original household sample (n = 9849) was designed to be representative of German households across various demographic characteristics, in alignment with the annual Microcensus of the Federal Statistical Office (Hübsch, 2021; Hübsch and Adlwarth, 2017).[5] However, we had to exclude some observations from our analysis (see above). As some household-(manager-)specific information, such as sex or gender, income, or federal state, was not available to us, we were unable to assess the extent to which our sample may be distorted. Consequently, we did not apply the original representative weights and do not claim that the final household sample used in our analyses (n = 6696) is still representative.

In both waves, in our final household sample, represented by the household manager, the largest share were older respondents: almost half of the respondents were aged over 60 and fewer than 20 % were under 40. In terms of education, around 47 % stated that they do not have an upper secondary education, while one third had a university degree. Most households had two members, and a large majority of 88 % of the observed households were located in urban areas ($\geq$ 20,000 inhabitants) whereas 12 % were located in rural areas ($<$ 20,000 inhabitants). Information on sex or gender of the responding household managers has not been made available to us, which is why we were unable to take this into account.

Out of our final sample of 35 food items, 21 food items (60 %) were classified under the food category “fresh fruit” and 14 food items (40 %) under the food category “fresh vegetables” (see Appendix Table A.1). On average, the included food items have 43 cal per 100 g. Salad has the lowest calorie content at 12 cal, while avocado has the highest at 131 cal. The average food price across all 35 food items and the months in which food item-specific price data were available (746 food-time combinations in all) was € 3.19 per kilogram, with a standard deviation of € 2.64. The lowest price was 66 cents per kilogram for potatoes in November 2020, and the highest was € 19.83 per kilogram for blueberries in October 2016. Food prices differed between food items, but also varied “within” food items over the 24-month observation period.

2.2. Variable description

Table 1 describes the variables used in our statistical analysis, including their coding.

[3] We are grateful to one reviewer for having raised this point.

[4] Unfortunately, no empirical data were available on the precise amounts of privately grown fruits and vegetables in Germany or their share in total consumption.

[5] More information on the study design and data collection, as well as results of this survey, can be found in Hübsch and Adlwarth (2017) and Hübsch (2021).

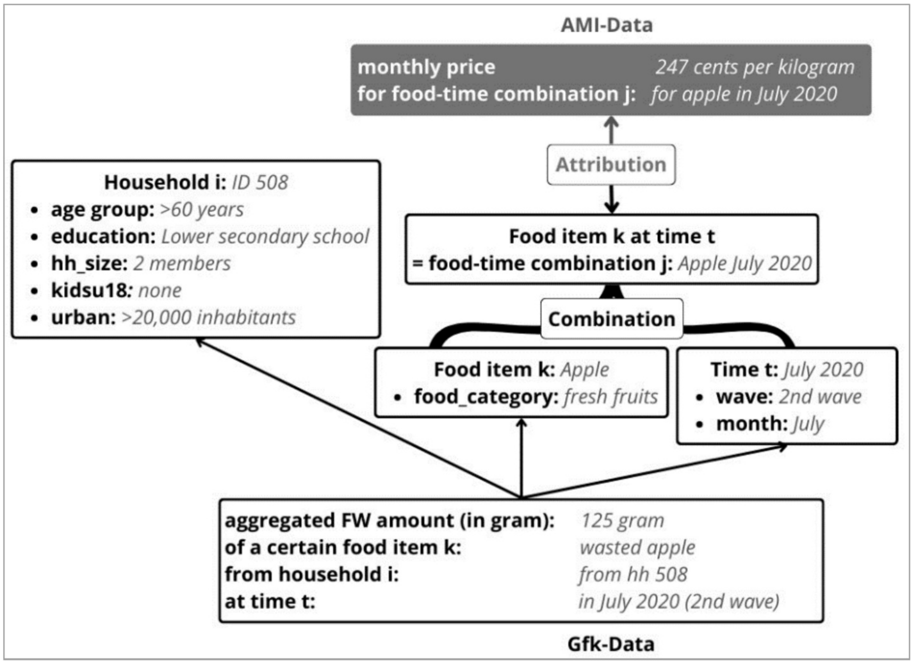

Fig. 1. Illustration of data processing and data structure.

Table 1
Description of variables.

Classification	Variables	Description
Dependent variable		
related to household and food-time combination	av_FW(_cal)	Avoidable FW amount per household and food item (continuous: in grams and calories, respectively))
Independent variables		
related to household	age_group	Age group (categorical: 1 ≤ 40 years, 2 = 40–59 years, 3 = ≥ 60 years)
	educ	Highest level of education achieved (categorical: 1 = (lower) secondary school, 2 = upper secondary school, 3 = university graduate)
	urban	Living environment of the household (dummy: 0 = rural ((< 20,000), 1 = urban (≥ 20,000 inhabitants))
	hh_size	Number of household members (continuous)
	kidsu18	Indicator for children under 18 living in the household (dummy: 1 = at least one; 0 = none)
related to food-time combination	wave2020	Survey wave (dummy: 0 = 1st wave (2016/2017), 1 = 2nd wave (2020))
	month	Observed month (categorical: 1 = January, (…), 12 = December)
	food_cat	Food category (dummy: 0 = vegetables, 1 = fruit)
	price(_cal)	Monthly AMI food price (continuous: in cents per kilogram and per 100 cal, respectively))
	m_price(_cal)	Food item-specific mean price over the observational period (continuous: in cents per kilogram and per 100 cal, respectively))
	d_price(_cal)	Food item-specific deviation from mean price in a certain month (continuous: in cents per kilogram and per 100 cal, respectively))

2.2.1. *Dependent variable: Avoidable FW amount of fresh fruit and vegetables*

As described in Section 2.1, we constructed our continuous dependent variable, namely the "avoidable FW amount per household and food item (in grams)" (av_FW) by aggregating the observed FW quantity of fresh FAV at household and food item level per month. In line with Landry and Smith (2019) we also examined the effect of food prices on FAV FW in a caloric metric. To convert the recorded FW amounts in gram into an alternative dependent variable, namely the "avoidable FW per household and food item (in calories)" (av_FW_cal), we matched the included food items to information from the German nutrient database "Bundeslebensmittelschlüssel" (BLS) (German Nutrient, 2014).

2.2.2. *Independent variables: Household-specific variables*

A unique household ID (hh_id) was assigned to each of the 6696 households. We controlled for sociodemographic heterogeneity within the sample by including several household characteristics as predictors: the age group of the household manager (age_group) and the highest level of education he or she achieved (educ), as well as an urbanity dummy (urban) to indicate whether a household is located in a more rural or urban area. Furthermore, we controlled for the number of household members (hh_size) and for children under 18 living in the household (kidsu18). Unfortunately, we were neither able to include information on sex of the household manager nor on household income as this could not be made available to us.

2.2.3. *Independent variables: Food-time-specific variables*

A unique food item ID (food_id) was assigned to each of the 35 food items (e.g., apples). In addition, each food-time combination, i.e. the observation of a certain food item in a certain month, was also assigned a unique ID (food-time_id) (e.g. apples in July 2020). Related variables for time and/or food items were considered in our analyses: a wave dummy (wave2020) to account for whether an observation of a FW act originates from the first wave of data collection (2016/2017) or the second

(2020). We controlled for seasonal influences by including a categorical month variable (month) that indicates the month in which a FW act was reported. In addition, we used a binary categorical variable (food_cat) to indicate whether a food item is classified as a vegetable (including potatoes and mushrooms) or as a fruit, as defined in the AMI consumer price index data.

In terms of food-time combinations, we also observed the variable of our main interest, namely the monthly food price in cents per kilogram of a specific food item (price) and for the alternative calorie-based analysis a converted food price in cents per 100 cal (price_cal). In an extended model version, which is explained in more detail in Section 2.3, we alternatively use the food item-specific mean price over the whole observational period (m_price) and the food item-specific deviation from that mean price in the corresponding month of observation (d_price).

2.3. Statistical modelling

2.3.1. Mixed-effects model

The structure of our data differs from a conventional econometric panel dataset in so far as each of the 20,204 FW observations belongs to a *combination* of one of the 6696 households and one of the 746 food-time combinations, which in turn belong to one of the 35 food items. Such a data structure can be referred to as being "crossed" between households and food-time combinations, which in turn are "nested" in the 35 food items (see also Fig. 1). In other words, FW observations from the same household can be attributed to different food-time combinations (i.e. food items), and FW observations of a certain food-time combination (i.e. food item) can come from different households. This kind of data structure can violate the assumption of ordinary regression models that responses are conditionally independent given the covariates: it is possible that a certain household systematically misestimates the quantities of all their wasted food items, or that the quantity wasted of a particular food item is systematically misestimated by all wasting households. Thus, applying ordinary linear regression would be inefficient and potentially biased (Dieleman and Templin, 2014; Rabe-Hesketh and Skrondal, 2022). To obtain more accurate inferences regarding the food price effect on FW, we need to explicitly take into account that our data structure has several layers. To do so, we used mixed effects (ME) models (also known as multilevel models), which can be viewed as generalisations of econometric panel data models as they allow for direct estimation of coefficients on variables (= "fixed effects" in the ME model terminology) related to different layers of data categorisation (i.e. households and food-time combinations/food items), and at the same time attribute unexplained variability to the different layers ("random effects" in ME model terminology) (Rabe-Hesketh and Skrondal, 2022; McNeish and Kelley, 2019; Melamed and Vuolo, 2019). ME models are estimated with a (restricted) maximum likelihood estimator. In consideration of our relatively large sample, we used maximum likelihood instead of restricted maximum likelihood. A robustness check showed that restricted maximum likelihood produces essentially the same results (see Appendix Table A.3).[6]

In our model, we treated household (hh_id), food-time combination (food_time_id) and food item (food_id) as random factors, and ended up with a ME model for cross-classified FW observations by households and food-time combinations, of which the latter are nested in food items.

Our model specification for the avoidable fresh FAV FW amount for household i and food-time combination j, which is nested in food item k, can be denoted as[7]:

Household variables Food-time comb. variables Random intercepts

$$\begin{aligned} \ln\_av\_FW_{ijk} = \alpha_0 + \\ \beta_1 age\_group_i + \beta_2 educ_i + \beta_3 urban_i + \beta_4 hhsize_i + \beta_5 kidsu18_i + \\ \beta_6 wave2020_{jk} + \beta_7 month_{jk} + \beta_8 food\_cat_{jk} + \beta_9 ln\_price_{jk} + \\ \zeta_i + \zeta_{jk} + \zeta_k \;+\; \varepsilon_{ijk} \end{aligned} \tag{1}$$

where α_0 is the generic intercept and the βs are the coefficients on the included covariates related to household i or related to food-time combination j nested in food item k, respectively, as described in Table 1. ζ_i is the random intercept for household i, ζ_{jk} is the random intercept for food-time combination j nested in food item k, and ζ_k represents the random intercept for food item k. Due to the crossed data structure, the household-specific random intercept ζ_i is shared across all food-time combinations jk (nested in food items k) for a given household i. Analogously, the food-time-specific random intercept ζ_{jk} and the food item-specific random intercept ζ_k are shared across all households i for a given food-time combination jk. ε_{ijk} is the residual error term. For our statistical analyses, we performed a logarithmic transformation with the outcome variable avoidable FW amount (ln_av_FW) and food price (ln_price).

It would also have been possible to include a random slope in our mixed-effects model specification to assess whether the food price effect on FW is equal across food items (Rabe-Hesketh and Skrondal, 2022). It turned out that the associated random effect had a small variance relative to the magnitude of the estimated price coefficient. Based on an insignificant likelihood ratio test statistic (Prob $> chi^2 = 0.45$ (gram-based) and Prob $> chi^2 = 0.08$ (calorie-based)), we concluded that the price effect is the same for each food item and decided against including a random slope for food price in order to keep the model parsimonious (McNeish and Kelley, 2019; Matuschek et al., 2017; Steele, 2010).

2.3.2. Within-between mixed-effects model

In total, our dataset contains 35 different food items and food item-specific monthly prices for up to 24 months (two waves of 12 months each). Accordingly, we observe two kinds of price variation, namely price differences between food items and price changes within food items over time. In the "basic" ME model, a weighted average of price differences between food items and price changes within food items is used, based on the assumption that there would be no difference between their effects. However, if this assumption is violated, the estimates are biased and cannot really be interpreted meaningfully (Raudenbush and Bryk, 2002; Schunck, 2013).

Indeed, it is easy to imagine that the effect of price differences between food items (i.e., the effect of generally high prices relative to other food items on FW like a € 12.52 mean price for raspberries) would differ from the effect of price changes within food items (i.e., effect of a high price for a food item relative to other months on FW like € 3.30 for tomatoes in February 2017). Instead of estimating a weighted average for the effect of price differences between food items and price changes within food items, we extended our ME model to combine it with the so-called within-between (WB) model (Bell et al., 2019; McNeish and Kelley, 2019). To do so, instead of the standard price variable (price) as in the basic ME model, we included two price-related variables as predictors in our model: the food item-specific mean price across all the observed months (m_price) to capture the effect of price differences "between" food items and the food item-specific deviation from this mean price in each observed month (d_price = price – m_price) to capture the effect of price changes within food items (Schunck, 2013; McNeish and Kelley, 2019; Allison, 2009):

$$\begin{aligned} \ln\_av\_FW_{ijk} = \alpha_0 + \\ \beta_1 age\_group_i + \beta_2 educ_i + \beta_3 urban_i + \beta_4 hhsize_i + \beta_5 kidsu18_i + \\ \beta_6 wave2020_{jk} + \beta_7 month_{jk} + \beta_8 food\_cat_{jk} + \beta_{B9} ln\_mprice_{jk} + \beta_{W9} ln\_dprice_{jk} + \\ \zeta_i + \zeta_{jk} + \zeta_k + \varepsilon_{ijk} \end{aligned} \tag{2}$$

β_{B9}, the coefficient on the m_price represents the estimated effect of

[6] See Leckie (2013) or Albright and Marinova (2015) for further information on the decision of likelihood versus restricted likelihood estimation.

[7] The model specifications presented refer to the gram-based models but similarly apply to the calorie-based models.

price differences between food items and indicates how a change in the food item-specific mean price is associated with a change in the food item-specific mean avoidable FW. β_{W9}, the coefficient on the d_price represents the estimated effect of price changes within a food item. This indicates how on average a within-food item change in food price is associated with a within-food item change in avoidable FW (Schunck, 2013; Snijders and Bosker, 2012). Thus, the WB-ME-model allows the effects of price differences between food items and price changes within food items to be disentangled, which we believe provides us with valuable insights related to our main effect of interest, namely the food price effect on avoidable FW. Also for the WB-ME model, we logarithmized the price variables. For the m_prices, this was straightforward. To obtain log values for the d_price, we first logarithmized the *absolute* value of the deviation from the mean price and then multiplied this value with −1 for all negative deviations. In one case, for plums in October 2010, we observe a zero-deviation from the mean price and insert zeros for the corresponding ln_dprice variable. Estimations of the ME models were carried out using the statistical software R (R Core Team, 2023) and the linear ME modelling package “lme4” (Bates et al., 2015). All tests and estimated coefficients were examined at a statistical significance level of 5 %.

3. Results & discussion

3.1. Descriptive statistics on analysed fresh FAV FW

The following descriptive statistics are based on the final sample of 20,204 FW observations for which we could attribute monthly price data from 35 fresh FAV food items. During the observation period of one month, or more precisely two weeks, FW from as few as 1 to as many as 24 of the 35 fresh FAV food items included was recorded within one household. The majority of households (65 %) reported that they had only thrown away one or two of these food items. On average, 2.4 different FAV food items were wasted in a household during the observed two weeks. In terms of the total FW from all 35 food items within the two-week observational period, the average household recorded an avoidable FW of 705 g, which corresponds to an average waste of 331 cal and € 1.44 in monetary value. Compared with the Italian sample used by Aureli et al. (2021) for which the converted household averages of FW for two weeks amounted to 699 g and € 1.84, our numbers appear relatively close. However, the two studies are not directly comparable because Aureli et al. (2021) included many more food categories, and the data collection was not based on FW diaries but on a recall methodology. In general, it should be noted that we only included selected fresh FAV food items in our analyses, and FW observations from the months for which we have price data. In addition, our household sample cannot be considered representative for the entire population (see Section 2.1), and underreporting due to measurement errors, social desirability or observational bias is a well-known problem with self-reported data (Podsakoff et al., 2003). However, since our main interest is the food price effect on FW and not the quantification of FW for the whole of Germany, this should not distort our results critically if the underreporting is not systematic (Wooldridge, 2020).

3.2. Mixed-effects model results

Table 2 presents the results of the ME models for avoidable FW of fresh FAV. As described in Section 2, we present a “basic” ME model

Table 2
ME and WB-ME models of avoidable fresh FAV FW.

	gram-based				calorie-based			
ln_av_FW(_cal)	ME (1)		WB-ME (2)		ME (3)		WB-ME (4)	
Fixed effects	Coeff.	s.e.	Coeff.	s.e.	Coeff.	s.e.	Coeff.	s.e.
age_group: 40–59 years	−0.02	0.03	−0.02	0.03	−0.02	0.03	−0.02	0.03
age_group: ≥ 60 years	−0.06	0.03**	−0.06	0.03**	−0.06	0.03**	−0.06	0.03**
educ: upper secondary school	−0.04	0.02*	−0.04	0.02*	−0.04	0.02*	−0.04	0.02*
educ: university graduate	−0.08	0.02***	−0.08	0.02***	−0.08	0.02***	−0.08	0.02***
urban: ≥ 20,000 inhabitants	−0.05	0.03*	−0.05	0.03*	−0.05	0.03*	−0.05	0.03*
hh_size	0.02	0.01	0.02	0.01	0.02	0.01	0.02	0.01
kidsu18	−0.05	0.03	−0.05	0.03	−0.05	0.03	−0.05	0.03
wave2020	−0.08	0.02***	−0.08	0.02***	−0.08	0.02***	−0.08	0.02***
month: February	0.01	0.05	0.01	0.05	0.01	0.05	0.01	0.05
month: March	0.00	0.05	0.00	0.05	0.00	0.05	0.00	0.05
month: April	−0.03	0.05	−0.03	0.05	−0.03	0.05	−0.03	0.05
month: May	0.04	0.05	0.04	0.05	0.04	0.05	0.04	0.05
month: June	0.11	0.05**	0.11	0.05**	0.11	0.05**	0.11	0.05**
month: July	0.10	0.05**	0.10	0.05**	0.10	0.05**	0.10	0.05**
month: August	0.19	0.05***	0.20	0.05***	0.19	0.05***	0.19	0.05**
month: September	0.13	0.05***	0.13	0.05***	0.13	0.05***	0.13	0.05**
month: October	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
month: November	0.07	0.05	0.07	0.05	0.07	0.05	0.07	0.05
month: December	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
food_cat: fruits	0.29	0.19	0.46	0.15***	1.03	0.26***	0.64	0.16***
ln_price(_cal)	−0.10	0.04**			−0.11	0.04***		
ln_m_price(_cal)			−0.69	0.12***			−0.84	0.09***
ln_d_price(_cal)			−0.01	0.00**			−0.01	0.00*
constant	5.49	0.27***	8.65	0.64***	3.95	0.28***	7.32	0.43***
Random effects	(Intercept) Variance		(Intercept) Variance		(Intercept) Variance		(Intercept) Variance	
hh_id	0.21		0.21		0.21		0.21	
food_item	0.29		0.17		0.54		0.18	
food-time_id:food_item	0.01		0.01		0.01		0.01	
residual	0.85		0.85		0.85		0.85	
AIC	57,739.64		57,718.98		57,761.76		57,722.79	
number of obs.	20,204		20,204		20,204		20,204	

Coefficients are given in the first column; standard errors are given in the second column;
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

with the standard food price variable, and a combined WB-ME model with a differentiation for effects of price differences between food items versus effects of price changes within food items. Both variants are estimated as a gram-based as well as a calorie-based FW model. For all four models, parameter estimates on the included predictors ("fixed effects") are reported in the upper part of the table: estimated coefficients (Coeff.) are presented in the first column and standard errors (s.e.) in the second column (** for $p < 0.05$). Estimated variance component parameters ("random effects") are reported below. To assess (relative) model fit, we provide Akaike Information Criterion (AIC) values calculated with the R package 'AICcmodavg' (Mazerolle, 2023) at the bottom of the regression table (Pinheiro and Bates, 2000).

It is apparent that the results of the gram- and the calorie-based FW models barely differ. Direction, size and significance of estimated parameters are very similar. In favor of parsimony and to avoid repetition, we therefore primarily discuss the gram-based model in the following analyses. However, intuition of results is essentially the same for the calorie-based model.

Our analysis starts with the gram-based basic ME model (column 1 of Table 2).

3.2.1. *Estimated random effects in the mixed-effects model*

The observed variability in reported avoidable FAV FW can be attributed roughly equally to differences between the households observed (Var(hh_id) = 0.21) and differences between the food items included (Var(food_item) = 0.29). This suggests that the application of an ME model was reasonable for our data, and that pooled OLS would probably have been inconsistent. For food-time combinations nested within food items, the estimated variance was close to zero. However, a highly significant likelihood ratio test statistic (Prob > $chi^2 = 0.00$) supported our decision to include the food-time combinations in our models as an additional grouping layer. In the calorie-based ME model (column 3 of Table 2), a substantially larger part of the observed variability in reported avoidable FAV FW is attributed to food items included (Var(food_item) = 0.54). This appears plausible considering that the calorie content varies considerably between food items.

3.2.2. *Estimated fixed effects in the mixed-effects model: household variables*

With respect to the household characteristics included, we found a significant negative effect of higher age and higher education. Compared with the reference age group of under 40-year-olds, households with heads aged over 60 reported 6 % less FW on average. This is in line with the findings of a qualitative study by van Geffen et al. (2016) in which older generations, who might have experienced poverty or food shortages in post-war periods, are generally perceived as less wasteful.

The statistically significant negative effect of education increased in size and significance with a higher level of education. For university graduates, the observed FW amount was significantly smaller compared with the reference group of (lower) secondary school graduates. On average, we found that university graduates waste 8 % less fresh FAV. There are several mechanisms that might determine the education-FW relationship: one line of argument is that more educated households have more food literacy. Better knowledge about how to appropriately store and efficiently use food items could lead to less FW (van Geffen et al., 2016; Ellison and Lusk, 2018; Landry and Smith, 2019). Another line of argument might be that a relationship between education and FW is (partly) driven by a correlation of education with income (Wolla and Sullivan, 2017). Higher income involves higher opportunity costs of time. Higher opportunity costs for efficiently planned meals and thoughtful use of food could result in more FW (Landry and Smith, 2019). Simultaneously, higher opportunity costs for accurately *reporting* generated FW (e.g., in FW diaries) could lead to systematic underreporting of FW in higher income (educated) households, which could (misleadingly) give the impression of less FW in these households. In any case, future studies should also include household income to avoid potential omitted variable bias and disentangle the effects of higher education from the effects of higher income on FW.

3.2.3. *Estimated fixed effects in the mixed-effects model: food-time combination variables*

Out of the variables referring to the period of the FW observations, the wave2020 dummy had a negative effect. In 2020, the documented FW amount was on average 8 % lower compared with the first wave in 2016/17. This could reflect societal trends towards greater awareness of avoiding FW (van Geffen et al., 2016). In particular, however, the COVID-19 pandemic and corresponding containment measures (e.g., lockdowns) that prevailed in 2020 have been found to have had a negative effect on FW (Ananda et al., 2023). Apart from the year of observation, some months were also found to have a significant effect. Compared with the reference month of January, FW was 10–20 % higher in all summer months from June to September. Due to the higher consumption of fruit in the summer months (Stelmach-Mardas et al., 2016), and the greater perishability of food in higher temperatures (Zainalabidin et al., 2019), this result appears plausible. Similarly, Grant et al. (2023) found that significantly more fruit is wasted in summer.

Looking at the effect of the food category (fruits vs. vegetables), we observe a substantial difference between the gram-based and the calorie-based model. While we did not find a significant effect in the gram-based ME model (column 1 of Table 2), we estimate a significant and large food category effect on FW of 1.03 in the calorie-based model (column 3 of Table 2): The number of wasted calories was on average more than twice as high for food items belonging to fresh fruit compared with vegetables. Considering that the included fruits have more than twice as many calories on average (54 cal/100 g) compared to the included vegetables (25 cal/100 g), this deviation seems plausible.

Finally, we turn to the effect that is our main interest: the food price effect. According to the basic ME model (column 1 of Table 2), we estimated a significant negative price effect on fresh FAV FW. This finding supports the results of qualitative research in European countries, where food prices have been identified as negative determinants of FW (van Geffen et al., 2016; Priefer et al., 2016; Garske et al., 2020). However, in two experimental studies with a hypothetical setting, no statistically significant effect of a higher (compared with a lower) food price on the decision to waste a certain food item was found (Ellison and Lusk, 2018; Dusoruth and Peterson, 2020).

We found FAV FW to be fairly inelastic in response to food price. We estimate that a 10 % higher food price is associated with 1 % less FW of the corresponding food item. Analogously, a 10 % higher food price per 100 cal is associated with 1 % less wasted calories of the corresponding food item.

While Hamilton and Richards (2019), based on their theoretical model (see Section 1), argue that higher fresh food prices increase FW in households with sufficiently price-elastic demand, we cannot empirically confirm such a positive relationship based on our results. However, we are also unable to reject the proposed theoretical effects by Hamilton and Richards (2019) for several reasons. First, we do not have information on households' price elasticities of demand, nor on food purchase data. Without the food purchase data, we are also not able to disentangle the extent to which changes in FW are driven by shifts in food purchase quantities or by changes in food utilization and FW rates. Moreover, our empirical setup is not directly comparable to their theoretical model: While Hamilton and Richards (2019) model price changes as a shift in a uniform price for all fresh foods relative to a uniform price for all processed foods, our analysis focuses exclusively on fresh FAV food items (e.g., apples).

Also, in relation to other quantitative empirical studies, it is only possible to contextualize our results to a limited extent, as there are barely any quantitative studies on the effect of food prices on FW, and those that do exist differ substantially in key aspects:

For 1142 Italian households, Aureli et al. (2021) found a negative correlation of −0.5 between recalled avoidable household FW in 20 food groups (in grams) and corresponding average unitary prices in July 2018. They conclude that the lower the price of a food group is, the greater the corresponding FW amount. However, they only refer to data from one specific month. Hence, only the effect of relative prices between different food groups at one point in time was examined, rather than the effect of price changes within a food group over time. Moreover, even though fresh fruit and fresh vegetables were each considered as a separate food group in their analysis, no differentiation was made between specific FAV food items within these broad food groups. Consequently, the results are not directly comparable to our findings as we examined specific food items and only focused on fresh FAV food items.

Landry and Smith (2019) estimated food price elasticities of FW for a calorie-based model with data from 2113 US households collected between April and June in 1977. Landry and Smith (2019) find FW to be responsive to food prices based on elasticity estimates ranging from −1.35 to −1.5. These estimates are substantially larger than our estimate of −0.1. However, the study design of Landry and Smith (2019) is essentially different: Most striking is that their US-data is 40 years older than our data and that they examine *total* food calories wasted in relation to *total* food value per calorie instead of fresh FAV food-item *specific* data. Nevertheless, our price effect appears to be comparatively small. This changes when we disentangle the general price effect into an effect of price differences between food items and an effect of price changes within food items by estimating the WB-ME model.

3.2.4. Within-between model

Turning to the WB-ME models (columns 2 and 4 of Table 2), we observe that the AIC values are lower for the WB-ME models compared to the basic ME models for both the gram- and calorie-based model versions, indicating a relatively better model fit for the WB-ME models (Pinheiro and Bates, 2000). Moreover, it is remarkable that the variance attributed to differences between the food items is substantially smaller in both the gram- and calorie-based model versions of the WB-ME models compared to the basic ME models. We computed price averages and deviations at the food item level to include them in the WB-ME models. Thus, it seems plausible that variability between observed food items would be absorbed. With respect to the fixed effects, apart from the price effect, estimated parameters were very similar between the basic ME models and the extended WB-ME models. Only the estimated effect of the food category (fruits versus vegetables) changed. While the estimated food category effects were substantially different comparing the gram- versus the calorie-based basic ME models (column 1 vs. 3 of Table 2), the estimated effects are much more similar in the WB-ME models (column 2 vs. 4 of Table 2): In the gram- and the calorie-based WB-ME model the effect is statistically significant and positive: For food items belonging to fresh fruit the amount in gram of FW compared to vegetables was on average 46 % higher (column 2 of Table 2) and the number of calories wasted was 64 % higher (column 4 of Table 2). Apart from this, the significance and effect sizes of the control variables were almost identical between the ME and WB-ME models.

The WB-ME model revealed interesting insights when we examined the food price effect on FW. The effect of price differences between food items (ln_m_price) was highly significant and of much greater size than the estimated price effect in the basic ME model. According to the gram-based model version (column 2 of Table 2), a food price difference of 10 % between two food items is associated with 7 % less FW from the more expensive food item compared with the cheaper one. In the calorie-based model (column 4 of Table 2), we estimate a difference in food prices per calorie of 10 % between two food items to be associated with 8 % fewer wasted calories from the more expensive food item. Findings of this magnitude are closer to the results of Aureli et al. (2021) and Landry and Smith (2019), which makes sense insofar as these studies basically only considered price variation in terms of price differences between food items.

In contrast, the estimated effect of price changes within food items (ln_d_price) was only marginally significant and close to zero in both the gram-based and calorie-based model. This would mean that a food price deviation from the mean price per gram (or price per calorie) of a certain food item is not associated with significantly less or more FW (or wasted calories) from the corresponding food item. This result may seem surprising. However, apart from seasonal variations that were controlled for, food prices were relatively stable during the period of observation. Shortly afterwards, when the war in Ukraine started in spring 2021, there was food price inflation (Mbah and Wasum, 2022). Unfortunately, this food price increase is not reflected in our dataset anymore. A follow-up study with additional data on FW and food prices for the period after food price inflation as well could provide valuable insights into whether the effect of price changes within food items is indeed negligible or whether the present study's findings are driven more by limited variation in the underlying price data. However, it does not seem far-fetched for the price difference between food items to play a more decisive role than price changes within food items over time. It is easy to imagine that even if the prices of relatively cheap food items, such as apples and potatoes, go up, they are still handled with less care than more expensive food items, such as berries and avocados. In addition, an insignificant effect of price changes within food items, and the considerations discussed, are consistent with the ***insignificant*** price effects found by Ellison and Lusk (2018) and Dusoruth and Peterson (2020). Both studies investigated whether a (hypothetical) higher price for a certain food item has an influence on the decision to waste the corresponding food item. This kind of price variation corresponds to a price change within a food item, for which no relevant effect was identified in our analysis either.

3.3. Implications, strengths and limitations

In Germany, the standard VAT rate is 19 %, while a reduced VAT rate of 7 % currently applies to most food items, including FAV. However, there is an ongoing discussion about completely abolishing VAT on FAV (i.e., introducing a 0 % VAT rate) to promote their consumption as part of a healthier diet (Daniel, 2023). While this measure might serve the government's objective of increasing FAV intake, the negative relationship between food prices and FAV-related FW identified in our ME models (columns 1 and 3 of Table 2) suggest that lower prices could also have the unintended effect of (slightly) increased levels of FAV-related FW. This could indicate potentially conflicting government objectives when setting VAT rates for FAV, namely, the goal of reducing FW versus promoting healthy eating.

However, the withdrawal of the VAT on FAV would apply to all FAV food items equally, which means that relative prices between different FAV food items would largely remain unchanged. The results of our WB-ME models (columns 2 and 4 of Table 2) suggest that price differences between FAV food items have a stronger effect on the amount of FW than price changes for a particular fruit or vegetable over time. Thus, our results could imply that in the context of abolished VAT on FAV, which would correspond to a negative price change within food items, unintended negative side effects in terms of higher FAV FW are not to be expected. However, an abolished VAT on FAV would at the same time correspond to a change in the price difference between FAV and non-FAV food items. Further research is required to understand if our results also apply to food items from and across other food categories. Corresponding results can lead to insights on what overall effect price variations (e.g., due to changes in VAT on FAV) might potentially have on FW. In addition, a richer dataset with simultaneous food purchase and FW data within households would enable subsequent studies to disentangle the channels through which food prices affect FW. Specifically, this would allow for distinguishing between changes in food purchase quantities, actual food intake, and the share of FW. This would contribute to the empirical examination of theoretical predictions and causal relationships underlying the effect of food prices on FW (e.g., Hamilton and Richards, 2019). It would also enable the derivation of informed policy implications, particularly when balancing FW reduction against other policy objectives, such as promoting healthier diets.

In general, the characteristics of the dataset imposed some challenges and limitations on our work, such as the self-reporting of the FW data and the lack of food purchase (and food price) or household income data. This also meant that we had to exclude all non-FAV food items from our analyses, particularly in order to ensure an adequate allocation of monthly food prices to FW observations. In addition, it should be considered that our estimates of the effects of food prices on FW represent only a rough aggregation across the included FAV food items. With a richer dataset, it would potentially be possible to estimate food item–specific own- and cross-price elasticities of FW. These limitations must be kept in mind when assessing our results and prevent us from drawing final conclusions on the effect of food prices on FW e.g., with respect to definite policy recommendations.

Nevertheless, our work makes an important contribution to the FW literature: We investigate the economically and politically highly relevant effect of food prices on FW, for which no comparable study has been conducted before. Our work relies on a considerably large sample of 20,204 FW observations from 6696 different households and covers a time period of several months in different years. The distinction of price variation into *price differences between* food items and *price changes within* food items provides novel insights into the relation between prices and FW and could also be employed in other areas of research.

4. Conclusions

We quantitatively investigated the effect of food prices on fresh fruit and vegetable food waste. By applying a mixed effects model with random intercepts, we accounted for the crossed structure of the observed food waste data between households and food items. Consistent with the few studies on the effect of food prices on food waste that have been carried out to date, our findings suggest that food prices have a negative effect on the wastage of fresh fruits and vegetables in general: We find the response of fresh fruit and vegetable food waste to food prices to be significantly negative, but inelastic: We estimate a 10 % higher food price to be associated with 1 % less food waste.

By applying a within-between - mixed-effects model, we were able to reveal that this finding is mainly driven by a more severe effect of price differences between fruit and vegetable food items: A price difference *between* two food items of 10 % is associated with 7 % less food waste for the more expensive food item, whereas the effect of *price changes within* a fruit or vegetable food item over time is almost negligible and not of economic relevance.

Building on these insights, it is up to future studies based on improved datasets to investigate whether these findings are confirmed and transferrable to and across other food categories. Our work contributes to what has so far been an understudied aspect of food waste research which is of high political and economic relevance. Ultimately, our findings and results based on improved datasets could inform the efficient design of future food policies like the optimal value added tax rate for food items to be aligned with the Sustainable Development Goal of reducing food waste.

CRediT authorship contribution statement

Vicky Heijnk: Software, Methodology, Formal analysis, Data curation, Conceptualization, Writing – original draft, Visualization. **Sebastian Hess:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Conceptualization.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used DeepL and ChatGPT (GPT-4-Turbo) in order to improve readability and language of some sentences. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Sebastian Hess reports a relationship with Milchindustrie-Verband e. V. that includes: unpaid board membership. If there are other authors, they 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 A. Appendix

Table A.1
Attribution of food items across data bases.

Food item (English translation)	Food item (Gfk-FW data)	Food item: mean price per kg (AMI-price data)	Allocation	Food item: calories (BLS-calorie-data)	Availability of AMI-price data in X/24 months
FRUITS					
Apples	Äpfel	Äpfel: € 1.95	identical	Apfel roh: 61 cal	24/24
Apricots	Aprikosen	Aprikosen: € 3.43	identical	Aprikose roh: 43 cal	9/24
Avocados	Avocado	Avodacos: € 4.76	identical	Avocado roh: 130 cal	24/24
Bananas	Bananen	Bananen: € 1.22	identical	Banane roh: 90 cal	24/24
Blueberries	Sonstige Beeren	Heidelbeeren: € 10.21	proxy	Heidelbeere: 37 cal	24/24
Cherries	Kirschen	Süßkirschen: € 6.29	identical	Kirschen roh: 60 cal	8/24
Grapes	Weintrauben	Tafeltrauben. helle Sorten. Kernlos: € 3.37	close	Weintrauben roh: 70 cal	24/24
Kiwis	Kiwi	Kiwi: € 3.62	identical	Kiwi roh: 54 cal	24/24

(*continued on next page*)

Table A.1 (*continued*)

Food item (English translation)	Food item (Gfk-FW data)	Food item: mean price per kg (AMI-price data)	Allocation	Food item: calories (BLS-calorie-data)	Availability of AMI-price data in X/24 months
Lemons	Zitronen	Zitronen: € 2.59	identical	Zitrone roh: 36 cal	18/24
Mangos	Mangos	Mango: € 3.77	identical	Mango roh: 59 cal	24/24
Nectarines	Nektarinen	Nektarinen inkl. Plattnektarinen: € 2.82	identical	Nektarine roh: 56 cal	18/24
Oranges	Orangen	Apfelsinen: € 1.61	identical	Orange roh: 43 cal	24/24
Peaches	Pfirische	Pfirsiche inkl. Paraguayos: € 2.58	close	Pfirsich roh: 41 cal	12/24
Pears	Birnen	Tafelbirnen: € 2.31	identical	Brine roh: 52 cal	24/24
Pineapple	Ananas	Ananas: € 1.34	identical	Ananas roh: 56 cal	24/24
Plums	Pflaumen, Zwetschgen	Pflaumen, ausländische/ Zwetschen, inländische[a]: € 2.95	identical	Pflaumen roh: 45 cal	23/24
Raspberries	Himbeeren	Himbeeren: € 12.52	identical	Himbeere roh: 34 cal	24/24
Strawberries	Erdbeeren	Erdbeeren: € 5.40	identical	Erdbeere roh: 32 cal	23/24
Sugar melons	Sonstige Melonen	Zuckermelone: € 1.67	proxy	Zuckermelone/ Honigmelone roh: 55 cal	24/24
Tangerines	Mandarinen, Clementinen	Mandarinen u.ä.: € 2.45	identical	Mandarine roh: 50 cal	21/24
Watermelons	Wassermelonen	Wassermelone: € 1.13	identical	Wassermelone roh: 38 cal	16/24
VEGETABLES					
Asparagus	Spargel	Spargel: € 7.20	identical	Spargel roh: 18 cal	10/24
Broccolis	Kohlgemuese (z. B. Weisskohl, Wirsing, Brokkoli)	Broccoli: € 2.38	proxy	Broccoli roh: 28 cal	24/24
Carrots	Karotten, Möhren, Rüben	Möhren, ohne Laub: € 1.03	close	Karotte (Mohrrübe. Möhre) roh: 33 cal	24/24
Champions	Pilze	Frische Champigons: € 3.75	proxy	Champignon roh: 21 cal	24/24
Cucumbers	Gurken, Salatgurken	Salatgurken: € 1.47	identical	Gurke roh: 12 cal	24/24
Kohlrabi	Kohlrabi	Kohlrabi: € 2.48	identical	Kohlrabi roh: 25 cal	24/24
Onions	Zwiebeln	Zwiebeln: € 1.15	identical	Zwiebeln roh: 28 cal	24/24
Pepper	Paprika	Paprika: € 3.01	identical	Gemüsepaprika rot roh: 37 cal	24/24
Potatoes	Kartoffeln	Kartoffeln: € 0.82	identical	Karoffeln geschält roh: 73 cal	21/24
Radishes	Radieschen	Radieschen: € 2.15	identical	Radieschen roh: 15 cal	24/24
Salad	Salat	Kopfsalat: € 3.27	proxy	Kopfsalat roh: 11 cal	24/24
Tomatoes (mini)	Minitomaten (z.B. Kirschtomaten)	Mini-tomaten, ohne Grün: € 4.34	identical	Tomate rot roh: 17 cal	18/24
Vine tomatoes	Tomaten (Strauch-. Fleischtomaten)	Strauchtomaten: € 2.30	close	Tomate rot roh: 17 cal	24/24
Zucchinis	Zucchini	Zucchini: € 1.95	identical	Zucchini roh: 21 cal	24/24

[a] In the months July–October prices for domestic plums were used, otherwise prices for foreign plums (separate reporting in AMI-price data).

Table A.2
Robustness check: ME and WB-ME models of avoidable fresh FAV FW excluding food items with approximately equal food item designations

	gram-based				calorie-based			
ln_av_FW(_cal)	ME		WB-ME		ME		WB-ME	
Fixed effects	Coeff.	s.e.	Coeff.	s.e.	Coeff.	s.e.	Coeff.	s.e.
age_group: 40–59 years	−0.00	0.03	−0.00	0.03	−0.00	0.03	−0.00	0.03
age_group: ≥ 60 years	−0.06	0.03**	−0.06	0.03**	−0.06	0.03**	−0.06	0.03**
educ: upper secondary school	−0.03	0.02	−0.03	0.02	−0.03	0.02	−0.03	0.02
educ: university graduate	−0.08	0.02***	−0.08	0.02***	−0.08	0.02***	−0.08	0.02***
urban: ≥ 20,000 inhabitants	−0.05	0.03*	−0.05	0.03*	−0.05	0.03*	−0.05	0.03*
hh_size	0.02	0.01	0.02	0.01	0.02	0.01	0.02	0.01
kidsu18	−0.05	0.04	−0.05	0.04	−0.05	0.04	−0.05	0.04
wave2020	−0.08	0.02***	−0.09	0.02***	−0.08	0.02***	−0.09	0.02***
month: February	0.01	0.05	0.01	0.05	0.01	0.05	0.01	0.05
month: March	−0.00	0.05	0.00	0.05	−0.00	0.05	−0.00	0.05
month: April	−0.04	0.05	−0.04	0.05	−0.04	0.05	−0.05	0.05
month: May	0.03	0.05	0.03	0.05	0.03	0.05	0.02	0.05
month: June	0.08	0.05*	0.09	0.05*	0.08	0.05*	0.08	0.05*
month: July	0.09	0.05*	0.10	0.05*	0.09	0.05*	0.09	0.05*
month: August	0.15	0.05***	0.16	0.05***	0.15	0.05***	0.16	0.05***
month: September	0.11	0.05**	0.11	0.05**	0.11	0.05**	0.11	0.05**
month: October	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
month: November	0.04	0.05	0.05	0.05	0.04	0.05	0.05	0.05
month: December	0.03	0.05	0.03	0.05	0.03	0.05	0.03	0.05
food_cat: fruits	0.27	0.20	0.45	0.17**	0.98	0.28***	0.65	0.18**
ln_price(_cal)	−0.10	0.04**			−0.11	0.04**		
ln_m_price(_cal)			−0.65	0.13***			−0.82	0.10**

(*continued on next page*)

Table A.2 (*continued*)

	gram-based				calorie-based			
ln_av_FW(_cal)	ME		WB-ME		ME		WB-ME	
Fixed effects	Coeff.	s.e.	Coeff.	s.e.	Coeff.	s.e.	Coeff.	s.e.
ln_d_price(_cal)			−0.01	0.00**			−0.01	0.00*
constant	5.51	0.29***	8.42	0.72***	4.02	0.30***	7.23	0.49***
Random effects	(Intercept) Variance		(Intercept) Variance		(Intercept) Variance		(Intercept) Variance	
hh_id	0.22		0.22		0.22		0.22	
food_id	0.28		0.18		0.52		0.20	
food-time_id:food_id	0.01		0.01		0.01		0.01	
residual	0.82		0.82		0.82		0.82	
AIC	49,519.74		49,504.55		49,538.59		49,508.72	
number of obs.	17,446		17,446		17,446		17,466	

Coefficients are given in the first column; standard errors are given in the second column;
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Note: All food items were excluded for which the allocation of prices was based on approximately equal and not exactly the same food item designations in the AMI-price data (n = 5). For corresponding food items, "proxy" is indicated in the Allocation-column in Table A.1.

Table A.3
Robustness check: ME and WB-ME models of avoidable fresh FAV FW with restricted maximum likelihood estimation (REML).

	Gram-based				Calorie-based			
ln_av_FW(_cal)	ME		WB-ME		ME		WB-ME	
Fixed effects	Coeff.	s.e.	Coeff.	s.e.	Coeff.	s.e.	Coeff.	s.e.
age_group: 40–59 years	−0.02	0.03	−0.02	0.03	−0.02	0.03	−0.02	0.03
age_group: ≥ 60 years	−0.06	0.03**	−0.06	0.03**	−0.06	0.03**	−0.06	0.03**
educ: upper secondary school	−0.04	0.02*	−0.04	0.02*	−0.04	0.02*	−0.04	0.02*
educ: university graduate	−0.08	0.02***	−0.08	0.02**	−0.08	0.02***	−0.08	0.02***
urban: ≥ 20,000 inhabitants	−0.05	0.03*	−0.05	0.03*	−0.05	0.03*	−0.05	0.03*
hh_size	0.02	0.01	0.02	0.01	0.02	0.01	0.02	0.01
kidsu18	−0.05	0.03	−0.05	0.03	−0.05	0.03	−0.05	0.03
wave2020	−0.08	0.02***	−0.08	0.02**	−0.08	0.02***	−0.08	0.02***
month: February	0.01	0.05	0.01	0.05	0.01	0.05	0.01	0.05
month: March	0.00	0.05	0.00	0.05	0.00	0.05	0.00	0.05
month: April	−0.03	0.05	−0.03	0.05	−0.03	0.05	−0.03	0.05
month: May	0.04	0.05	0.04	0.05	0.04	0.05	0.04	0.05
month: June	0.11	0.05**	0.11	0.05*	0.11	0.05**	0.11	0.05**
month: July	0.10	0.05**	0.10	0.05*	0.10	0.05**	0.10	0.05**
month: August	0.19	0.05***	0.20	0.05**	0.19	0.05***	0.19	0.05***
month: September	0.13	0.05***	0.13	0.05**	0.13	0.05***	0.13	0.05***
month: October	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
month: November	0.07	0.05	0.07	0.05	0.07	0.05	0.07	0.05
month: December	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
food_cat: fruits	0.29	0.19	0.46	0.15**	1.03	0.26***	0.64	0.16***
ln_price(_cal)	−0.10	0.04**			−0.11	0.04***		
ln_m_price(_cal)			−0.69	0.12**			−0.84	0.09***
ln_d_price(_cal)			−0.01	0.00*			−0.01	0.00*
constant	5.48	0.27***	8.65	0.67**	3.94	0.28***	7.32	0.45***
Random effects	(Intercept) Variance		(Intercept) Variance		(Intercept) Variance		(Intercept) Variance	
hh_id	0.21		0.21		0.21		0.21	
food_id	0.31		0.18		0.57		0.20	
food-time_id:food_id	0.01		0.01		0.01		0.01	
residual	0.85		0.85		0.85		0.85	
AIC	57,847.75		57,836.27		57,868.61		57,839.76	
number of obs.	20,204		20,204		20,204		20,204	

Coefficients are given in the first column; standard errors are given in the second column;
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Data availability

The authors do not have permission to share data.

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