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The impact of nutrition claims on purchase behavior for food products

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ABSTRACT

Faced by increasing emphasis on health, manufacturers try to persuade consumers by using nutrition claims on their packaging. Although experimental research suggests that such claims influence consumer behavior in different ways, it remains unknown whether and to what extent they have an effect in actual grocery situations with large amounts of information to process. In this study, the authors investigate the effect of presence (stressing the presence of a healthy ingredient) and absence nutrition claims (stressing the absence of an unhealthy ingredient) on consumer purchase behavior using UK household scanner purchase data from 17 product categories during the years 2009–2012. They find that presence nutrition claims increase choice while absence nutrition claims decrease choice. Both types of nutrition claims do not influence the quantity purchased. Importantly, a nutrition claim's effectiveness depends on SKU and category characteristics. Presence nutrition claims are more effective in healthy categories, and absence nutrition claims for SKUs with fewer promotions. At the same time, both nutrition claims are less effective for higher priced SKUs and more effective for brands with higher advertising spending. Absence nutrition claims are more effective when fewer SKUs in the category have the same type of nutrition claim, but presence nutrition claims benefit when more SKUs have the same type of nutrition claim.

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1. Introduction

The current marketplace reveals a mounting emphasis on nutrition claims such as "high in fiber" or "low in fat". Research shows that approximately 35 % of food and beverages carry one or more of these nutrition claims (Ropero et al. 2020). Although food marketers are encouraged to use nutrition claims to produce healthier food (Nutrition Labeling and Education Act, 1990; Dietary Supplement Health and Education Act, 1994), the main objective is to create a maximally persuasive message designed to hit the sweet spot in consumers' minds (Nestle, 2007). Indeed, nutrition claims allow food companies to abstract or highlight specific nutrients and directly or indirectly imply health benefits with the aim of increasing purchases. Importantly, these nutrition claims are very different from food scoring systems such as NuVal (Nikolova & Inman, 2015), Nutri-Score (Dubois et al., 2020), or the Choices symbol (Maesen et al., 2021), which summarize and interpret the *overall*

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healthiness of a product into one indicator (Talati et al., 2016b). Nutrition claims, in contrast, only refer to *one specific ingredient* (e.g., low in fat) and leave room for overgeneralization and potentially incorrect inferences on the overall healthiness of the product (Andrews et al., 1998; Ikonen et al., 2020). As a result, nutrition claims are also very different from *nature claims* (e.g., wholegrain, organic, no artificial colors) which make no reference to nutrients, but focus on the health benefits of the absence of human interventions (Chandon & Cadario, 2023).

Driven by the popularity of nutrition claims in the marketplace, academic research on their effect proliferated (as we summarize in Table 1). Most of these studies entail experimental consumer research providing many insights into how these nutrition claims influence perceptions and (intended) behavior (see also Ikonen et al. (2020) for a recent overview). For example, consumers facing nutrition claims tend to perceive the product as healthier, and tend to consume more of this product, compared to consumers faced with the same product without nutrition claim (Geyskens et al., 2007; Wansink & Chandon, 2006). Purchase behavior in a real grocery context is, however, a complex decision, and hence difficult to capture in a lab environment.

In reality, households typically choose among dozens of product varieties in each product category with many different nutrition claims. Faced with these large amounts of information, consumers develop mechanisms for limiting information acquisition (Malhotra, 1984), such as simply ignoring parts of the information (e.g., nutrition claims) (Wansink, 2003) or relying on simple heuristics (Kahneman, 2011). Such simplified heuristics can lead to a "health halo" in the consumers' minds: they may incorrectly ascribe the product with positive health attributes unrelated to the nutrition claim (Roe et al., 1999, Chandon & Wansink, 2007). Importantly, recent research suggests that the impact of nutrition claims depends on whether the nutrition claim emphasizes the presence of positive attributes (i.e., presence nutrition claims such as "high in fiber") or the absence of negative attributes (i.e., absence nutrition claims such as "low in fat") (André et al., 2019; Chandon & Cadario, 2023). Thus, the effect of nutrition claims (if any) on consumers' purchase behavior may depend on the type of nutrition claim.

The scarce studies that research the effect of nutrition claims in a real grocery setting (see Table 1) neglect the possible differential impact of presence and absence nutrition claims. Moreover, most of these studies zoom in on a single or small number of SKUs and product categories and, thereby, neglect the potential moderating impact of SKU and category characteristics. Similarly, experimental studies examining perceptions and behavioral intentions often ignore the differential effects of various types of nutrition claims, concentrating narrowly on specific products and claims.

The findings from these studies are inconclusive, with some suggesting no observable influence, while others reveal varying effects depending on the specific food item or claim being examined. Therefore, it is imperative to encompass a wide array of product categories and nutrition claims simultaneously.

The key contribution of the current study lays in studying the actual impact of nutrition claims on household SKU purchase behavior in the real marketplace, where other factors like category and SKU characteristics have substantial effects. In contrast to prior controlled (choice) experiments, we assess the full impact of nutrition claims on SKU purchase behavior using incidence-choice-quantity models. We analyze a unique dataset of UK household scanner data containing 9,945 households and 1,018 SKUs in 17 food categories, complemented with information on the presence and type of nutrition claims. This allows us to derive empirical generalizations on the effect of presence- and absence-based nutrition claims on consumer SKU purchase behavior, addressing calls by Ma et al. (2013) and Dubois et al. (2020) for studies on nutrition labeling executed in the marketplace.

We also identify important SKU and category moderators which play a crucial role in determining the impact of nutrition claims. We posit that the net effect of nutrition claims on SKU purchase behavior depends on different SKU (i.e., SKU price, SKU price promotions, brand advertising, the type of brand) and category characteristics (i.e., category healthiness, claim penetration). Studying these moderating effects allows to identify boundary conditions, which is of theoretical importance. Unlike prior studies, which tend to focus on a narrow set of SKUs and categories (see Table 1), our study provides a more generalized overview of the impact of nutrition claim type on real-life grocery SKU purchase behavior.

2. Conceptual framework

Many health labeling programs exist. We focus on *nutrition claims*, that suggest or imply that a food has beneficial nutritional properties due to its composition regarding one nutrient (e.g., "source of", "free of", "high", "low", or "reduced in") (Ballco & Gracia, 2022; European Parliament, Council of the European Union, 2006). The usage of nutrition claims in the European Union is guided by law, which determines the specific nutrient limits a product needs to fulfill to qualify for a specific nutrition claim.

Nutrition claims are very different from front-of-package (FOP) nutrient profiling systems that consist of summative measures such as NuVal (Nikolova & Inman, 2015), NutriScore (Dubois et al., 2020) and the Choices Health symbol (Maesen et al., 2021). While these summative measures give consumers an assessment of the overall healthiness of a product, a nutrition claim only makes a claim about one (or sometimes multiple) ingredient(s). As a result, nutrition claims are also different from *nature-based* claims (e.g., wholegrain, no added preservatives) that make no reference to specific nutrients, but instead focus on the health benefits of a product that are derived without any human intervention (Chandon & Cadario, 2023). Nutrition claims are also distinct from FOP health claims, functional claims and disease-risk reduction claims, which specifically link a nutrient to health outcomes (Ballco & Gracia, 2022). In contrast, nutrition claims do not explicitly link the claim to the

Table 1
Overview of studies on nutrition claims (in alphabetical order).

Paper	Presence nutrition claim	Absence nutrition claim	#SKUs	#Categories	Perception[a]	Choice/ PI[b]	Quantity	Real-life supermarket purchase behavior
André et al. (2019)	√	√	16	2	√			
Andrews et al. (1998)		√	2	1	√	√		
Andrews et al. (2000)		√	2	1	√	√		
Ares and Gámbaro (2007)	√		5	5	√	√		
Ares et al. (2008)	√	√	4	4	√	√		
Ares et al. (2009)	√		1	1	√	√		
Aschemann-Witzel and Hamm (2010)	√		3	3		√		
Barreiro-Hurle et al. (2010)		√	2	2		√		
Bech-Larsen and Grunert (2003)	√		3	3	√			
Belei et al. (2012)	√	√	2	2			√	
Berning and Sprott (2011)		√	4	4		√		
Bialkova et al. (2016)		√	2	2	√	√		
Carrillo et al. (2012)	√	√	1	1				
Chandon and Cadario (2023; study 2)	√	√	1	1	√	√		
Cleeren et al. (2016)		√	1	1			√	√
Ebneter et al. (2013)		√	1	1	√		√	
Faulkner et al. (2014)		√	1	1				
Franco-Arellano et al. (2020)	√		1	1	√	√		
Garretson and Burton (2000)	√	√	1	1	√	√		
Geyskens et al. (2007)		√	1	1	√		√	
Jahn et al. (2023)		√	1	1	√	√		
Keller et al. (1997)		√	1	1	√	√		
Kemp et al. (2007)		√	1	1	√	√		
Kiesel and Villas-Boas (2013)		√	1	1		√	√	√
Kozup et al. (2003)		√	1	1	√	√		
Lähteenmäki et al. (2010)	√		3	3	√			
Mai and Hoffmann (2015; study 3)		√	1	1	√	√		
Orquin and Scholderer (2015)	√	√	3	3	√	√		
Prasad et al. (2008)			23,036	10		√	√	√
Roe et al. (1999)	√	√	3	3	√	√		
Steinhauser et al.(2019)	√		2	2		√		√
Talati et al. (2016a)	√	√	4	5	√	√		
Talati et al. (2016b)	√	√	4	4	√	√		
Van Kleef et al. (2005)	√	√	10	10	√	√		
Van Trijp and Van der Lans (2007)	√		1	1	√			
Verbeke et al. (2009)	√		3	3	√	√		
Wansink and Chandon (2006)		√	2	2	√		√	
Current paper	√	√	**1,018**	**17**		√	√	√

Notes: [a] Includes studies that use measures related to the perceived healthiness, tastiness, credibility and liking. [b] Includes studies that use willingness to try and purchase intention as dependent variable.

health outcomes and as a result may lead to (incorrect) inferences on the healthiness of a product due to a halo effect (i.e., rating the product higher on other health attributes not mentioned in the nutrition claim) and a magic-bullet effect (i.e., attributing inappropriate health benefits to the product) (Roe et al., 1999) as consumers have the tendency to generalize claims to the overall healthiness of the product (Andrews et al., 1998; Wansink, 2003). Because of these important differences, results of prior research on other FOP labels do not necessarily generalize to nutrition claims.

We investigate the effect of presence and absence nutrition claims on SKU choice and SKU quantity. As, a priori, we do not predict a different effect of nutrition claims across SKU choice and SKU quantity, we discuss these effects together as *SKU purchase behavior*. Presence and absence nutrition claims may lead consumers to overgeneralize the healthiness of the product (Roe et al., 1999). Recent research, however, suggests that presence nutrition claims are perceived as both healthier and tastier than their absence counterparts (André et al. 2019; Chandon & Cadario, 2023). Importantly, these perceptual distinctions between presence and absence nutrition claims do not manifest when consumers are tasked with choosing among products from multiple brands, some with claims and some without (André et al., 2019). Thus, it is pertinent and valuable

to explore how the effects of presence and absence nutrition claims may differentially influence purchase behavior in a real grocery context.

We argue that the net effect of the two types of nutrition claims on SKU purchase behavior is moderated by different SKU and category characteristics. Our study relies on two underlying mechanisms to select the specific moderating variables and argue for their impact on SKU purchase behavior: (i) the credibility of the nutrition claim, and (ii) the weight of the nutrition claim in the SKU purchase behavior. While our data do not allow to verify that these theoretical mechanisms are driving our results, these mechanisms provide a theoretical foundation for understanding how and why nutrition claims influence real-world SKU purchase behavior.

First, previous research has demonstrated that more credible claims increase consumer confidence in the claim, which leads to a higher effectiveness of the claim (Erdem & Swait, 1998). We argue below that the credibility of the nutrition claim is influenced by the category healthiness, the SKU price, type of brand, brand advertising, and category-level claim penetration. Second, the weight of the nutrition claim in the SKU purchase behavior is determined by the diagnosticity of the nutrition claim and the attention paid to other product attributes. We argue that the weight of the nutrition claim in the purchase decision is lower for SKUs with more marketing activity, and in categories in which many SKUs contain nutrition claims (i.e., claim penetration is high). We continue with a discussion on the main and moderating effects which we summarize in Table 2.

2.1. The impact of presence and absence nutrition claims on SKU purchase behavior

While nutrition claims can contribute to the improvement of public health by assisting consumers in making better-informed food choices through the simplification of nutritional information (Bettman et al., 1986; Roe et al., 1999), André et al. (2019) show that these claims often fail to accurately represent a product's true nutritional quality. Additionally, consumers frequently overestimate the health benefits associated with products displaying such claims (Roe et al., 1999). In line with the overall healthiness trend, this suggests that nutrition claims may increase the SKU purchase behavior. Importantly, however, recent research suggests that the healthiness and tastiness inferences drawn from these claims depends on the type of nutrition claim (André et al., 2019; Chandon & Cadario, 2023). Two types of nutrition claims were identified. On the one hand, nutrition claims can focus on the presence of nutrients perceived as beneficial for health (e.g., "high in fiber"), also referred to as *presence nutrition claims*. On the other hand, *absence nutrition claims* hint to the absence or the reduced quantity of nutrients considered as unhealthy (e.g., "low in fat"). Interestingly, presence claims are perceived as both healthier and tastier than their absence counterparts (André et al., 2019). This distinction may be explained by the phenomena of additivity-dominance and subtracted-ingredient effects, which put forward that additions have a much stronger effect than deletions (e.g., Rozin et al., 2009; Scott & Rozin, 2017). Ingredient removal or reduction might thus be perceived as more detrimental to taste perceptions than ingredient addition (André et al, 2019). Given the pivotal role of taste in food decisions (Glanz et al. 1998; Verbeke, 2006), absence nutrition claims may have a negative impact on SKU purchase behavior, while we expect a positive effect of presence nutrition claims.

2.2. The perceived credibility of the nutrition claim

Research has demonstrated that the effectiveness of a particular product claim depends on its perceived credibility. The perceived credibility of a claim increases perceived quality, decreases consumer perceived risk and information costs, and thus increases consumer expected utility (Erdem & Swait, 1998). Erdem and Swait (1998) posit that credibility underlies consumer confidence in a firm's product claims. In the context of nutrition claims, the credibility of a nutrition claim has been shown to be driven by the fit between the nutrition claim and the product carrier (Ares & Gámbaro, 2007; Bech-Larsen & Grunert, 2003; Verbeke et al., 2009; Van Kleef et al., 2005). Below, we argue how different SKU and category moderators link to the credibility of presence and absence nutrition claims.

Category Healthiness. Consumers classify food products into healthy and unhealthy product categories, and their choices are driven by perceived category healthiness (Ma et al., 2013; Nikolova & Inman, 2015). Specifically, healthy categories are consistent with long-term self-control goals (e.g., losing weight) but do not per se offer immediate gratification. Unhealthy product categories, in contrast, are consistent with short-term goals of immediate gratification (e.g., eating a chocolate cake) but are inconsistent with long-term self-control goals (e.g., Wertenbroch, 1998). We expect that nutrition claim credibility will be influenced by the (un)healthiness of the product category. Prior research demonstrates that nutrition claims are more credible for healthy (vs. unhealthy) food products because of higher fit between the nutrition claim and product healthiness perceptions (e.g., Ares & Gámbaro, 2007).

Importantly, however, we expect category healthiness to have different effects for presence and absence nutrition claims. Numerous studies have demonstrated that claims emphasizing positive contributions (i.e., presence nutrition claims) are more credible for products that are intrinsically healthy since they are perceived as more credible carriers (Ares & Gámbaro, 2007; Verbeke et al., 2009). In contrast, absence nutrition claims stress the reduction of an unhealthy ingredient and fit better with an unhealthy product category in which the presence of the unhealthy ingredient is generally accepted (Bech-Larsen & Grunert, 2003).

SKU Price. Research demonstrates that consumers believe that healthier food is more expensive than less healthy food (Haws et al., 2017). Following the high quality = expensive conjecture, this healthy = expensive intuition is inferred even

Table 2
Expected effects of SKU and category moderators.

	Credibility		Weight		SKU purchase decision	
	Presence	Absence	Presence	Absence	Presence	Absence
Category healthiness	+	–			+	–
SKU price	+	–			+	–
Private label	–	–			–	–
Brand Advertising	+	+	–	–	+/-	+/-
SKU Price promotions			–	–	–	–
Category Claim Penetration	+	+	–	–	+/-	+/-

if not objectively true. Together with research demonstrating that nutrition claims are more credible when they are congruent with the healthiness image of the base product (e.g., Ares & Gámbaro, 2007), this suggests that nutrition claims will be perceived as more credible for higher-priced products.

Nutrition claim type is also expected to play an important role in this relationship. Specifically, prior research defines the perceived value from acquiring a product as a tradeoff between what is received (i.e., the benefit) and what is given (i.e., sacrifice) (Dodds et al., 1991; Zeithaml, 1988). That is, the perceived value of a product is positively influenced by the benefits while it is negatively impacted by the sacrifices (Zeithaml, 1988). Presence nutrition claims, which emphasize the presence of a healthy nutrient, are likely to enhance the perceived value by emphasizing added benefits. In contrast, absence nutrition claims, which emphasize the absence or reduction of less desirable ingredients, may reduce perceived value by emphasizing what is taken away. This implies that presence nutrition claims will align better with a high price, as the higher perceived value may justify a higher cost. Absence nutrition claims, on the other hand, may be perceived lower in overall value, and thus will fit better with a lower price, even though the actual development cost may be higher due to ingredient removal or reformulation.

Brand advertising. Brand advertising is often used to build brand equity (e.g., Ailawadi et al., 2003). Brand equity serves as a general market signal of the credibility of brand associations (Erdem & Swait, 1998). As a result, strong brands are seen as credible information sources of product attributes (Erdem & Swait, 1998). Therefore, brand advertising is expected to increase the effectiveness of both types of claims.

Type of brand. Private labels typically have lower brand strength than national brands (Ailawadi et al., 2003). Moreover, although store brands are becoming largely quality-equivalent to national brands, they are – in general – still perceived as lower in quality than their national brands counterparts (Pauwels & Srinivasan, 2009; Rossi et al., 2015). Since brand equity and brand quality are considered credible information sources about product attributes (Erdem & Swait, 1998), we expect that the credibility of nutrition claims for private labels is smaller than for national brands. Therefore, both types of nutrition claims are expected to be less effective for private labels than for national brands.

Category Claim Penetration. Drawing on the 'truth effect', the percentage of SKUs holding a presence or absence nutrition claim in a particular category can impact the credibility of these claims. According to this 'truth effect', repeated exposure to statements increases the rated truth of these statements compared to a single exposure (Arkes et al., 1989; Hawkins & Hoch, 1992; Hawkins et al., 2001). The repeated encounter induces a feeling of familiarity – driven by enhanced processing fluency – leading to higher subjectively perceived statement credibility (e.g., Reber & Schwarz, 1999). Therefore, presence and absence nutrition claims are expected to be perceived as more credible when more SKUs in a given product category hold the same type of nutrition claim (high penetration) compared to when less SKUs hold the same type of nutrition claim (low penetration).

2.3. The weight of the nutrition claim in the purchase decision

Purchase behavior in a grocery context is a complex decision as consumers typically process a lot of information on many product varieties in each product category. Consumers confronted with large amounts of information develop mechanisms for limiting information acquisition (Malhotra, 1984), such as simply ignoring parts of the information. Thus, the effect of nutrition claims depends on whether they are considered important enough to weigh in the purchase decision. Nutrition claims weigh more when the claims are perceived as more diagnostic (Chernev, 2006). In addition, as consumers can only process a limited amount of information (Malhotra, 1984), the attention paid to other product attributes distracts from the information in the nutrition claims, and hence decreases their weight in the purchase decision. In this regard we consider the marketing activities (price promotions and brand advertising) and claim penetration in the category as moderators.

Marketing activities: SKU Price promotions and Brand advertising. Marketing actions such as SKU price promotions and brand advertising tend to distract the consumer's attention from the nutrition claim. While price promotions tend to make the price attribute of the SKU more prominent because of an increased price sensitivity (Mela et al., 1998), brand advertising spending leads to an increased focus on the brand attribute of the SKU. As a result, marketing actions lead to a stronger focus on SKU attributes such as the price or the brand, at the expense of other sources of information such as the nutrition claim. Hence, marketing activities are expected to reduce the weight of these claims in the SKU purchase decision.

Category Claim Penetration. The percentage of SKUs holding a presence or absence nutrition claim in a particular category is inversely related to the distinctiveness of the nutrition claim in the category and hence may impact the diagnostic value of the attribute. Indeed, research has argued that when many items share the same attribute, perceived distinctiveness is lower and the diagnostic value and salience of that attribute decreases (Chernev, 2011; Van Herpen & Pieters, 2002). In a similar vein, differentiation, rather than parity, in assortment pricing aids consumer choice when consumers are unsure of their preferences (Chernev, 2006). Hence, price information is only diagnostic when products are priced differently. We thus expect that nutrition claims affect purchase behavior more when their penetration is lower, or the category has less products with a similar nutrition claim.

In Table 2, we summarize the expected effects of the different SKU and category moderators on the credibility and the weight of presence and absence nutrition claims and show the expected effects on SKU purchase behavior.

3. Data

We use household panel data from Kantar UK to study the impact of nutrition claims on households' SKU purchase behavior, tracking purchase information for 48,561 UK households in 29 food product categories from January 2009 to August 2012.[1] The data contains purchases at the SKU-level in all UK-based grocery and mass-market chains.[2] To ensure the stability of the estimated parameters, we focus our analysis on the top 80 % best-selling SKUs in each category (in total 2,049 SKUs, see Gordon et al., 2013 for a similar data selection).

We combine the purchase data with information on these SKUs' nutrition claims and nutritional content, which were transcribed by an independent consulting firm using scanned pictures of the front side of the packages from 2009. Some packages were not scanned in a sufficiently high resolution, leaving them unreadable. We obtain a good coverage of 1,519 out of 2,049 SKUs (74 %) that account for 81 % of the total quantity purchased in the 29 categories. After this classification, to make the estimated effects more comparable across categories, we select those 17 categories (1,018 SKUs) that carry at least two SKUs with a presence nutrition claim, at least two SKUs with an absence nutrition claim, and at least two SKUs without any nutrition claim.

Several inclusion criteria applied to households. First, to be included in a specific category dataset, households must have made at least one purchase in the category in the initialization period, and at least one in subsequent years to identify our independent variables, leaving 23,930 households.[3] Next, we removed households from the category data who have ever purchased an SKU with missing claim information in that particular category, leaving 15,263 households in the initial sample of 29 categories. In the limited situation in which households buy more than one SKU in a category in the same shopping trip (only 7 % of all shopping trips), we assume that choice occurs sequentially. Our final sample consists of 9,945 households in 17 categories and 417,649 household-category-retail chain shopping trips. We define a shopping trip as an occasion at which a household makes a purchase in at least one (but possibly more) of the original set of 29 categories for which we have data at a specific retailer at one specific day.

3.1. Independent variables at the SKU level

Table 3 shows summary statistics per category. Correlation tables are given in Web Appendix A, as well as additional household-level summary statistics. Our main variables of interest relate to nutrition claims. We define a nutrition claim as a claim that suggests or implies that a food has particular beneficial nutritional properties due to its composition regarding a particular nutrient (e.g., "source of", "free of", "high", "low", or "reduced in a particular nutrient") (European.

Parliament, Council of the European Union, 2006). This corresponds to the definition of science claims in André et al. (2019).

We classify each nutrition claim as a presence or absence nutrition claim. Two coders classified 1,004 unique nutrition claims into two categories (i.e., presence, or added quantity of healthy ingredients, versus absence, or reduced quantity of unhealthy ingredients). The inter-coder reliability was high (i.e., 95.2 %), and all coding conflicts were solved in a post-discussion. Two dummy variables capture whether an SKU has one or more presence nutrition claims (i.e., *PresClaim*) and one or more absence nutrition claims (i.e., *AbsClaim*). 126 SKUs (11.6 %) carry presence nutrition claims and 329 SKUs (30.2 %) carry absence nutrition claims,[4,5].

[1] We tested whether the situation in 2009–2012 is reflective for the more recent situation in 2021–2022 using acquired data of a market research firm by comparing the percentage of nutrition claims on SKUs in the selected categories for the two time periods. While in the estimation dataset, 42% of the SKUs in the selected categories contained at least one claim, this number declined slightly to 34% and 29% for 2021 and 2022, respectively. Hence, we find that the number of nutrition claims in the UK was rather stable (and even slightly decreased) for the selected categories.

[2] We focus on all major UK-based grocery and mass-market chains, excluding online retailers. 13 chains are included: Aldi, Asda, Co-op, Iceland, Lidl, Marks & Spencer, Morrisons, Sainsbury, Tesco, Tesco Express, Tesco Extra, Tesco Metro, and Waitrose. We exclude Netto and Somerfield, because Kantar does not track all SKUs in these chains. This selection of chains reduces the number of available households to 46,465.

[3] We use an initialization period of 52 weeks (starting in 2009) to operationalize, for example, our inventory and purchase rate variables.

[4] In a separate Excel file that is included as appendix, we provide the nutrition claims per SKU for each category.

[5] We also used automated natural language processing without human intervention to validate our coding and the results were very similar. Details can be requested from the authors.

Table 3
Summary statistics per category.

Category	Products					Product characteristics								Category characteristics	
	No. of SKUs	No. of brands	No. of forms	No. of flavors	No. of pack sizes	No. of SKUs (brands) with pres nut claims	No. of SKUs (brands) with abs nut claims	No. of SKUs (brands) with nature claims	No. of SKUS with (un)colored traffic light	No. of SKUs with pres(abs) nut claim & traf. light	Avg. nutritional value (C/A score)[a]	Avg. regular price[b]	Avg. price promotion[c]	Healthiness	Claim penetration (pres/abs)
Cereal bars	72	11	2	5	6	10 (4)	17 (6) [d]	12 (5)	3 (42)	9 (14)	3.1/21.0	1.07	0.04	17.79	0.14/.24
Breakfast cereals	156	7	3	10	7	61 (5) [d]	50 (3)	24 (4)	74 (46)	12 (8)	4.2/14.6	0.41	0.02	24.9	0.39/.32
Pasta						(canned)	40	6	5	2	3	5 (2)	4 (2) [d]	3 (1)	3 (5)
0 (3)	0.2/2.3	0.18	0.02	32.69	0.13/.10										
Baked beans	25	3	2	2	4	4 (2) [d]	5 (2) [d]	1 (1) [d]	3 (4)	2 (2)	3.7/4.2	0.17	0.02	34.64	0.16/.20
Chocolate bars	42	7	3	4	6	3 (2) [d]	4 (2) [d]	4 (2) [d]	3 (19)	2 (3)	2.6/24.4	0.63	0.04	12.54	0.07/.10
Sweet biscuits	69	9	6	9	6	2 (2)	24 (5) [d]	24 (5) [d]	13 (32)	0 (17)	2.7/24.0	0.44	0.03	13.91	0.03/.35
Plain & savoury biscuits	47	6	3	4	7	3 (2)	9 (4) [d]	9 (4) [d]	9 (22)	0 (5)	3.1/22.4	0.58	0.02	15.96	0.06/.19
Chocolate biscuits	80	17	2	6	4	6 (3)	30 (12) [d]	29 (11) [d]	7 (47)	5 (26)	1.9/24.9	0.15	0.03	11.78	0.08/.38
Yoghurt	99	9	6	8	5	6 (3)	52 (8) [d]	15 (7) [d]	10 (31)	0 (23)	0.18/5.4	0.31	0.02	30.f09	0.06/.53
Margarine	29	10	3	1	3	2 (3) [d]	5 (3)	0	0 (11)	0 (2)	0.0/21.6	0.29	0.02	13.57	0.07/.17
Processed meat	36	5	1	3	6	2 (2) [d]	13 (3) [d]	13 (3) [d]	20 (3)	0 (1)	1.5/10.5	0.55	0.03	26.5	0.06/.36
Processed fish	40	4	7	2	2	3 (1) [d]	10 (1) [d]	8 (1) [d]	18 (8)	0 (4)	0.9/8.4	0.80	0.03	27.05	0.08/.25
Crispy snacks	83	6	3	5	8	5 (2) [d]	21 (4) [d]	17 (3) [d]	3 (36)	2 (11)	4.2/22.0	0.62	0.03	17.06	0.06/.25
Savoury snacks	128	6	3	9	10	2 (3) [d]	38 (4) [d]	33 (3) [d]	15 (55)	1 (19)	2.6/24.2	0.80	0.03	13.37	0.02/.30
Fruit juice	70	9	2	7	8	2 (2)	18 (3) [d]	17 (3) [d]	5 (7)	6 (6)	0.2/3.4	0.20	0.04	34.02	0.03/.26
Milkshakes	31	4	2	4	5	7 (2) [d]	17 (4) [d]	8 (2) [d]	5 (11)	0 (3)	0.1/1.00	0.18	0.04	31.12	0.23/.55
Colas	43	4	1	2	7	3 (2)	12 (3) [d]	4 (2) [d]	2 (8)	0 (6)	0.0/.8	0.11	0.03	34.23	0.07/.28

[a] Nutritional value is based on the UK Nutrient Profile (NP) score. We separately report the 'good' nutrient C score (based on fiber) and the 'bad' nutrient A score (based on fat, sugar, sodium and energy). Higher values indicate more presence of 'good'/'bad' nutrients. [b] Regular price per 100 mg/ml of product [c] Price promotion in cents [d] Indicates that in this category at least one private label uses this claim.

We obtain information on each SKU's *brand name*, *form*, *size*, and *flavor* from the household scanner data. Store brands are all re-classified under a common label (i.e., Private Label). Next, we group flavors into larger groups (e.g., from "Grapefruit + Pineapple" to "Mixed Fruit"). Finally, we create package size brackets (e.g., from a continuous variable containing values like 202 g, 204 g, 210 g, 250 g, 300 g, to 200–250 g, 250–300 g). We do this thoroughly for each category to accommodate every category's specific needs. All these attribute levels are included in the intercept term as separate dummy variables (as described in the methodology section). An overview of the attribute levels per category is provided in Web Appendix B.

We summarize the operationalization of all included variables in our models in Table 4.

3.2. Model free evidence

We provide some model free evidence on the effects of nutrition claims. We find that SKUs with presence (absence) nutrition claims have a median 1.44 (4.17) percentage point higher (lower) choice share relative to SKUs without claims. Conditional on choice, households buy a median of 37.76 (33.52) units fewer SKUs with presence (absence) nutrition claims relative to SKUs without claims. Overall, these patterns suggest a positive (negative) relationship between presence (absence) nutrition claims and choice, while the relationship with quantity bought seems negative for both nutrition claim types. We formalize these patterns using econometric models as we discuss next.

4. Econometric model

We study the impact of nutrition claims on SKU choice and purchase quantity. We use an incidence-choice-quantity approach (e.g., Andrews & Currim, 2009; Ailawadi et al., 2007). Given category-specific attribute levels, we estimate these models separately for all categories. For each category, we model the probability that household i buys q units of SKU j on shopping trip t as:

$$P_{it}(j\&q) = P(I_{it}) \times P\left(C_{ijt}|I_{it}\right) \times P\left(q_{ijt}|I_{it}, C_{ijt}\right), \tag{1}$$

where

$P(I_{it})$ = the probability that household i purchases in the category at shopping trip t,

$P(C_{ijt}|I_{it})$ = the probability that household i purchases SKU j at shopping trip t given a purchase in the category, and.

$P(q_{ijt}|I_{it}, C_{ijt})$ = the probability that household i buys q units of SKU j at shopping trip t given a purchase of SKU j in the category.

In line with previous studies (e.g., Andrews & Currim, 2009; Ailawadi et al., 2007), category incidence and SKU choice are handled in a nested logit framework, and quantity is modeled using a zero-truncated Poisson model. Like these studies, we account for heterogeneity in preferences across households. We also account for the potential endogeneity in prices, price promotions, brand advertising and in the presence of both types of nutrition claims (see more details below). Different from these prior studies, our model for SKU choice accounts for the fact that variation in our key independent claim variables occurs at the SKU-level, and hence we model at the SKU rather than at the more traditional brand level. As the number of SKUs in a particular category can be quite large (e.g., 156 SKUs in the breakfast cereals category), inclusion of SKU-specific intercepts should be avoided due to a large number of parameters. Instead, we use the attribute-based model as introduced by Fader and Hardie (1996). We outline each of the three model components below.

4.1. Category incidence

The category incidence model in the nested logit framework takes the form of a binary logit model. For each category, the probability that household i makes a purchase in the category on purchase occasion t is given as:

$$P(I_{it}) = \frac{\exp(W_{it})}{1 + \exp(W_{it})}, \tag{2}$$

where the deterministic part of utility is given as:

$$W_{it} = \kappa_{oi} + \kappa_1 AvgConsumption_i + \kappa_{2i} Inventory_{it} + \kappa_{3i} IncVal_{it}. \tag{3}$$

Following Andrews and Currim (2009) and Ailawadi et al. (2007), we include average consumption (*AvgConsumption)* and the inventory (*Inventory*) as the explanatory variables of purchase incidence. $IncVal_{it}$ is the inclusive value, defined as the log of the denominator of Equation (4). As $AvgConsumption_i$ does not vary over time, we do not specify a household-specific coefficient for this variable.

4.2. SKU choice

In the nested logit framework, the choice model takes the multinomial logit form. The choice probability for household i for SKU j on shopping trip t is given as

Table 4
Operationalization of independent variables.

Variable	Operationalization	Source
SKU level variables		
$Presclaim_j$	Dummy variable indicating whether SKU j has one or more presence nutrition claims	FOP scans
$Absclaim_j$	Dummy variable indicating whether SKU j has one or more absence nutrition claims	FOP scans
$Brand_j$	Set of dummy variables per category indicating the brand of SKU j.	Kantar
$Form_j$	Set of dummy variables per category indicating the form of SKU j.	Kantar
$Flavor_j$	Set of dummy variables per category indicating the flavor group of SKU j.	Kantar
$Size_j$	Set of dummy variables per category indicating the size group of SKU j.	Kantar
SKU $Price_{ijt}$	Regular price per volume unit of an SKU j in a given chain in a given week t, where the regular price is defined as the maximum price in the preceding three weeks (Hendel & Nevo, 2006).[a]	Kantar
$SKUPricePromo_{ijt}$	Discount depth of SKU j in a given chain in a given week t defined as the difference between the actual and the regular price (e.g., Jedidi et al., 1999).	Kantar
Private $label_j$	Dummy variable that indicates whether the brand is a private label (=1) or a national brand (=0).	Kantar
$BrandAdvertising_{jt}$	Advertising spending (in £1,000) for the brand of SKU j in a given week t.[b]	Nielsen
$NutrValGood_j$	Nutritional value score (0–5) of 'good' ingredients (i.e., fiber) based on UK Nutrient Profiling "C score".[c] Higher values indicate a higher presence of 'good' ingredients.	Kantar
$NutrValBad_j$	Nutritional value score (0–40) of 'bad' ingredients (i.e., sum of fat, sugar, sodium, and energy) based on UK Nutrient Profiling "A score".[c] Energy is based on converting SKU calories to kJ. Higher values indicate a higher presence of 'bad' ingredients.	Kantar
$Nature_j$	Dummy variable indicating whether SKU j has one or more nature claims following André et al. (2019).[d]	FOP scans
$GDATraffic_j$	Dummy variable indicating whether a traffic light-style Guideline Daily Amount label is present on SKU j. These labels provide FOP nutritional content information supported by red–orange-green color coding. [d]	FOP scans
$GDANoTraffic_j$	Dummy variable indicating whether a non-traffic light-style Guideline Daily Amount label is present on SKU j. These labels provide FOP nutritional content information only. [d]	FOP scans
$LabelIngre_j$	Dummy variable indicating whether one or more ingredient-related labels (other than nutrition claims) are present. These include labels as wholegrain, protein, no artificial colors/preservatives/flavours/ingredients, kosher, vegetarian, organic, fair trade and gluten free. [d]	FOP scans
$LabelHealth_j$	Dummy variable indicating whether one or more health advice labels are present. Includes five-a-day, health easy, weight watchers and breakfast labels. [d]	FOP scans
Household level variables		
$AvgConsumption_i$	Average daily consumption of household i, computed as the total amount bought in the category during the initialization period divided by the number of days in the initialization period.	Kantar
$Inventory_i$	Inventory of household i, where inventory of household i at day d is defined as $Inventory_{id} = \max(Inventory_{i,d-1} + Q_{i,d-1} - AvgConsumption_{id}, 0)$, where $Q_{i,d}$ is the quantity bought on day d.	Kantar
$PurchaseRate_i$	Purchase rate of household i, computed as average quantity bought during initialization, conditional on purchase (Andrews & Currim, 2009).	Kantar
Category level variables		
CatHealth	Category healthiness score, computed as sales-weighted average nutritional value score (=NutrValBad-NutrValGood)[c]. Weights are based on SKU share of volume sales in initialization period.	Kantar
CatClaimPenetration	Category claim penetration, separately computed as the share of SKUs in a category with a presence or absence nutrition claim (two variables).	FOP scans

[a] To compute this variable from our household scanner data, we create store-week-SKU-level price matrices, recording weekly purchases and average price per store. For SKUs without price information, we first check whether price information from other stores belonging to the same banner is available, and use the average price of those stores. Next, we check for stock-outs following Campo et al. (2003, Appendix A). For weeks without a stockout and no price information, we impute using the price of the week before or, when unavailable, with the week after. SKUs with more than 80% missing price information after this procedure are removed from the choice set.

[b] Nielsen provides monthly advertising spending. This was converted to the weekly level by computing average daily advertising spending, and aggregating that to the weekly level.

[c] See https://www.gov.uk/government/publications/the-nutrient-profiling-model for a guide on how to compute the Nutrient Profiling score. Lim et al. (2020) is an example of prior research in marketing using this score model.

[d] In contrast to nutrition claims, which are regulated textual labels present on packaging, these labels provide additional textual and/or visual information on the content of the product, not regulated by law.

$$P(C_{ijt}|I_{it}) = \frac{\exp(V_{ijt})}{\sum_k \exp(V_{ikt})} \tag{4}$$

with

$$V_{ijt} = b_{ij} + \sum_{k=1}^{K} \sum_{l=1}^{L_K} \gamma_{ikl} AttLoy_{klit} + \beta_{5i} SKUPrice_{ijt} + \beta_{6i} SKUPricePromo_{ijt} + \beta_{7i} BrandAdvertising_{jt} + \tau_{jt} \tag{5}$$

$$b_{ij} = \sum_{k=1}^{K} \sum_{l=1}^{L_K} \alpha_{ikl} A_{kl} + \beta_{1i} PresClaim_j + \beta_{2i} AbsClaim_j + \beta_{3i} NutrValueGood_j + \beta_{4i} NutrValueBad_j + B_i XLabel_j + \epsilon_{ij}, \tag{6}$$

We model the household's utility as a function of two dummy variables indicating whether presence nutrition claims ($PresClaim_j$), or absence nutrition claims ($AbsClaim_j$) are present on the front of the package of the SKU. We control for nutritional value ($NutrValueGood_j$ and $NutrValueBad_j$), SKU price ($SKUPrice_{ijt}$), SKU price promotions ($SKUPricePromo_{ijt}$), brand advertising ($BrandAdvertising_{jt}$), and other types of claims and labels on the SKU ($XLabel_j$) as specified in Table 4. We specify a multilevel model structure as several SKU-level variables do not vary across shopping trips. The normally distributed random effect ε_{ij} captures this time-invariant dependence across households and products. Finally, the unobserved common demand shock τ_{jt} allows for contemporaneous correlation between the incidence/choice and quantity models (Andrews & Currim, 2009). We further extend this model with interaction terms to assess the moderating impact of SKU and brand characteristics on the effect of the two types of nutrition claims on SKU choice.

To address the large amount of required SKU-specific intercepts, we include time-invariant attribute intercepts A_{kl} (e.g., Fader & Hardie, 1996). That is, we specify K categorical attributes (k = 1,. . .,K) each with L_k attribute levels (l_k = 1,. . ., L_k) representing physical characteristics for which different combinations uniquely identify each SKU. These four SKU attributes (K = 4; brand, form, flavor and size) were identified for all categories. The specific attribute levels L_k are category-specific. In Web Appendix B, we detail the attribute levels for each category. One of these levels for brand is private label (PL_j), which we use to test for its moderating impact on the effect of nutrition claims. Because each SKU is identified through a unique combination of attribute levels, the attribute-based approach only requires estimation of intercepts for each attribute level. The intercept for one level in each attribute is constrained to zero for identification. Finally, we include the variables $AttLoy_{klit}$ to capture attribute-level loyalties of consumers (Fader & Hardie, 1996). The variable for level l of attribute k is defined as $AttLoy_{klit} = \rho_{kl}\, AttLoy_{kli,t-1} + (1-\rho_{kl})I_{kli,t-1}$, where $I_{kli,t-1}$ is an indicator variable equal to 1 if attribute level l of attribute *k* was purchased at time t-1, and 0 otherwise.

4.3. Purchase quantity

Conditional on incidence and choice, the probability that household i buys q units of SKU j at shopping trip t is modeled using a zero-truncated Poisson distribution:

$$P(q_{ijt}|I_{it}, C_{ijt}) = \frac{\exp\left(-\lambda_{ijt}\right)\left(\lambda_{jit}\right)^{\text{qijt}}}{[1-\exp\left(-\lambda_{iht}\right)]\text{q}_{\text{ijt}}!}, q_{ijt} = (1, 2, \cdots, \infty), \tag{7}$$

where the rate parameter of the Poisson distribution is a function of covariates as follows:

$$\begin{aligned}\lambda_{ijt} = \exp\big(&\delta_{0i} + \delta_{1i}PresClaim_j + \delta_{2i}AbsClaim_j + \delta_{3i}NutrValueGood_j + \delta_{4i}NutrValueBad_j \\ &+\delta_{5i}SKUPrice_{jt} + \delta_{6i}SKUPricePromo_{jt} + \delta_{7i}BrandAd\,vertising_{jt} + \delta_8 PurchaseRate_i + \delta_{9i}In\,ventory_{it} + \delta_{10i}PL_j + \Delta_i \text{XLabel}_j + \theta_{jt}\big)\end{aligned}. \tag{8}$$

Most variables included in this model are standard (e.g., Andrews & Currim, 2009; Ailawadi et al., 2007), while the rest has been defined before. The SKU-week specific error term θ_{jt} is correlated with τ_{jt} in the incidence/choice model to account for contemporaneous correlation (Andrews & Currim, 2009). As $PurchaseRate_i$ does not vary over time nor over SKUs, we do not specify a household-specific coefficient for this variable. We extend this equation with interaction terms to test the moderating impact of SKU and brand characteristics.

4.4. Estimation

We use a multivariate normal random coefficients approach to account for heterogeneity in preferences across households (e.g., Gordon et al., 2013) for those parameters specified to be household-specific. That is, we assume $\{\kappa_i, \alpha_{ikl}, \gamma_{ikl}, \beta_i, \partial_i\} \sim \text{MVN}(\{\kappa, \alpha_{kl}, \gamma_{kl}, \beta, \partial\}, \Sigma)$. We jointly estimate the model using a simulated maximum likelihood approach with 500 Halton draws (Gordon et al.,2013). The full likelihood is given as:

$$\text{L} = \prod_i \prod_t \prod_j \left(\frac{\exp\left(W_{it}\right)}{1+\exp\left(W_{it}\right)}\right)^{I_{it}} \left(\frac{1}{1+\exp\left(W_{it}\right)}\right)^{(1-I_{it})} \left(\frac{\exp\left(V_{\text{ijt}}\right)}{\sum_{\text{k}}\exp\left(V_{\text{ikt}}\right)}\right)^{C_{itj}} \left(\frac{\exp\left(-\lambda_{jit}\right)\left(\lambda_{jit}\right)^{q_{itj}}}{[1-\exp\left(-\lambda_{jit}\right)]q_{itj}!}\right)^{C_{itj}} \tag{9}$$

4.5. Correcting for endogeneity

The presence of two nutrition claim types, the SKU price, SKU price promotions and brand advertising are variables under managerial control which may be driven by unobserved factors which also drive SKU purchase behavior, leading to a potential endogeneity bias.

First, the presence of the two nutrition claim types varies across SKUs and categories and could be correlated with (unobserved) SKU characteristics resulting from strategic decisions made by managers (cross-sectional endogeneity). To control for this source of endogeneity, we employ a control function approach (Papies et al., 2017, p. 589), which is particularly applicable in our case as we are dealing with non-linear models, have binary endogenous variables, and several interaction terms (Papies et al., 2017, p. 613-617). We perform two binary probit regressions per category with $PresClaim_j$ and $AbsClaim_j$ as dependent variables, modeling the probability that a manufacturer includes a presence/absence nutrition claim on SKU j.

Our independent variables consist of variables included in the SKU models (average SKU price, average SKU price promotion, average brand advertising, good and bad nutritional value, a set of other label dummy variables, and the size, flavor, form and brand dummy variables), as well as a set of instrumental variables (see below). Given the large number of variables relative to the number of observations for some categories, we use a jackknife instrumental variables estimator (JIVE, Hansen & Kozbur, 2014) based ridge-regularized probit models; see Web Appendix D for more detailed information. After estimation, we include the generalized residuals as a control variable in our models (Germann et al., 2015). We do not specify heterogeneous parameters across households to keep the model concise.

To identify valid instruments for the control function approach, we carefully studied the process leading to the decision to include nutrition claims on an SKU. To the best of our knowledge, academic literature has not described this process. We thus relied on three FMCG brand managers as well as an academic nutrition claims expert to provide insights in factors driving nutrition claim usage. Based on our interviews and suggestions during the review process, we identified three valid sets of instruments.

First, we use the *number of potential nutrition claims*, as determined by the nutritional composition of each SKU. Given that legislation determines if and which nutrition claims can be used, this provides manufacturers a natural selection criterion to consider nutrition claim usage. We identify for each SKU the number of eligible presence and absence nutrition claims on the basis of the nutritional composition and create two instruments for the potential number of presence and absence nutrition claims on an SKU. As a second instrument we use *competitive claim intensity*, as across our interviews it emerged that competitive claim usage also plays an important role in the nutrition claim usage decision. We measure competitive intensity using a Herfindahl index (Raju, 1992) based on the share of SKUs of the second-degree peers of each manufacturer that carries a presence (absence) nutrition claim (cfr. Shi et al., 2021). Following Moon et al. (2023), we compute these instruments for both 3- and 4-digit SIC codes industry groups. This gives rise to two instruments for each nutrition claim type. Finally, we use *competitive horizontal and vertical differentiation* as instruments to capture assortment-related drivers of nutrition claim usage.[6] Using the same 3- and 4- digit SIC industry groups, we use average differentiation within the second-degree peer groups as instruments. Following Schamp et al. (2024), we use SKU breadth (i.e., the number of form-flavor-size package combinations) as a measure of horizontal differentiation, and price dispersion (i.e., the (normalized) difference between a manufacturer's maximum and minimum price) as a measure of vertical differentiation. This provides four instruments for each type of nutrition claims. Web Appendix D provides more details on instrument motivation and construction.

Our first-stage regression results support that our IV's are relevant, as all instruments are significant in at least a quarter of the estimated per-category models, and with face-valid directions (see Web Appendix D). Statistical evidence also supports *instrument strength*, with high first stage R^2 statistics ($\geq$.498), and high regular and Sanderson-Windmeijer incremental F-statistics for nearly all categories.

We also argue that our instruments are *excludable*, as they do not directly influence consumers faced with an SKU purchase task within the specific category but do affect manufacturer's propensity to use nutrition claims. Indeed, the *number of potential nutrition claims* are not observable by individual consumers, as they are not directly derivable from the choice context or SKU information. Our competitive claims and differentiation instruments are excludable by construction, as the second-degree peers' decisions are uncorrelated with unobserved shocks affecting the focal company (Shi et al., 2021p.525). Our use of both 3- and 4-digit SIC codes industry groups further guards against excludability concerns, because even if firms' decisions are affected by close second-degree peers (within the same 3-digit SIC code), it is unlikely they are affected by all second-degree peers (within the same 4-digit SIC code) (Germann et al., 2015). Non-significant Sargan tests ($p > 0.10$) support the above intuition regarding excludability.

Another, but second-order, source of endogeneity may arise through our moderating variables SKU price, SKU price promotion and brand advertising, given that they are likely correlated with the unobserved part of utility, causing temporal endogeneity. We use Gaussian copulas that model the joint distribution of these three potential endogenous variables and the error terms of our SKU models (Park & Gupta, 2012), and hence explicitly model the potential correlation between both. The copula method can be efficiently used when there are multiple endogenous regressors (Park & Gupta, 2012, p. 573-574). For details on the estimation procedure, we refer to Park and Gupta (2012, p. 574). Distribution plots and a Shapiro-Wilks test at $p < 0.05$ confirm that the endogenous variables are not normally distributed in all categories, fulfilling the method's identification criterion (Park & Gupta, 2012, p. 572).

4.6. Comparing coefficients across categories and assessing the impact of moderators

As our data cannot be pooled given the category-specific attribute levels, we estimate the above category incidence, SKU choice and, purchase quantity models for each category separately. We obtain up to 17 estimates for each parameter, because not all categories allow to identify each interaction effect. We cannot directly compare the parameters across categories due to non-linearity and differing scale parameters (e.g., Swait &d Louviere, 1993). We therefore use category-level elasticities η_c as an effect size measure, which can be compared across models and can be computed for the incidence-choice-quantity models. Web Appendix E reports the original parameters of all models per category.

[6] We thank an anonymous reviewer for this suggestion.

To assess the significance of the elasticities across categories, we perform random effects *meta*-analytic regressions. As our selected categories form a subset of all categories in the data and the market, and different households are active in different categories, random effects regression is appropriate to allow for heterogeneity (Borenstein et al., 2021). We thus estimate

$$\eta_c = \mu + \zeta_c + \epsilon_c, \tag{10}$$

where μ reflects the average effect across categories for that particular variable, and ζ_c is a normally distributed random effect independent of ε_c accounting for between-study heterogeneity. The sampling variances of ε_c are fixed to the known (squared) standard errors of our estimates, allowing identification of both ζ_c and ε_c.[7] To assess the moderating impact of category characteristics for our focal presence and absence nutrition claims variables, we include these as additional regressors in the relevant regression models:

$$\eta_{presclaim,c} = \mu + \phi_1 CatHealth_c + \phi_2 CatPresClaimPenetration + \zeta_c + \epsilon_c, \tag{11}$$

$$\eta_{absclaim,c} = \mu + \phi_1 CatHealth_c + \phi_2 CatAbsClaimPenetration + \zeta_c + \epsilon_c, \tag{12}$$

The parameters ϕ assess the moderating impact of category healthiness and nutrition claim penetration. Given small sample sizes ($\leq$ 17), we follow Guolo and Varin (2017) and compute p-values based on the Skovgaard (1996) statistic to ensure sufficient power and acceptable Type 1 error rates.

5. Results

Table 5 summarizes the most important weighted least-squares estimates of the choice (Equation (5) and quantity (Equation (7) models across categories. We report meta-analytical results across categories with the endogeneity correction as described in the model section. Given the non-linearity of our choice model, we used the corrected expressions of Ai and Norton (2003) for the interaction effects and associated standard errors.[8] We refer to Web Appendix E and F for, respectively, estimation results and model fit statistics for individual categories and a fuller set of results including incidence and control variables.[9]

5.1. The effect of presence and absence nutrition claims

To interpret the main effects of presence and absence nutrition claims, we first focus on the results for the main effects model in Table 5. Note that the results for the main effects are very similar in the model with interaction effects. Presence nutrition claims, on average, increase the choice probability ($Elast_{Presclaim,\ choice}$ = 0.041, p = 0.040), while absence nutrition claims decrease the choice probability ($Elast_{Absclaims,choice}$ = -0.010, p = 0.044). While households hence seem to prefer SKUs with a presence nutrition claim over regular product varieties, absence nutrition claims decrease the choice probability. For purchase quantity, we find that neither presence nutrition claims ($Elast_{Presclaims,\ quantity}$ = 0.051, p = 0.479) nor absence nutrition claims ($Elast_{Absclaims,\ quantity}$ = -0.003, p = 0.950) significantly alter the quantity bought.

Fig. 1 visualizes elasticities per category, highlighting substantial heterogeneity across categories. In particular, the effect of presence nutrition claims on choice (quantity) is significantly positive in 9 (10) categories and significantly negative in 8 (7) categories. For absence nutrition claims the effects on choice (quantity) are significantly positive in 6 (7) categories and significantly negative in 11 (10) categories. Our moderator analysis investigates this across-category heterogeneity.

5.2. The moderating impact of SKU and brand characteristics on nutrition claim effectiveness

Table 5 also provides results for the moderating impact of SKU and brand characteristics. We visualize the significant interactions in Fig. 2; Web Appendix G provides visualizations of all interaction effects.

SKU price. In line with our expectations, we find that price has a negative effect on the impact of absence nutrition claims on SKU choice ($Elast_{AbsclaimxPrice,\ choice}$ = -0.017, p < 0.001). In contrast to our expectations, we find that SKU price also reduces the effect of presence nutrition claims on choice ($Elast_{PrebsclaimxPrice,\ choice}$ = -0.012, p < 0.001). Because of lower perceived value for absence nutrition claims compared to presence nutrition claims (Dodds et al., 1991; Zeithaml, 1988), we expected that price has a negative impact on the effectiveness of absence nutrition claims and a positive impact on presence nutrition claims. While we confirm the former, our result for SKU choice shows that presence claims also reduce choice probabilities

[7] See https://www.metafor-project.org/doku.php/tips:rma_vs_lm_lme_lmer?s[]=lme for background on the random effects *meta*-analysis model and a comparison to standard multilevel models.

[8] An interaction parameter βdoes not fully reflect the interaction between two variables in case of a nonlinear model as it is comprised of both main effect parameters and the levels of the independent variables (Ai & Norton, 2003). For example, the interaction effect between $PresClaim_j$ and $SKUPrice_{jt}$ is found by differentiating Equation (5) with respect to both $PresClaim_j$ and $SKUPrice_{jt}$, that is $\widehat{\mu_{12}} = \frac{\Delta^2 \mu_{jt}(U)}{\Delta Claim \Delta Price}$, and its standard error derived using the Delta Method. We evaluate the interaction effects between two specific variables with remaining variables set at their mean value.

[9] Transforming model parameters to elasticities can induce sign changes, explaining differences between coefficients in Appendix E and Fig. 1 (Ai and Norton 2003; Mood 2010).

Table 5
Meta-analysis results of choice and quantity models across categories.

		Model 1: Main effects		Model 2: Interaction effects	
	Expectation	Coefficient	Std. error	Coefficient	Std. error
SKU choice					
Presence claim	+	0.041*	0.020	0.001†	0.000
Absence claim	–	−0.010*	0.005	−0.001*	0.000
SKU Price		−1.213**	0.275	−1.273**	0.264
SKU Price Promotion		0.017*	0.007	0.020**	0.006
Brand Advertising		0.015*	0.006	0.004*	0.002
Private Label (PL)		0.058†	0.030	0.098†	0.051
Presence claim * Price	+			−0.012**	0.002
Absence claim * Price	–			−0.017**	0.002
Presence claim * SKU Price Promo	–			−0.001	0.002
Absence claim * SKU Price Promo	–			−0.029**	0.002
Presence claim * Brand Advertising	+			0.005*	0.002
Absence claim * Brand Advertising	+			0.007†	0.003
Presence claim * PL	–			0.003	0.004
Absence claim * PL	–			0.005	0.008
Purchase quantity					
Presence claim	+	0.051	0.072	0.038	0.112
Absence claim	–	−0.003	0.047	−0.035	0.042
SKU Price		−0.272**	0.030	−0.316**	0.033
SKU Price Promotion		0.006*	0.002	0.006*	0.003
Brand Advertising		0.002	0.005	0.002	0.004
Private Label (PL)		0.107	0.069	0.116†	0.056
Presence claim * Price	+			0.012	0.013
Absence claim * Price	–			0.001	0.009
Presence claim * SKU Price Promo	–			0.020	0.095
Absence claim * SKU Price Promo	–			−0.017	0.045
Presence claim * Brand Advertising	+			−0.000	0.003
Absence claim * Brand Advertising	+			0.001	0.002
Presence claim * PL	–			−0.023	0.112
Absence claim * PL	–			0.061	0.053

Notes: Meta-analytic random effects regression using elasticities as dependent variables, weighted over categories by the associated inverse standard error. p-values computed using Skovgaard (1996) small sample correction
† $p < 0.10$; * $p < 0.05$; ** $p < 0.01$.

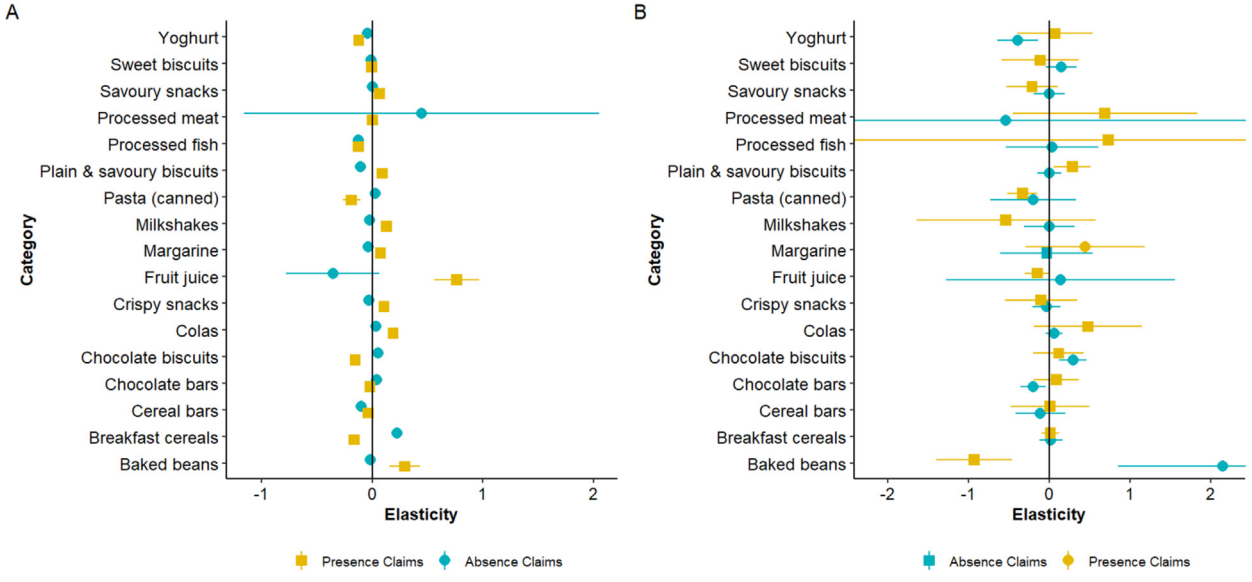


Fig. 1. Elasticity estimates per category for choice model (A) and quantity model (B). Error bars represent 95% confidence intervals around the point estimates.

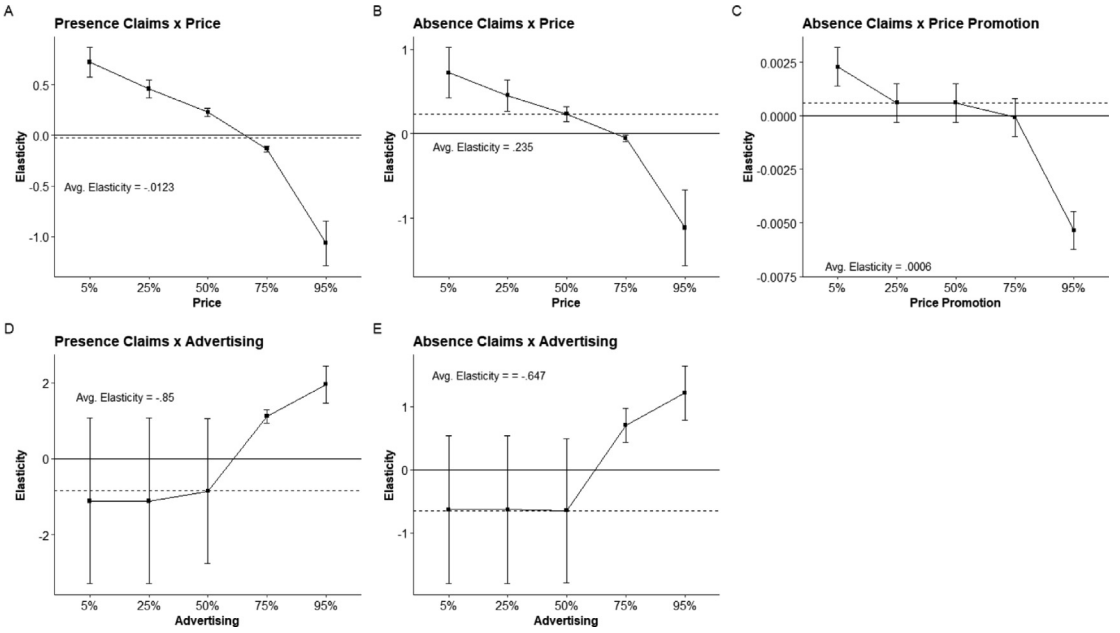


Fig. 2. Moderating effects on choice impacting nutrition claim effectiveness (Note that price, price promotion and advertising have skewed distributions, such that values in the 95th percentile are much larger than those in the 75th percentile. This results in the kinks in the graphs at the 95th percentile.).

for higher priced SKUs. As shown in Fig. 2 (panel A and B), presence nutrition claims retain their positive impact on choice for lower priced SKUs but have a negative impact on SKU choice if prices are too high. Similarly, absence nutrition claims have positive effects on choice for lower priced SKUs but not for higher prices SKUs.

SKU price promotions. In line with our expectations, we find that price promotions negatively influence the impact of absence nutrition claims on SKU choice ($Elast_{AbsclaimxPrice\ promo,\ choice}$ = -0.029, $p < 0.001$). Fig. 2 (panel C) illustrates this effect, where we note that for low discount levels absence nutrition claim positively influence choice. The interaction effect between absence nutrition claims and price promotions is not significant for the quantity decision ($Elast_{AbsclaimxPrice\ promo,\ quantity}$ = -0.017, p = 0.705). Price promotions do not significantly influence the impact of presence nutrition claims on SKU choice ($Elast_{PresclaimxPrice\ promo,\ choice}$ = -0.001, p = 0.624), nor quantity ($Elast_{PresclaimxPrice\ promo,\ quantity}$ = 0.020, p = 0.833).

Private label. We expected the effectiveness of presence and absence nutrition claims to be smaller for private labels than for national brands. However, all interaction effects between the two types of claims and the private label dummy variable are non-significant in all models.

Brand Advertising. We find that brand advertising increases the effectiveness of both types of nutrition claims for SKU choice ($Elast_{PresclaimxAdvertising,\ choice}$ = 0.005, p = 0.012; $Elast_{AbsclaimxAdvertising,\ choice}$ = 0.007, p = 0.080), while it does not influence the quantity decision for either type of nutrition claim ($Elast_{PresclaimxAdvertising,\ quantity}$ = -0.000, p = 0.894; $Elast_{AbsclaimxAdvertising,quantity}$ = 0.001, p = 0.616). These results indicate that advertising increases the effectiveness of nutrition claims, but as Fig. 2 (panel D and E) shows, these effects only hold for very high (>75 %) levels of brand advertising. These results may reflect a higher credibility of the claim for brands with high equity. Alternatively, brand advertising may increase the effectiveness of nutrition claims when advertising campaigns explicitly focus on the nutrition claims.

5.3. The moderating impact of category characteristics on nutrition claim effectiveness

In Table 6, we report the results of the moderator analysis of category characteristics on SKU choice and quantity (Equations (11) and (12). Fig. 3 plots the moderating effects.

Category healthiness. In line with our expectations, we find that category healthiness positively moderates the impact of presence nutrition claims on the SKU choice probability ($b_{PresclaimsxHealthiness,\ choice}$ = 0.252, p = 0.049). In contrast, category healthiness does not impact the effect of absence nutrition claims on the choice probability ($b_{AbsclaimsxHealthiness,\ choice}$ = -0.129, p = 0.177).

Panels A and C of Fig. 3 illustrate these effects, with presence nutrition claims showing positive elasticities for high levels of healthiness and negative elasticities for low levels of healthiness, while the effect is non-significant for all levels of category healthiness for absence nutrition claims. Category healthiness does not impact the effectiveness of either of the nutrition claims on quantity purchased given non-significant moderating effects.

Claim Penetration. Our results show that the penetration of nutrition claims in the category only influences SKU choice. We find that presence nutrition claims are more effective in stimulating SKU choice in categories with a high presence claim

Table 6
Moderating effect of category characteristics on SKU choice and quantity.

		Choice: Presence Claims		Quantity: Presence Claims	
	Expectation	Coefficient	Std. error	Coefficient	Std. error
Intercept		0.013	0.014	0.026	0.094
Category healthiness	+	0.252*	0.127	0.711	0.413
Presence claim penetration	+/-	0.493**	0.126	−0.268	0.786
		Choice: Absence Claims		**Quantity: Absence Claims**	
Intercept		0.032	0.032	0.059	0.125
Category healthiness	−	−0.129	0.091	−0.638	0.681
Absence claim penetration	+/-	−0.447†	0.243	−0.938	1.222

Notes: Meta-analytic random effects regression using elasticities as dependent variables, weighted over categories by the associated inverse standard error. p-values computed using Skovgaard (1996) small sample correction
† p < 0.10; * p < 0.05; ** p < 0.01; Moderating variables are mean-centered.

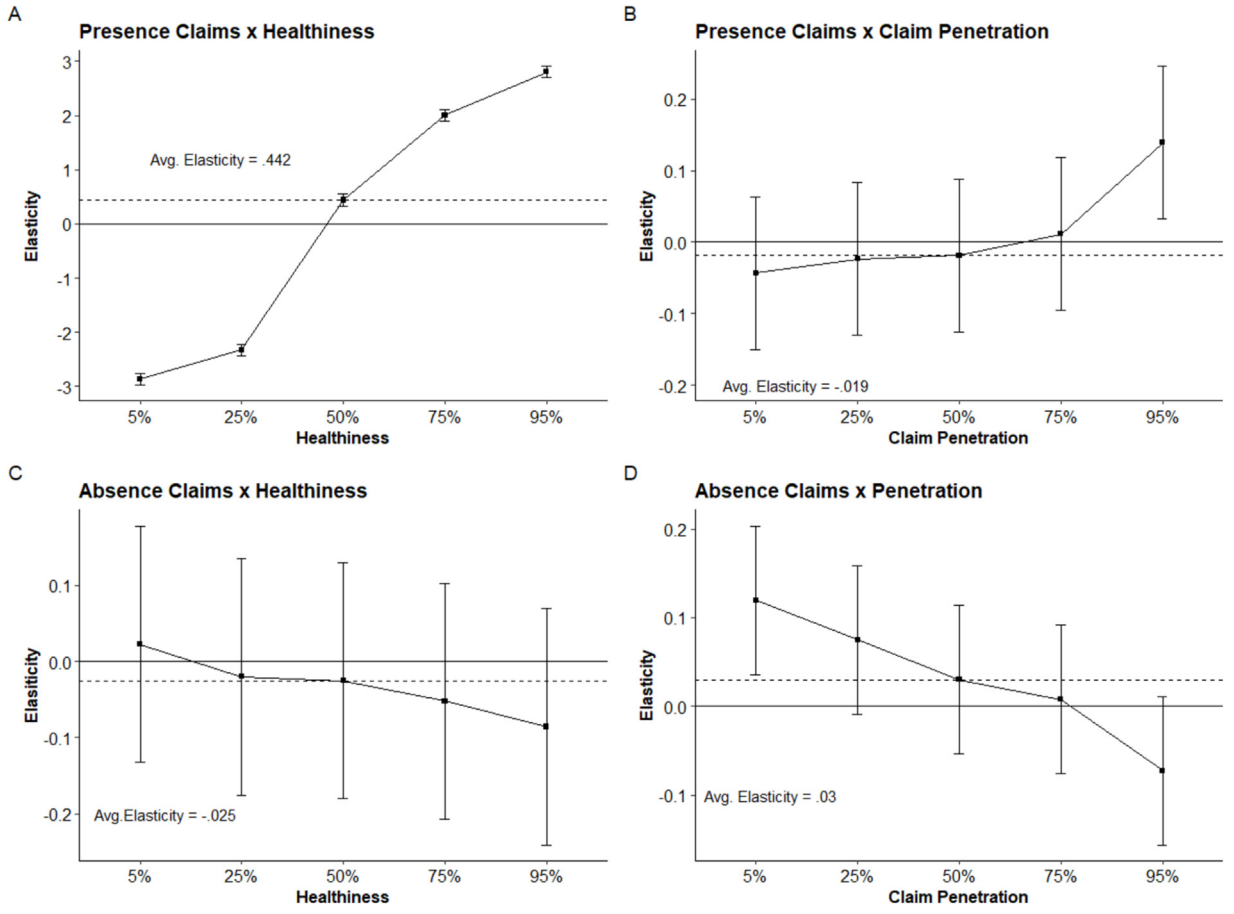


Fig. 3. The impact of healthiness and claim penetration on nutrition claim effectiveness.

penetration ($b_{PresclaimsxPenetration,\ choice}$ = 0.493, p = 0.002), while absence nutrition claims do so in categories with lower absence nutrition claim penetration ($b_{AbsclaimsxPenetration,\ choice}$ = -0.447, p = 0.088). While presence nutrition claims hence profit from a higher amount of claims in the category, absence nutrition claims suffer from more competition. Panels B and D in Fig. 3 illustrate the positive effect for presence nutrition claims and the negative effect for absence nutrition claims, showing that elasticities are negative (positive) for low levels of presence (absence) nutrition claim penetration, while they are positive (negative) for high penetration levels.

5.4. Robustness of findings

The results above are a consequence of specific choices and assumptions made during the research process. To assess the sensitivity of results hereto, we explored several alternative specifications. The results of these analyses are reported in Web Appendix H. First, we used data from 2010 to 2012 for our model estimation, with 2009 as an initialization period. As our claims information from 2009 is static, it could be SKUs changed claims or nutritional composition in later years, which is not captured by our data. We re-estimated our models with data from 2010 only (the year closest to 2009) and find no change to our findings (Table H1). This alleviates the concern that unobserved SKU changes affect our results. Second, rather than measuring whether a presence/absence nutrition claim is included on an SKU in a binary way, we re-estimated our models using a count variable operationalization for presence/absence nutrition claims (Table H2), yielding robust results. Third, we test the robustness of our results with regard to the selection of the length of the initialization period (52 weeks). Shortening the initialization period to 26 weeks does not change the results (Table H3).

5.5. Post hoc analysis using experimental data

The cross-sectional nature of our dataset limits our ability to assess the causal impact of adding or removing a nutrition claim. To address this limitation, we conducted a controlled, small-scale, preregistered experiment (N = 1202) examining consumer responses to nutrition claims. This allows us to (1) determine whether the addition of presence or absence claims (vs. those without) alters purchase intentions, and (2) investigate whether the effectiveness of presence or absence claims varies depending on category healthiness. We examined how different nutrition claims influence purchase likelihood across two categories (dairy and biscuits) in healthy (yogurt, wholegrain cookies) and unhealthy (chocolate-flavored milk drink, sweet cookies) products. To enhance credibility, nutrition claims were tailored to each product category: low fat (absence) and high calcium (presence) for dairy, and low sugar (absence) and high fiber (presence) for biscuits (see Web Appendix I for more details). Participants were randomly assigned to one of 12 conditions in a 3 (nutrition claims: no claim, presence claim, absence claim) $\times$ 2 product healthiness levels (healthy, unhealthy) $\times$ 2 product categories (dairy, biscuit) between-subjects design. Results indicated that presence claims increased purchase likelihood compared to no claims or absence claims for healthy products but not for unhealthy ones, aligning with our panel data findings. However, the experiment did not replicate the panel result that absence claims reduce purchase likelihood. Interestingly, absence claims led to a higher purchase likelihood for unhealthy products compared to healthy ones (M_{UH} = 4.50, SD_{UH} = 1.47; M_H = 4.17, SD_H = 1.53; p = 0.027), providing partial support for our panel data results. While our household panel data show that absence claims consistently reduced purchase intentions across all levels of product healthiness, this effect was not observed in the experiment. This difference highlights key contrasts between experimental and panel data outcomes. Experiments, which directly ask consumers for their preferences, may not capture the unconscious influence of absence claims. In addition, experiments typically cover a limited number of product categories, potentially oversimplifying the decision-making complexity found in real-world shopping.

6. Discussion

Claims stressing the presence or absence of a particular nutrient have become commonplace to differentiate products from dozens of other products in the category. While prior consumer lab research has provided many insights into (processes underlying) the effect of these nutrition claims, we lack insights into the impact of nutrition claims in a real grocery context. In this study, we provide generalizable results on the effect of nutrition claims on SKU purchases and moderating SKU and category characteristics by analyzing unique household panel data with SKU purchase behavior for 1,018 SKUs in 17 categories. Fig. 4 summarizes our findings.

The impact of nutrition claims on purchase behavior depends on claim type. Nutrition claims emphasizing the presence of positive attributes (i.e., presence nutrition claims) positively impact consumer choice but not quantity. The increasing focus of consumers on healthier lifestyles and healthy food (Global Market Development Center, 2016) leads consumers to choose products with presence nutrition claims over products without such claims. In contrast, nutrition claims emphasizing the absence of negative attributes (i.e., absence nutrition claims) negatively impact choice probabilities, but not purchase quantities. This may relate back to the suggestion put forward by André et al. (2019) that presence claims hold promise in augmenting healthiness without compromising taste. However, as we only observe purchase behavior and not health or taste perceptions, we cannot make direct inferences of the impact of absence and presence claims on healthiness or taste perceptions. Future research could investigate these potential underlying mechanisms.

An alternative explanation for the negative main effect of absence nutrition claims on SKU choice may be that absence nutrition claims are targeted at niche markets. To verify this intuition, we follow Gijsenberg (2017) to classify SKUs as mass versus niche products (based on median advertising spending). We find that the percentage of SKUs carrying a nutrition claim is very similar in the group of mass products (41 %) as in the group of niche products (37 %). Hence, nutrition claims are not a niche differentiator, but a wide-spread tool used by manufacturers regardless of product type.

Despite finding no direct effects on the overall amount purchased, the positive (negative) effect of presence (absence) nutrition claims on consumer choice translates into significant sales effects. Simulating across categories, compared to a sce-

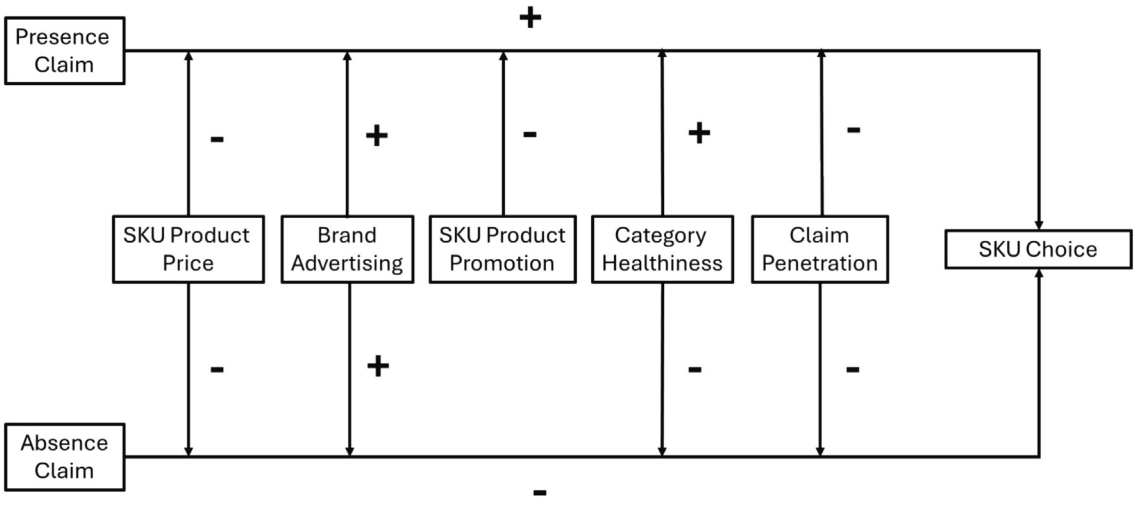


Fig. 4. Summary of findings.

nario without claims and at average values of all other independent variables, we find that SKUs with a presence nutrition claim sell on average 6.1 % more than SKUs without a presence claim, while SKUs with an absence nutrition claim sell 3.0 % less than SKUs without an absence nutrition claim.

Our study seems to contradict prior studies that have warned for a potential overconsumption of products with nutrition claims as they prevent self-control mechanisms to intervene, the so-called boomerang effect (e.g., Cleeren et al., 2016; Geyskens et al., 2007). In contrast, we do not find evidence for an effect on the purchased amount after consciously choosing the SKU. While prior studies examined the effect of a single or first consumption of a 'healthier' product on consumed amount (Cleeren et al., 2016), our results, based on numerous SKUs and categories across multiple purchase occasions, provide a more nuanced view. Presence nutrition claims seem to encourage consumers to choose the 'healthier' variant without buying more of that SKU. Absence nutrition claims, in contrast, reduce choice probabilities. This contrasts with Cleeren et al. (2016), who showed that the first purchase of low-fat crisps increases subsequent purchase quantity and calorie intake in the crisps category. Importantly, however, our study focuses specifically on SKU-level choices and quantities, not category-level consumption, meaning we cannot draw conclusions about broader purchasing patterns at the category level.

While the prior results hold for the average claim effects across SKUs and categories, our moderation analyses show that the impact of nutrition claims depends heavily on SKU and category characteristics. In line with the results for the main effects which show that nutrition claims influence the choice decision but not the quantity decision, we find that the moderating variables only significantly influence nutrition claim effectiveness for the choice decision.

The SKU's marketing mix elements (i.e., price, price promotions, and advertising) impact the effectiveness of presence and absence nutrition claims. Our findings suggest that SKU price is a key factor, but they challenge the "healthy = more expensive" conjecture (Haws et al., 2017), which predicts a better alignment between high-priced items and nutrition claims. Instead, we find that higher prices reduce the impact of both presence and absence nutrition claims on SKU choice (but not quantity purchased). For absence nutrition claims, these results may be due to the negative framing, which may be interpreted as a sacrifice by consumers (Dodds et al., 1991; Zeithaml, 1988). For presence nutrition claims an explanation is less straightforward, and more research is needed to reveal underlying mechanisms.

Not only the regular price matters, but our results demonstrate that also price promotions significantly influence the effectiveness of absence nutrition claims. We argued that price promotions may turn the attention of the consumers to the price attribute (Mela et al., 1998) at the expense of the attention to nutrition claims. Our results for absence claims are in line with this premise: SKUs with an absence nutrition claim are less likely to be chosen if the SKU runs a price promotion. For presence claims the level of price promotions does not matter.

We put forward contrasting expectations about the moderating impact of brand advertising. We find that both presence and absence nutrition claims are more effective in influencing choice when brands are heavily advertised. This result is in line with prior research showing that strong brands are seen as credible information sources (Erdem & Swait, 1998). Alternatively, brand advertising may also render nutrition claims more effective when these claims are the focus of the advertising campaign.

For private labels, we expected the impact of nutrition claims to be smaller than for national brands since they are still perceived lower in quality. However, we do not find any significant moderating effect of the type of brand. Hence, the effectiveness of nutrition claims is not different between private labels and national brands, which may be explained by the strong position of private labels in the UK.

Next to SKU-level marketing mix effects, the category in which nutrition claims are used also plays a role. We find that presence nutrition claims are more effective in healthier categories than in unhealthier categories, while we find no such difference for absence nutrition claims. This is partially in line with prior research that suggests that the effectiveness of a claim depends on the fit of the claim with the product carrier (Van Kleef et al., 2005). Specifically, presence nutrition claims are more effective in triggering consumer choice for healthier products in which the presence of the healthy ingredient is more credible.

For category claim penetration, we find a contrast between presence and absence nutrition claims. While the choice of SKUs with a presence nutrition claim is positively affected by the percentage of SKUs with such a claim in the category, this effect is negative for absence nutrition claims. Thus, while for absence nutrition claims claim penetration reduces choice, presence nutrition claims benefit from increased claim penetration. The on average lower penetration across categories of presence nutrition claims (10 % of SKUs, Table 3) compared to absence nutrition claims (29 % of SKUs) could induce this difference. Indeed, as absence nutrition claims are omni-present in most categories, this type of nutrition claims is not an effective tool to differentiate from the other SKUs in the category. In contrast, as presence nutrition claims are not widely available yet in all considered categories, including a presence nutrition claim will allow to increase the distinctiveness from the other SKU using an SKU from the competition (Chernev, 2011; Van Herpen & Pieters. 2002).

6.1. Management implications

Our study provides some important implications for manufacturers that consider using presence and absence nutrition claims on their SKUs. The impact of nutrition claims is strongly determined by their type, as well as specific SKU and category characteristics.

First, manufacturers need to be aware that the type of nutrition claim matters, as (in general across considered SKUs and categories) only presence claims help SKUs stand out positively in terms of choice. Absence nutrition claims, in contrast, decrease SKU choice on average. Hence, if food manufacturers aim to have successful products with a nutrition claim, our results suggest developing products with a nutrient composition that can support the presence nutrition claim. Second, managers should be aware that specific SKU and category characteristics influence the effectiveness of nutrition claims. Indeed, nutrition claims are more effective when placed on less expensive and heavily advertised SKUs, increasing choice probabilities. Particularly in the case of absence nutrition claims these SKUs make good carriers, as the negative effects of absence claims are reversed for these SKUs. Similarly, presence nutrition claims are more effective within healthier categories than in unhealthier categories, while absence claims perform equally well on both. Thus, if food manufacturers aim to develop products with a presence nutrition claim, they should do this in healthier categories. When manufacturers heavily support their products with price promotions, they should be aware that the impact of absence claims on choice is further diminished. In contrast, low levels of price promotions help offset the negative effect of absence nutrition claims. Hence, when firms have adopted a strategy focusing on adding value in the market with absence nutrition claims, they should not undermine this strategy with a strong focus on promotions. Finally, when many SKUs use nutrition claims in a category, the effectiveness of absence nutrition claims is reduced, but presence nutrition claims benefit. Hence, while introducing an absence nutrition claim on a package, managers should focus on categories with a low percentage of absence nutrition claims, while the opposite is true for presence nutrition claims.

7. Limitations

As any study, our study has limitations. First, our results are based on a dataset from 2009 to 2012. While we demonstrated that the number of claims in this older dataset reflects the situation in a more recent dataset (see footnote 1), it may still be possible that the content of claims has changed or that consumers' response to claims has changed due to increased health concerns or higher familiarity with nutrition claims. Our results should thus be interpreted against this specific background. Second, this study analyzes the purchase behavior of a household panel, which make choices between SKUs with and without nutrition claims. We use a control function approach to control for the potential endogenous nature of the managerial decision as to whether to add a nutrition claim to a package. We further strengthen our results in a controlled, pre-registered experiment (Web Appendix I). However, because of the cross-sectional nature of our data, we cannot make explicit causal claims about the impact of the addition of nutrition claims. We are thus cautious with giving full causal explanation of the phenomenon of nutrition claims. Third, we used the presence versus absence claims categorization from André et al. (2019). Within these categories, however, nutrition claims are heterogenous in the exact representation of the nutrition claim (e.g., numerical versus graphical; concrete versus abstract; simple versus complex) which may have different effects on choice and quantity.

7.1. Directions for Future research

Our study shows important insights on nutritional claims. However, important questions remain unanswered which may form interesting avenues for future research. First, our study concentrates on the impact of nutrition claims only. Other claims that stress increased healthiness of SKUs can also be used, such as nature claims, health claims and disease reduction

claims. While we control for their presence in our models, future research can extend our work by further investigating the effectiveness of these claims. In addition, a more fine-grained analysis of nutrition claims would be valuable to study more detailed differences in the exact presentation of nutrition claims (e.g., numerical versus other presentations, abstract versus concrete, the complexity of the claim). Second, while nutrition claims were seen as an instrument to incentivize nutrient improvements among manufacturers, our interviews suggest taste rather than health is leading product development. Consequently, governments introduced other regulations to nutrient content. In the UK, a soft drinks sugar tax was introduced in 2018, while price promotions were restricted for HFSS products from 2022 onwards.[10] Such legislation can incentivize nutrient change but can also impact use and informativeness of the nutrition claims. Future research could study the impact of these developments on the effectiveness of nutrition claims. Third, we only focus on sales effects and do not consider the quality of the nutrients purchased, which is highly relevant for policy makers. For example, Cleeren et al. (2016) have investigated the impact of a low-fat claim on subsequent calories purchased in the crisps category. Future research could study the effect of the nutrition claims on different values of nutritional quality across many categories, and asses the moderating influence of SKU and category characteristics.

CRediT authorship contribution statement

Niels Holtrop: Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Data curation. **Kathleen Cleeren:** Writing – review & editing, Writing – original draft, Supervision, Funding acquisition, Data curation, Conceptualization. **Kelly Geyskens:** Writing – review & editing, Writing – original draft, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Peter C. Verhoef:** Writing – review & editing, Writing – original draft, Supervision, Funding acquisition, Conceptualization.

Data availability

The authors do not have permission to share data.

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 A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ijresmar.2024.11.001.

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