Do Pharmacists Buy Bayer?
Informed Shoppers and the Brand Premium

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Abstract

We estimate the effect of information and expertise on consumers' willingness to pay for national brands in physically homogeneous product categories. In a detailed case study of headache remedies we find that more informed or expert consumers are less likely to pay extra to buy national brands, with pharmacists choosing them over store brands only 9 percent of the time, compared to 26 percent of the time for the average consumer. In a similar case study of pantry staples such as salt and sugar, we show that chefs devote 12 percentage points less of their purchases to national brands than demographically similar non-chefs. We extend our analysis to cover 50 retail health categories and 241 food and drink categories. The results suggest that misinformation and related consumer mistakes explain a sizable share of the brand premium for health products, and a much smaller share for most food and drink products. We tie our estimates together using a stylized model of demand and pricing.

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1 Introduction

A 100-tablet package of 325mg Bayer Aspirin costs $6.29 at cvs.com. A 100-tablet package of 325mg CVS store-brand aspirin costs $1.99 (CVS 2013). The two brands share the same dosage, directions, and active ingredient. Aspirin has been sold in the United States for more than 100 years, CVS explicitly directs consumers to compare Bayer to the CVS alternative, and CVS is one of the the largest pharmacy chains in the country, with presumably little incentive to sell a faulty product. Yet the prevailing prices are evidence that some consumers are willing to pay a three-fold premium to buy Bayer.[1]

This is not an isolated case. In our data (described in more detail below), we find that consumers would spend $44 billion less per year on consumer packaged goods (CPG) if they switched from a national brand to a store-brand alternative whenever possible. Prior work documents substantial brand price premia in a wide range of non-CPG categories, such as automobiles (Sullivan 1998), index funds (Hortaçsu and Syverson 2004), and online books (Smith and Brynjolfsson 2001).

Economists have long debated the origins of brand premia. On the one hand, national brands may offer superior quality or reliability,[2] or may deliver direct utility benefits (Becker and Murphy 1993). On the other hand, consumers may be willing to pay a premium for brands because they overestimate the benefits of the brand, or are otherwise confused or misled.[3] Determining which story holds is important for evaluating the efficiency of consumer goods markets and the welfare effects of advertising, and may be relevant to policy decisions in consumer protection and regulation.

In this paper, we seek to separate these stories by asking how the propensity to buy CPG brands varies with consumer information and expertise. We introduce a novel database that matches household purchase data from the 2004-2011 Nielsen Homescan panel to a new survey containing direct measures of consumer product knowledge, as well as three broader proxies: completed schooling, college major, and occupation.

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[1]Indeed, in our data (described in more detail below), 25 percent of aspirin sales by volume (and 60 percent by expenditure) are to national-brand products.

[2]In one instance, the FDA determined that a generic antidepressant performed less well than its branded counterpart, likely due to differences in their "extended release" coatings (Thomas 2012). A widely publicized recall of store-brand acetaminophen in 2006 resulted from the discovery that some pills could contain metal fragments (Associated Press 2006); such risks could conceivably be lower for national brands. Hortaçsu and Syverson (2004) conclude that purchases of high-cost "brand name" index funds partly reflect willingness to pay for non-financial objective attributes such as tax exposure and the number of other funds in the same family.

[3]Braithwaite (1928) writes that advertisements "exaggerate the uses and merits" of national brands, citing aspirin and soap flakes as examples. Simons (1948) advocates government regulation of advertising to help mitigate "the uninformed consumer's rational disposition to 'play safe' by buying recognized, national brands" (p. 247). Scherer (1970) discusses premium prices for national-brand drugs and bleach, and writes that "it is hard to avoid concluding that if the housewife-consumer were informed about the merits of alternative products by some medium more objective than advertising and other image-enhancing devices, her readiness to pay price premiums as large as those observed here would be attenuated" (pp. 329-332). More recently, a growing body of theoretical work considers markets with uninformed or manipulable consumers (Gabaix and Laibson 2006; Ellison and Wolitzky 2012; Piccione and Spiegler 2012).

The database includes purchases made by domain experts: pharmacists, physicians, or other healthcare workers in the context of health products, and chefs or other food preparers in the context of food products. Our measures of consumer knowledge capture both knowledge of facts in the narrow sense, and broader sophistication and expertise that allows consumers to translate such knowledge into optimal decisions. For simplicity of exposition, we will refer to all of these aspects of decision-making simply as "information."

We entertain throughout the possibility that brands really do deliver more utility, even in physically homogenous categories such as painkillers. Bayer aspirin might be better for consumers due to non-active ingredients, reliability, safety, packaging, or psychic utility such as comfort or familiarity associated with the brand itself. The extent to which this is the case is not something we take a stand on *a priori*, but rather the empirical object of interest. Our key assumption is that this true utility is the same for informed and uninformed consumers—in other words, that all consumers would be better off if they weighed the relative merits of brands and non-brands in the same way as an informed expert. Under this assumption, comparing the choices of informed and uninformed consumers lets us infer the extent to which the latter misestimate the benefits of brands.

We frame our descriptive analysis with a stylized model that makes this interpretation explicit. In the model, households choose between a national brand and a store brand. The national brand may deliver greater benefits to the household, whether psychic or instrumental. Households choose brands according to their perceptions of these benefits. Households may misperceive the benefits of brands, but there is a set of households whose perceptions are known to be accurate. To fix ideas we think of this latter group of households as "informed," and refer to the source of errors by other consumers as "misinformation," but the model is general enough to allow for non-informational frictions in choice, such as decision errors or heuristics.

The model shows that identification requires us to hold constant both the choice environment and the true preferences of the households when comparing the behavior of the informed to that of the uninformed. To limit confounding variation in the choice environment, we compare informed and uninformed consumers who shop in the same chain, market, and time period.[4] To limit confounding variation in preferences, we focus our analysis on choices between store and national brands that are matched on all physical attributes measured by Nielsen. This matching does not guarantee that the products are of identical quality (and, indeed, that is what we seek to learn from the behavior of experts), but it eliminates variation in important horizontal attributes (e.g., active ingredient) that might lead to large differences in preferences between the

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[4]We address confounds related to workplace purchases (e.g., pharmacists receiving free samples or discounts that affect their purchasing behavior) by studying experts who are no longer employed at their specialty, and by studying the effect of college major.

informed and the uninformed. We further include detailed controls for income and other demographics, and compare occupations (e.g., physicians and lawyers) with similar socioeconomic status but different levels of product-specific expertise. We show that, conditional on income and other demographics, well-informed consumers look similar to other consumers in their preferences for measured product attributes, making it more plausible that they are similar in their preferences for unmeasured attributes. We argue that whatever unmeasured preference heterogeneity remains would likely lead us to understate the extent of misinformation.

We begin the descriptive portion of our empirical analysis with a detailed case study of headache remedies. For these products, we measure information directly through a survey of a subset of Nielsen panelists in which we ask the panelists to name the active ingredient in various national-brand headache remedies. This direct measure of information is highly correlated with our indirect proxy measures. The average respondent answers 59 percent of our active ingredient questions correctly. For the college-educated, this fraction rises to 62 percent. For those whose major was science or health, it is 73 percent. For registered nurses it is 85 percent, for pharmacists it is 89 percent, and for physicians and surgeons it is 90 percent. Occupational specialty is important enough to outweigh large differences in general human capital. For example, registered nurses are far better informed about headache remedies than lawyers, despite having completed less schooling and earning less in the labor market on average.

We find that more informed households are consistently more likely to buy store-brand headache remedies. The average household devotes 74 percent of headache remedy purchases to store brands. Controlling for household income, other demographics, and interacted fixed effects for the market, chain, and quarter in which the purchase is made, a household whose primary shopper correctly identifies all active ingredients is 19 percentage points more likely to purchase a store brand than a shopper who identifies none. A household whose primary shopper believes that store brands are "just as safe" as national brands is 21 percentage points more likely to purchase a store brand than a shopper who does not believe that statement.

A similar pattern emerges when we proxy for information with the schooling and occupation of the primary shopper. Having a college-educated primary shopper predicts an increase of 4 percentage points, having a primary shopper with a healthcare occupation other than pharmacist or physician predicts an increase of 8 percentage points, and having a primary shopper who is a pharmacist or physician predicts an increase of 15 percentage points, with pharmacists buying store brands 91 percent of the time. Primary shoppers with science majors buy more store brands than those with other college degrees, and the effect of occupation is sizable among consumers not currently employed.

We find evidence that education and occupation capture similar variation to our more direct measures of

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information. When we restrict attention to households whose primary shopper correctly identifies all active ingredients and believes that store brands are just as safe as national brands, the estimated effect of college education and occupation become economically small and statistically insignificant.

In a second case study of pantry staples (salt, sugar, and baking soda), we find that chefs devote 77 percent of their purchases to store brands, as compared to 60 percent for the average consumer. The effect of being a chef is large and highly significant after including our detailed vector of controls for income, demographics, and the choice environment. Food preparers who are not chefs are also significantly more likely to buy store brands than others who are demographically similar.

We find that the effects of consumer information are largely domain-specific. Neither knowledge of headache remedy active ingredients nor working in a healthcare occupation predicts store-brand purchases in pantry staple categories. Similarly, working in a food preparer occupation other than chef does not predict store-brand headache remedy purchases. We do find that chefs buy more store-brand headache remedies, suggesting that some of their knowledge may be transferred across domains.

We extend the approach from our two case studies to the full set of products in which there is a comparable store-brand alternative to national brands and sufficient purchase volume to perform a reliable analysis. Among 50 health-related categories, the effects of knowledge of headache remedy active ingredients, working in a healthcare occupation other than pharmacist or physician, and working as a pharmacist or physician are positive for 43, 43, and 34 categories respectively. A substantial number of these positive coefficients— including a large share of those for over-the-counter medications—are both economically and statistically significant. On average across these categories, working as a pharmacist or physician reduces the probability of buying the national brand by roughly a fourth. Results are less consistent for the 241 food and drink categories that we study, with the effect of being a chef positive for 148 categories and negative for 93. Several of the positive coefficients are economically and statistically significant—including a number of pantry staples and other products such as baking mixes and dried fruit—but a large majority are not individually distinguishable from zero. The average effect of working as a chef is to reduce the probability of buying a national brand by 2 percent. For health products, we find some suggestive evidence that the effect of information on the propensity to buy the store brand is greater in categories with higher advertising intensity and in categories with more agreement among experts regarding the equivalence of store and national brands.

Taken together, our estimates suggest that misinformation explains a sizable portion of the brand premium in many health categories, as well as in certain food categories (such as pantry staples) with little physical variation across brands. At the same time, our results suggest a smaller role for information in the many categories—including the majority of foods and beverages—in which even experts are willing to pay

a premium to buy national brands.

To sharpen these conclusions, in the final section of the paper we add structure to our stylized model of choice to allow us to make quantitative statements about the effect of consumer information on welfare and pricing. We impose a set of assumptions on the pricing conduct of retailers and manufacturers and make functional form assumptions about the distribution of consumer preferences over brands and retailers. We choose the parameters of the distribution of preference heterogeneity to match the market shares and price-cost margins of store- and national-brand goods. We choose a parameter that governs the gap in perceived brand value between informed and uninformed shoppers to match our descriptive estimates of the effect of information on the propensity to buy the store brand.

The estimated model implies that consumer information greatly affects the distribution of surplus in health categories. Making all consumers as informed as a pharmacist or physician, while holding prices constant at current levels, would reduce the variable profits of the national headache remedy brands by half, equivalent to 19 percent of total expenditure. The profits of store brands would increase by 5 percent of expenditure, and consumer surplus would increase by 4 percent of expenditure. If prices were to adjust to reflect the change in consumer demand, the consumer surplus gains would be even greater. In health categories other than headache remedies, the effects are smaller though still economically significant. In food and drink categories, by contrast, information effects are quantitatively small, with effects on profits and consumer surplus of a few percent in pantry staples and less than one percent in other food and drink products. Although these conclusions are contingent on the functional form and other assumptions embedded in the model, together with the coefficient estimates they paint a consistent picture of the relative importance of information in different product categories.

We stress three caveats to our welfare conclusions. First, we consider the effect of consumer information only on consumer choice and product pricing. In the longer run, if consumers were to become better informed, firms would adjust their advertising expenditures and product offerings, leading to additional welfare effects. Second, our model assumes that information per se does not affect the utility a consumer receives from a product. If, for example, believing that national-brand aspirin works better actually makes national-brand aspirin more effective at reducing headaches, then informing consumers could actually make them worse off.[5] Third, while we refer to the welfare effects we calculate as effects of information, in fact they incorporate all of the ways in which experts make decisions differently from non-experts. A pharmacist differs from a non-pharmacist not only in knowing more facts about medications, but also in knowing which

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[5]This is a limitation of any revealed-preference evidence on the effect of information, but it is especially salient here as drugs are known to have brand-related placebo effects (Branthwaite and Cooper 1981; Kamenica et al. 2013).

facts are relevant to a given situation, and in knowing what process to use to make good decisions about medication. Our analysis is silent on which of these differences is the most important in driving shopping behavior.

The primary substantive contribution of this study is to use novel data and methods to quantify the importance of information in consumer choice in an important real-world market.[6] We add to existing survey and experimental evidence[7] by exploiting multiple sources of variation in consumer information, including occupational expertise.[8] Our work complements concurrent research by Carrera and Villas-Boas (2013), who use a field experiment to assess the impact of informative product labels on the propensity to purchase store-brand headache remedies. Although we focus on over-the-counter products, our findings are relevant to policy debates about substitution between branded and generic prescription medications.[9]

Methodologically, the approach of comparing the choices of demographically similar households with different levels of product information parallels that of Bartels' (1996) study of the role of information in voting, and is close in spirit to recent work in economics by Levitt and Syverson (2008), Handel and Kolstad (2014), and Johnson and Rehavi (2013).[10] Our model-based extrapolation of changes in prices and welfare in a world of perfect consumer information builds on recent work that uses an equilibrium framework to evaluate the size and determinants of brand premia (Goldfarb et al. 2009) and relates to recent empirical work that studies equilibrium consequences of consumer misinformation (Grubb and Osborne 2015).

The remainder of the paper is organized as follows. Section 2 describes our data. Section 3 lays out our empirical strategy. Section 4 presents our results for headache remedies and pantry staples. Section 5 presents our results for other health and food categories. Section 6 presents evidence on aggregate effects

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[6]A sizable literature examines the demographic and attitudinal correlates of purchasing store-brand consumer packaged goods (e.g., Dick et al. 1995; Richardson et al. 1996; Burton et al. 1998; Sethuraman and Cole 1999; Kumar and Steenkamp 2007; Bergès et al. 2009; Steenkamp et al. 2010) and generic prescription drugs (e.g., Shrank et al. 2009). A literature on blind taste tests finds that consumers cannot distinguish among national brands (Husband and Godfrey 1934; Allison and Uhl 1964) or between national-brand and store-brand goods (Pronko and Bowles 1949), though there are exceptions (Mason and Batch 2009). Wills and Mueller (1989) and Caves and Greene (1996) use aggregate data to estimate the role of advertising and quality in brand premia. Sethuraman and Cole (1999) analyze the drivers of willingness to pay for national brands using hypothetical choices reported on a survey.

[7]Existing evidence indicates that perceptions of similarity between national- and store-brand painkillers are correlated with stated purchase intentions (Cox et al. 1983; Sullivan et al. 1994). Cox et al. (1983) find that informing consumers of active ingredient similarity does not have a discernible effect on purchase selections.

[8]We are not aware of other research on the brand preferences of healthcare professionals. An existing literature examines the health behaviors of doctors (Glanz et al. 1982), including their propensities to use certain categories of medications like sleeping pills (Domenighetti et al. 1991). Most studies of the relationship between occupation and store-brand purchases code occupation at a high level of aggregation (white collar, blue collar, etc.) without reference to specific expertise (see Szymanski and Busch 1987 for a review). An exception is Darden and Howell (1987), who study the effect of retail work experience on elements of "shopping orientation," such as attitudes toward store clerks.

[9]Purchases of branded prescription drugs with available generic alternatives are a significant component of health costs (Haas et al. 2005). A range of policies including mandatory substitution (NIHCM 2002) and financial incentives for physicians (Endsley et al. 2006) and patients (Huskamp et al. 2003) have been used in an effort to increase the generic share.

[10]At a broader level, our approach also relates to recent efforts to develop modes of welfare analysis that do not assume rational consumers (e.g., Bernheim and Rangel 2009; Green and Hojman 2007; Spinnewijn 2013).

and welfare. Section 7 concludes.

2 Data

The backbone of our data is the Nielsen Homescan Panel, which includes purchasing behavior for a panel of households from 2004 to 2011. To this we add data on occupation and product knowledge from two custom surveys administered to Nielsen Homescan panelists in September 2008 and October 2011. We classify products using product-level information supplied by Nielsen. We measure prices and aggregate expenditures using store-level data from 2008, also supplied by Nielsen. Finally, we measure wholesale prices using data from National Promotion Reports' PRICE-TRAK database. We now discuss each dataset in turn.

2.1 The Nielsen Homescan Panel

We obtained data from the Nielsen Homescan Panel through a partnership between the Nielsen Company and the James M. Kilts Center for Marketing at the University of Chicago Booth School of Business.[11] The data include purchases made on more than 77 million shopping trips by $125,114$ households from 2004 to 2011. Panelist households are given optical scanners and are asked to scan the barcodes of all consumer packaged goods they purchase, regardless of outlet or store format.[12]

For each purchase, we observe the date, the universal product classification (UPC) code, the transaction price, an identifier for the store chain in which the purchase was made, and the size of the item, which we convert to equivalent units specific to a given product category (e.g., pill counts for headache remedies or pounds for salt). We compute the share of purchases going to store brand or national brand products as the share weighted by equivalent units unless otherwise noted.

Nielsen supplies household demographic characteristics including the education of the household head, a categorical measure of household income, number of adults, race, age, household composition, home ownership, and the geographic market of residence.[13]

Nielsen recruits panelists through a mixture of direct mail and Internet advertising. Nielsen calibrates its recruitment effort in order to improve the representativeness of the sample according to a range of prespeci-

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[11]Information on access to the data from the partnership between the Nielsen Company and the James M. Kilts Center for Marketing at the University of Chicago Booth School of Business is available at http://research.chicagobooth.edu/nielsen/.

[12]The data include purchases from supermarkets, convenience stores, mass merchandisers, club stores, drug stores, and other retail channels for consumer packaged goods.

[13]A household's geographic market is its Nielsen-defined Scantrack market. A Scantrack market can be a metropolitan area (e.g., Chicago), a combination of nearby cities (e.g., Hartford-New Haven), or a part of a state (e.g., West Texas). There are 76 Scantrack markets in the United States.

fied demographic characteristics. Households are asked to complete multiple brief surveys prior to inclusion in the panel, and are told in advance about the process of recording purchase information. Nielsen offers panelists regular prize drawings, sweepstakes, and a system of "gift points." See Kilts Center for Marketing (2013) and Muth et al. (2007) for more detail on the process of recruiting and retaining panelists.

A variety of studies have considered the representativeness of the Homescan panel.[14] Aguiar and Hurst (2007) find that Homescan panelists in Denver, CO are similar to a comparable sample of the Panel Study of Income Dynamics. Harding et al. (2012) find that the demographic characteristics of cigarette smokers in Homescan are similar to those in datasets such as the Behavioral Risk Factor Surveillance System or the National Health and Nutrition Examination Survey.[15] Lusk and Brooks (2011) find that, relative to a random digit dial sample, Homescan panelists are older, more educated, and more likely to be white, and that, even after controlling for demographics, Homescan panelists are more price-sensitive in a hypothetical choice experiment.[16] Consistent with these findings, we show in the online appendix that Homescan panelists purchase more store-brand products than others who shop in the same store.

In light of the selection of the Homescan panel there are two reasonable ways to interpret our estimates. First, we may think of the estimates as internally valid for the sample of Homescan panelists, or the population that they represent. Second, we may think of the estimates as valid for the entire population under the strong assumption that the effect of information is homogeneous.

2.2 PanelViews Surveys

We conducted two surveys of Homescan panelists as part of Nielsen's monthly PanelViews survey. The first survey was sent electronically to $75,221$ households in September of 2008 with the request that each adult in the household complete the survey separately. In total, $80,077$ individuals in $48,951$ households responded to the survey for a household response rate of 65.1 percent. The second survey was sent electronically to $90,393$ households in October 2011 with the request that each adult in the household complete the survey separately. In total, $80,205$ individuals in $56,258$ households responded to the survey for a household response rate of 62.2 percent. We show in the online appendix that the administration of the survey is

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[14] See also Zhen et al. (2009) for a comparison of expenditure data between the Consumer Expenditure Survey and the Homescan panel. Einav et al. (2010) find that Homescan panelists are more accurate in recording quantities than in recording prices. Accordingly, we draw on the store-level data described below for much of the pricing information that we use in our analysis.

[15] See Broda and Weinstein (2010), Handbury and Weinstein (2015), and Kaplan and Menzio (forthcoming) for other recent economic applications of Homescan data.

[16] Nielsen provides projection factors to aggregate their panelists into a representative population. These projection factors are designed to match the sample frequencies of nine demographic characteristics to the corresponding population frequencies. Muth et al. (2007) provide more detail on the construction of the projection factors. As the projection factors are not designed for the subpopulations that we study, we do not use them in our main analysis. In appendix table 1 we show our core results in specifications that weight by the projection factors.

not associated with any changes in the likelihood of purchasing the store brand. The online appendix also compares the demographics of respondents to non-respondents. Notably, we find that, relative to non-responding households, households that responded to the survey tend to be smaller, higher-income, more educated, and more likely to be white.

Both surveys asked for the respondent's current or most recent occupation, classified according to the 2002 Bureau of Labor Statistics (BLS) codes (BLS 2002).[17] We match these to data on the median earnings of full-time full-year workers in each occupation in 1999 from the US Census (2000). We group occupations into categories (healthcare, food preparer) using a combination of BLS-provided hierarchies and subjective judgment. The online appendix lists the occupations in these groupings.

The first survey included a set of additional questions relating to household migration patterns. These questions were used in the analysis of Bronnenberg et al. (2012). We ignore them in the present analysis.

The second survey, designed for this study, included a series of questions about households' knowledge and attitudes toward various products. In particular, for each of five national brands of headache remedy (Advil, Aleve, Bayer, Excedrin, Tylenol), we asked each respondent who indicated familiarity with a national brand to identify its active ingredient from a list of six possible choices, or state "don't know / not sure."[18] For each respondent we calculate the number of correct responses, treating "don't know" as incorrect. We also asked respondents whether they agreed or disagreed with a series of statements, including "Store-brand products for headache remedies / pain relievers are just as safe as the brand name products," with responses on a 1 (agree) to 7 (disagree) scale. For each respondent, we construct an indicator equal to one if the respondent chose the strongest possible agreement and zero otherwise.

The second survey also asked respondents about their college major using codes from the National Center for Education Statistics (U.S. Department of Education 2012). We define two groups of majors for analysis: health majors, which includes all majors with the word "health" in their description,[19] and non-health science majors, which includes all majors in the physical and biological sciences.

Both surveys asked respondents to indicate whether they are their household's "primary shopper" and whether they are the "head of the household." For each household we identify a single primary shopper whose characteristics we use in the analysis, following the criteria used in Bronnenberg et al. (2012).[20]

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[17]In the small number of cases where an individual provided conflicting responses to the occupation question across the two surveys we use the value from the second survey.

[18]The correct active ingredients are ibuprofen (Advil), naproxen (Aleve), aspirin (Bayer), aspirin-acetaminophen-caffeine (Excedrin), and acetaminophen (Tylenol). In each case, the six possible answers were the five correct active ingredients plus the analgesic hydrocodone.

[19]Examples include "Health: medicine," "Health: nursing," and "Health: dentistry."

[20]We start with all individuals within a household who respond to the survey. We then apply the following criteria in order, stopping at the point when only a single individual is left: (i) keep only self-reported primary shopper(s) if at least one exists; (ii)

In appendix table 1 and the online appendix, we show that our findings go largely unchanged when we incorporate data on the characteristics of secondary shoppers into our analysis.

Throughout the paper, we restrict attention to households in which at least one member answered the occupation question in one or both of our PanelViews surveys. The online appendix reports the number of households whose primary shopper works in each healthcare and food preparer occupation.

2.3 Product Classification

Nielsen provides a set of attribute variables for each UPC code purchased by a Homescan panelist. Some of these, such as size, are available for all categories. Others are category-specific. For example the data include a variable that encodes the active ingredient for each headache remedy in the data. We harmonize the codes for essentially identical descriptors (e.g., "ACET" and "ACETAMINOPHEN" both become "ACETAMINOPHEN").

We use these descriptors to aggregate UPCs into *products*. A product is a group of UPCs that are identical on all non-size attributes provided by Nielsen. For instance, in the case of headache remedies, a product is a combination of an active ingredient (e.g., aspirin, naproxen), form (e.g., tablet, gelcap), formula (e.g., regular strength, extra strength), and brand (e.g., Bayer, Aleve, store brand). We classify products as store brands using Nielsen-provided codes, supplemented with manual corrections.

To compare store brands and national brands we aggregate products into *comparable product groups*, which are sets of products that are identical on all product attributes except for brand and item size.[21] We will use the abbreviated term *comparable* to stand in for *comparable product group* throughout the paper.

We restrict attention to comparables in which we observe at least 500 average annual purchases in Homescan, with at least some purchases going to both store-brand and national-brand products.[22] We eliminate categories in which the available attribute descriptors do not provide sufficient information to identify comparable products.[23] We also eliminate categories in which the average retail price per equivalent unit for national-brand products is lower than store-brand products.[24] This leaves us with a universe of 420 comparables.

We analyze headache remedies and pantry staples in detail. We chose these two case studies because

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keep only household head(s) if at least one exists; (iii) keep only the female household head if both a female and a male head exist; (iv) keep the oldest individual; (v) drop responses that appear to be duplicate responses by the same individual; (vi) select one respondent randomly.

[21]In appendix table 1 we show the robustness of our main results to conditioning on item size.

[22]We further eliminate comparable product groups in which fewer than 50 retail chains ever sell a store brand according to the retail scanner data we discuss in section 2.4 below.

[23]These are: deli products, fresh produce, nutritional supplements, miscellaneous vitamins, and anti-sleep products.

[24]Retail prices are from retail scanner data we discuss in section 2.4 below. We exclude 34 comparables based on this condition.

they have both sufficient purchase volume and a sufficient number of expert households (healthcare workers and food preparers) to permit reliable analysis, and because our prior was that the scope for horizontal differentiation between national and store brands in these categories would be especially small. Our universe of headache remedies consists of the comparables classified by Nielsen as adult, non-migraine, daytime headache remedies. Our universe of pantry staples consists of the comparables classified by Nielsen as table salt, sugar, or baking soda.

We restrict our sample to transactions such that at least one comparable national-brand purchase and at least one comparable store-brand purchase are observed in the Homescan data in the same retail chain and quarter as the given transaction. This restriction limits the likelihood that a national-brand product is purchased because no store-brand alternative is available (or vice versa).

Although we compute summary statistics for the universe of 420 comparables, we conduct regression analysis using only those comparables with at least 5,000 sample purchases. We do this to ensure sufficient data to estimate models with a rich set of controls. With this restriction, there are 332 comparables available for regression analysis, including 6 headache remedies, 44 other health-related products, 6 pantry staples, 235 other food and drink products, and 41 remaining products. The online appendix lists all comparables that we use in our regression analysis.

2.4 Retail Scanner Data

To estimate prices and aggregate expenditure, we use 2008 store-level scanner data from the Nielsen Retail Measurement Services (RMS) files, which we obtained through a partnership between Nielsen and Chicago Booth's Kilts Center. These data contain store-level revenue and volume by UPC and week for approximately 38,000 stores in over 100 retail chains. We use our product classification to aggregate UPCs into products.

For each comparable, we compute average price per equivalent unit for national and store brands respectively as the ratio of total expenditure to total equivalent units across all grocery, drug, and mass merchandise stores across all weeks in 2008. We also estimate total US expenditure on national and store brands respectively by multiplying the number of equivalent units purchased in the Homescan data by (i) the ratio of total equivalent units for the comparable in RMS and Homescan, (ii) the average price per equivalent unit, (iii) the ratio of 2008 US food, drug, and mass merchandise sales to total 2008 expenditure measured in RMS.[25]

The sum of estimated total US expenditure across the comparables in our sample is $196 billion. If all

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[25]The Annual Retail Trade Survey of the United States Census Bureau reports 2008 annual sales in grocery stores, pharmacies and drug stores, and warehouse clubs and superstores of $512 billion, $211 billion, and $352 billion, respectively, totaling $1,075 billion (U.S. Census 2013).

observed equivalent units were purchased at the average price per equivalent unit of store brands, this sum would fall by \$44 billion or 22 percent.

2.5 Wholesale Price Data

We estimate retail margins by brand using data from National Promotion Reports' PRICE-TRAK product, obtained through Chicago Booth's Kilts Center. These data contain wholesale price changes and deal offers by UPC in 48 markets from 2006 until 2011, along with associated product attributes such as item and pack sizes. The data are sourced from one major wholesaler in each market, which is representative due to the provisions of the Robinson-Patman (Anti-Price Discrimination) Act.

We compute the average wholesale price of each product as the unweighted average post-deal price across markets. We compute retail margins by matching wholesale prices with retail prices by UPC, item size, and year. We then compute the median retail margin of national-brand and store-brand products within each comparable.[26]

3 Model of Choice by Uninformed and Informed Households

In this section we lay out a stylized model of choice by uninformed and informed households. The model clarifies the assumptions necessary to identify the effect of information on household choice and welfare.

3.1 Choice Model and Interpretation

Let there be a set of households indexed by i. Each household must choose between a national brand and a store brand of some product. At the store where household i shops, the national brand costs $\Delta p_i > 0$ dollars more than the store brand.

Household i believes that the national brand delivers $\Delta v_i \geq 0$ more money-metric utility than the store brand, but the true difference is $\Delta \tilde{v}_i \geq 0$, which may be greater or lesser than Δv_i. The household buys the national brand if and only if $\Delta v_i \geq \Delta p_i$. We refer to the counterfactual in which the household buys the national brand if and only if $\Delta \tilde{v}_i \geq \Delta p_i$ as *informed choice*.

If $\Delta v_i, \Delta \tilde{v}_i \geq \Delta p_i$ or $\Delta p_i > \Delta v_i, \Delta \tilde{v}_i$ then the household's decision is identical under informed choice so its welfare does not change. If $\Delta v_i \geq \Delta p_i > \Delta \tilde{v}_i$ then under informed choice the household switches from

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[26]We compute the median rather than the mean retail margin to avoid the influence of outlier observations that arise due to mismatch in item size etc.

the national brand to the store brand and gains $\Delta p_i - \Delta \tilde{v}_i$. If $\Delta \tilde{v}_i \geq \Delta p_i > \Delta v_i$ then under informed choice the household switches from the store brand to the national brand and gains $\Delta \tilde{v}_i - \Delta p_i$.

The model does not specify why there is a gap between true and perceived brand utility. However it is general enough to be consistent with several intuitive reasons for such a gap:

1. *Perceptions of quality.* Let Δq_i be the perceived quality difference between the two products and let $\Delta \tilde{q}_i$ be the true difference in quality (say, clinically efficacy for a medication). Let m_i be the household's marginal utility of money in units of quality. Then we can write $\Delta v_i = \Delta q_i / m_i$ and $\Delta \tilde{v}_i = \Delta \tilde{q}_i / m_i$.

2. *Perceptions of failure risk.* The product may succeed, delivering value $\bar{v}$, or it may fail, delivering value $\underline{v}$. These values are the same for the national and store brands but the risk of failure is different. A household perceives that the national brand's risk of failure is lower by Δr_i but in fact it is lower by $\Delta \tilde{r}_i$. Then $\Delta v_i = \Delta r_i (\bar{v} - \underline{v})$ and $\Delta \tilde{v}_i = \Delta \tilde{r}_i (\bar{v} - \underline{v})$.

3. *Attention to irrelevant factors.* The national and store brand differ by amounts Δx_1 and Δx_2 in each of two dimensions (say, taste and packaging). Utility is a weighted average of the two dimensions. Household i attaches weight ω_i to the second dimension but the correct weight is 0. Then $\Delta v_i = (1 - \omega_i) \Delta x_1 + \omega_i \Delta x_2$ and $\Delta \tilde{v}_i = \Delta x_1$.

Different microfoundations may be appropriate for different product categories. For example, we might expect that perceptions of failure risk are especially important for medications, whereas attention to factors like packaging is especially important for food and drinks.

Note that, while our framework accommodates many reasons for a departure between true and perceived brand utility, it cannot accommodate cases in which information affects utility directly. Suppose, for example, that the true utility informed consumers receive from the national brand and the store brand is the same. Denote this $\Delta \tilde{v}_i^{informed} = 0$. Uninformed consumers receive the same true utility from the store brand, but they receive an additional placebo benefit from the national brand, so $\Delta \tilde{v}_i^{uninformed} > \Delta p_i > 0$. For both types, perceived and true utility are equal. In this case, providing information to a consumer i would cause her to lose the value of the placebo effect, and she would suffer a welfare *loss* of $\Delta \tilde{v}_i^{uninformed} - \Delta p_i$ instead of reaping a welfare gain of Δp_i.

3.2 Identifying the Welfare Gains from Informed Choice

We now consider how to recover the effect of informed choice on the aggregate welfare of households.

Begin with the special case in which $\Delta \tilde{v}_i = 0$ for all i. This would be an appropriate assumption if we knew that national and store brands were identical in all respects except for the brand itself, and if we were prepared to assume away any psychic benefit of brands. In this case any household buying the national brand would switch to the store brand under informed choice, gaining welfare Δp_i. We can compute the aggregate gain in household welfare from informed choice by aggregating the price premia paid by all households who buy the national brand.

Identification is more difficult in the more general case in which $\Delta \tilde{v}_i$ is not known. Because choices are based on perceived utility Δv_i, we cannot use price variation to recover true utility $\Delta \tilde{v}_i$. Our approach in this paper is to parametrize the relationship between $\Delta \tilde{v}_i$ and Δv_i by assuming that more informed households act according to $\Delta \tilde{v}_i$ and less informed households act according to Δv_i.

Let $\phi_i \in [0,1]$ be an index of household i's information. Suppose that, for all i, $\Delta \tilde{v}_i = \Delta \tilde{v}$ and $\Delta v_i = \phi_i \Delta \tilde{v} + (1 - \phi_i) \Delta v$, where $\Delta \tilde{v} \geq 0$ and $\Delta v \geq 0$ are constants representing perceived utility from the national brand for perfectly informed and perfectly uninformed households, respectively. Suppose further that all households shop in the same store, so that, for all i, $\Delta p_i = \Delta p$ for some constant $\Delta p > 0$.

We observe ϕ_i and an indicator y_i for whether household i chooses the store brand. There are three possible cases. If $y_i = 1$ or $y_i = 0$ for all possible ϕ_i then $\Delta p > \Delta \tilde{v}, \Delta v$ or $\Delta \tilde{v}, \Delta v \geq \Delta p$, respectively, so households do not gain from informed choice. If $y_i = 0$ if and only if ϕ_i is below a threshold value, then $\Delta v \geq \Delta p > \Delta \tilde{v}$ and households buying the national brand would gain $\Delta p - \Delta \tilde{v}$ from informed choice. If $y_i = 0$ if and only if ϕ_i is above a threshold value, then $\Delta \tilde{v} \geq \Delta p > \Delta v$ and households buying the store brand would gain $\Delta \tilde{v} - \Delta p$ from informed choice.

From the sign of the cross-sectional relationship between y_i and ϕ_i, it is therefore possible to learn whether households as a whole are buying too much of the national brand, too much of the store brand, or the right brand. This argument motivates our descriptive analysis of the relationship between household information and the propensity to buy the store brand in sections 4 and 5.

Notice that the cross-sectional relationship between y_i and ϕ_i does not tell us how much households would gain from informed choice. To recover that quantity, suppose that we observe choices by a large number of households in which $\phi_i = 1$ and that we can vary the prices paid Δp. Then we can learn $\Delta \tilde{v}$ by finding the price gap at which informed households switch brands. Once we know $\Delta \tilde{v}$, we can compute the aggregate welfare gain from informed choice at current prices by aggregating the welfare gains across all households that buy a different brand from the one chosen by informed households. This argument motivates the structural analysis in section 6, in which we use a combination of functional form and conduct assumptions to recover the necessary magnitudes.

3.3 Estimation and Implementation

Here we flesh out the practical implications of the preceding discussion for our descriptive analysis of the effect of information on brand choice. We defer details of our structural exercise until section 6.

To execute the cross-sectional test that we describe above, we need to ensure three conditions.

First, we need to observe variation in household information ϕ_i. We form a vector K_i of proxies for ϕ_i, including knowledge of active ingredients, completed schooling, college major, and occupation.[27] These measures are proxies in the sense that we do not know how the units of K_i map to ϕ_i. We cannot say, for example, that completing college closes the gap between true and perceived preferences by some given number of percentage points, as we could if we measured ϕ_i directly. These measures are also proxies in the sense that the correlation of an element of K_i with choice y_i reflects both a direct causal effect (e.g., knowing that Tylenol's active ingredient is acetaminophen directly affects choice) and an indirect effect of information correlated with K_i (e.g., consumers who know Tylenol's active ingredient also tend to be well informed about other characteristics of headache remedies).

Second, we need to compare more to less informed households while holding constant prices Δp_i and any other contextual drivers of choice (e.g., in-store displays or shelf position). We do this by assuming that all such drivers are a function of observable store and time characteristics Z_i. In our preferred specifications, Z_i will include interacted indicators for market, chain, and calendar quarter. In appendix table 1, we show that our results survive even richer controls for the timing and location of purchases.

Third, we need to compare more and less informed households with identical true preferences $\Delta \tilde{v}_i$. This consideration means we need to exclude cases in which the national and store brand differ on horizontal attributes (e.g., cherry vs. orange flavor) over which households may have different preference orderings. We therefore focus on brand choice within comparable product groups that are homogeneous on measured attributes. We show empirically that preferences for measured attributes (e.g., tablet vs. caplet) do not correlate with our information proxies K_i, which supports our assumption that preferences for unmeasured horizontal attributes are not correlated with K_i.

This consideration also means we need to hold constant households' willingness to pay for quality. Income is the most obvious source of heterogeneity in willingness-to-pay for quality. We control for income in our analysis and we find that doing so often strengthens our results. We also show that a relationship

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[27]Past purchase experience may also serve as a proxy for a household's knowledge of the category. As past purchases are endogenous both to preferences and to the choice environment, we do not include this proxy in our main analysis. In appendix table 1 we show that our core findings are unchanged if we estimate specifications that control for average annual purchase volume. In these specifications, higher purchase volume is consistently associated with a statistically significant increase in the propensity to buy store brand.

between information and choice is present even among occupational groups that are similar in socioeco-nomic status (e.g., lawyers and physicians). We further control for a range of demographic characteristics (e.g., age and household composition). We expect that any remaining preference heterogeneity will work against our main findings: if national brands are of higher quality and more informed households have a stronger preference for quality (physicians have if anything a greater taste for high-quality medicine, and chefs have if anything a greater taste for high-quality food), our estimates will tend to understate the effect of information on choice.

To describe the relationships among choice y_i, information K_i, household characteristics X_i and choice environment Z_i, we will estimate linear probability models of the following form:

$$\Pr(y_i = 1 | K_i, X_i, Z_i) = \alpha + K_i\beta + X_i\gamma + Z_i\rho, \tag{1}$$

where α, β, γ, and ρ are vectors of parameters.[28] Although for notational ease we have written the model at the level of the household, a given household can make multiple purchases. We therefore estimate the model at the level of the purchase occasion, reporting standard errors that allow for correlation at the level of the household, and weighting transactions by purchase volume. Appendix table 1 shows that our main conclusions are unaffected if we estimate binary logit models instead of linear probability models.

4 Case Studies

4.1 Headache Remedies

We begin our analysis with a case study of adult, non-migraine, daytime headache remedies. The first rows of table 1 show summary statistics for the six comparables in this category. These products span four active ingredients, each associated with a familiar national brand: aspirin (Bayer), acetaminophen (Tylenol), ibuprofen (Advil), and naproxen (Aleve). We estimate total annual expenditure on these comparables to be $2.88 billion. Store-brand purchases account for 74 percent of pills and 53 percent of expenditures.[29]

On average, the per-pill price of a store brand is 40 percent of the price of a comparable national brand. For aspirin, a mature product that has been off patent since 1917, the per-pill price of store brands is 22 percent of the national-brand price. These price differences are not due to differences in where these products are sold or to volume discounts: among cases in our panel in which we observe at least one national-brand

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[28]When we pool data across multiple comparables, we will allow the intercept α to differ by comparable.

[29]Among households with multiple headache remedy purchases, 31 percent bought only store brands and 16 percent bought only national brands. The remaining 52 percent bought both store brands and national brands.

and one store-brand purchase for the same active ingredient and package size in the same market, chain, and week, the per-pill price paid for store brands is on average 26 percent of the price of an equivalent national brand. The median gap is 31 percent, and the national brand is cheaper in only 5 percent of cases.

Store-brand alternatives for national-brand headache remedies are widely available. Using our store-level data, we estimate that 82 percent of national-brand headache remedy purchase volume is purchased when a store brand with the same active ingredient and form and at least as many pills is sold in the same store and quarter at a lower price.[30] In our PanelViews survey data, only 3.6 percent of households report that no store-brand alternative was available at their last purchase.

In figure 1 we look at the relationship between knowledge of active ingredients and our indirect knowledge proxies—completed schooling, occupation, and college major. The relationships are as expected. Panel A shows that shoppers with a college education correctly identify the active ingredient in 62 percent of cases, as against 52 percent for those with a high school degree or less. Panel B shows that nurses correctly identify the active ingredient in 85 percent of cases, pharmacists in 89 percent, and physicians and surgeons in 90 percent. Panel C shows that shoppers whose college major is health or science related are more informed than other shoppers. In the online appendix, we confirm these relationships in a regression framework, showing that they remain strong even after controlling for a rich set of household characteristics, including income.

Having validated our proxies, we turn to our main question of interest: the impact of information on the share of purchases that go to store brands. Figure 2 shows that greater knowledge of active ingredients predicts more purchases of store brands. Those who can name no active ingredients buy just over 60 percent store brands. Those who can name all five active ingredients buy nearly 85 percent store brands. Though these differences are large, they could be due to reverse causality: those interested in saving money buy store brands and also take the time to read ingredient labels. By contrast, while demographic characteristics like completed schooling may be correlated with unobserved product preferences, such characteristics are most likely not determined by households' preferences for store-brand vs. national-brand products. We therefore turn next to examining variation in information induced by completed schooling, occupation, and college major.

Figure 3 shows the relationship between store-brand share and completed schooling. With no controls, we see that those with education beyond high school buy more store brands than those with a high school

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[30]The analogous estimates at the store-month and store-week level are 77 percent and 62 percent, respectively. These statistics can underestimate the availability of store-brand alternatives because a store-brand can be available but not purchased in a given time period (Handbury and Weinstein 2015). These statistics can also overstate availability because a product can be purchased but not available throughout the entire time period, for example due to stockouts (Matsa 2011).

degree or less, but that there is no clear difference between those with some college, a college degree, or more than a college degree. The main confound here is income, which is strongly negatively correlated with store-brand purchases.[31] This is consistent with the "perceptions of quality" example in section 3, in which households differ in both the marginal utility of money and in the perceived quality gain from the national brand. After controlling for income, we find a monotonic positive relationship between completed schooling and store-brand share.

Figure 4 shows the relationship between store-brand share and occupation. Here we see a negative relationship between store-brand share and median occupational income among non-healthcare occupations. Households whose primary shopper is a healthcare professional buy far more store brands than others of similar income. Pharmacists, physicians, and nurses buy more store brands than lawyers, who have high levels of schooling but different occupational expertise.

Pharmacists, who stand out in the survey data in figure 1 as among the most informed about active ingredients, also stand out for having the largest store-brand share among large healthcare occupations. Only 8.5 percent of volume bought by pharmacists are national-brand headache remedies, an amount small enough to be explained by the occasional stock outs of store brands, and the fact that some purchases are made by the non-pharmacist member of a pharmacist's household.[32]

Table 2 presents the relationship between store-brand share and knowledge of active ingredients in a regression framework. The table presents estimates of equation 1, where the information variables of interest K_i are the share of active ingredients known and an indicator for college education. All specifications allow the intercept α to differ by comparable. Columns (1), (2), and (3) include market and calendar quarter indicators in the vector of choice environment measures Z_i; column (4) and (5) add interacted indicators for the market, chain, and calendar quarter. Column (1) includes controls for demographics other than income

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[31]The online appendix presents a plot of a household's store-brand share of purchases against annual household income and confirms a strong negative relationship.

[32]The fact that 8.5 percent of purchases by households whose primary shopper is a pharmacist are to national-brand goods suggests at first that 8.5 percent of the time a pharmacist is willing to pay a significant price premium to buy a national brand.

There are three main reasons to interpret the finding differently.

First, the primary shopper need not be the only shopper in the household. In the small number of cases (12 households, 37 transactions) in which a household with both a primary shopper and a secondary shopper who are pharmacists buy a headache remedy, only 1.6 percent of purchases are to national brands. In the case of single-person households in which the only person is a pharmacist (22 households, 109 transactions), only 5 percent of purchases are to national brands.

Second, although we have focused on transactions in retailers who stock both national brands and store brands, some stockouts may nevertheless occur. Matsa (2011) estimates the stockout rate for over-the-counter drugs to be 2.8 percent. In the face of a stockout of the store brand, pharmacists who are unable to delay their purchase may switch to buying a national-brand good.

Third, although the average price premium for national brands is very large in this category, there is some price variation, and pharmacists may be buying when the price difference is unusually small. In the Homescan data, we find that, for purchases made by households in which the primary shopper is a pharmacist, the ratio of the average store-brand price to the average national-brand price is 6 percent greater than for the average purchase. For purchases made by households in which the only person is a pharmacist, the price ratio is 14 percent greater than for the average purchase.

in the vector of household characteristics X_i; column (2) adds the log of imputed household income; column (3) through (5) include income category indicators.[33]

Column (2) shows that a 10 percent increase in household income reduces the propensity to purchase the store-brand by 0.3 percentage points. Because income and education are positively correlated but have opposite effects on store-brand purchasing, the effect of education gets larger when income controls are added. In the preferred specification, column (4), college education increases the propensity to buy store brand by 2.6 percentage points. The effect of knowledge of active ingredients is fairly stable across specifications; column (4) shows that going from knowledge of no active ingredients to knowledge of all increases the store-brand share by 19 percentage points.

Column (5) of table 2 augments the specification in column (4) by adding to K_i an indicator for whether the shopper reports that store brands are "just as safe" as national brands. This is a less convincing measure of information than active ingredient knowledge, as the correct answer is arguably unclear. Still, it is worth noting that it is a very strong correlate of brand choice: believing store brands are just as safe as national brands has an additional effect of 21 percentage points over and above the effect of active ingredient knowledge. The effect of having this belief *and* being able to name all active ingredients correctly is 35 percentage points.

Table 3 presents regression evidence on the effect of occupation. The model and controls in the first three columns are the same as in columns (1), (2), and (4) of table 2, but now the vector K_i of information proxies consists of an indicator for college education, an indicator for being a pharmacist or physician, and an indicator for being in a healthcare occupation other than pharmacist or physician. The estimated occupation effects remain stable as we add controls. In the preferred specification of column (3) we find that being a pharmacist or physician increases the propensity to buy store brands by 15 percentage points; being in another healthcare occupation increases the propensity by 8 percentage points.

Column (4) of table 3 presents evidence on the role of college major. We restrict the sample to respondents who completed college and who reported their college major in our survey. We find that non-health science majors are 5 percentage points more likely to buy store brand. Column (5) of table 3 presents occupation results for the subsample of households whose primary shoppers are not currently employed for pay. The online appendix shows that these households' primary shoppers are less likely to be prime working age, more likely to be women, and more likely to be living with young children, relative to primary shoppers who are currently employed for pay. The coefficients on the occupation indicators remain large in magni-

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[33]In our main specifications, we proxy for income using the categorical household income variable supplied by Nielsen. Appendix table 1 presents specifications that additionally control for average annual grocery spending and median occupational income.

tude and statistically significant in this subsample, though less precisely estimated than in the full sample. Taken together, columns (4) and (5) suggest our results are unlikely to be driven by factors specific to current employment in a healthcare profession, such as the availability of employee discounts or free samples. As further evidence, in the online appendix we use data on occupational knowledge requirements to show that the propensity to buy store brand is greater among shoppers whose occupations require medical knowledge. This holds true even if we exclude shoppers who we have classified as having occupations in healthcare.

Column (6) of table 3 presents evidence on the extent to which our direct and indirect knowledge measures capture the same underlying variation. We repeat the preferred specification of table 3 column (3), this time restricting to respondents who answered all active ingredients questions correctly, and believe that store brands are "just as safe" as national brands.[34] Restricting attention to well-informed consumers reduces the occupation coefficients by more than 70 percent and renders them statistically indistinguishable from zero. These findings are consistent with the interpretation that all of our measures capture variation along a common dimension, which we interpret as information.

As further support for our identifying assumptions, appendix figure 1 shows that healthcare professionals and non-healthcare professionals look similar in their choices over observed product attributes such as active ingredient and physical form. The online appendix presents analogous plots for average annual purchase volume and item size, respectively.

4.2 Pantry Staples

We now turn to the analysis of food purchases. Here our proxies for knowledge are indicators for whether the primary shopper is a chef ("chef or head cook") or other food preparer.[35] We begin with a case study of pantry staples: salt, sugar, and baking soda. We choose these products because they are uniform in chemical composition and purpose, and thus analogous to headache remedies in being relatively homogeneous.

The lower portion of table 1 includes summary statistics for the six comparables we classify as pantry staples: baking soda; regular iodized and plain salt (sold in boxes); and regular granulated, light brown, and powdered sugar (sold in bags). Collectively, these comparables account for $1.81 billion of expenditure. Store-brand purchases account for 60 percent of volume and 57 percent of expenditure. On average, the ratio of store-brand to national-brand price per equivalent volume is 0.92.

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[34]Imposing this restriction requires us to use only the sample of households that responded to the second survey wave. We show in the online appendix that the results from our baseline specification are comparable in this subsample.

[35]Our second survey wave asked respondents to identify the most common additive to table salt (iodine), the scientific name for baking soda (sodium bicarbonate), and the most common ingredient of granulated sugar (sucrose). The share of these questions answered correctly is positively correlated with working as a chef but not with being a non-chef food preparer, and is positively correlated (but not statistically significantly so) with the propensity to buy store-brand pantry staples. Results for these knowledge measures are presented in the online appendix.

Figure 5 shows the relationship between store-brand share and occupation. As with headache remedies, there is a strong negative relationship between store-brand share and median occupational income. Households whose primary shopper is a food preparer or food service manager buy more store brands than others of similar occupational income. Chefs—the occupational group we would have expected *ex ante* to be most informed about the quality of food products—buy more than 77 percent store brands in these categories, more than any other occupation of meaningful size.

Table 4 shows the relationship with occupation in a regression framework. The specifications in the five columns are the same as in the analogous columns of table 3, with the information proxies of interest K_i now consisting of an indicator for college education, an indicator for being a chef, and an indicator for being a food preparer but not a chef. In our preferred specification of column (3), we estimate that being a chef increases the probability of buying store brands by 12 percentage points, and working in a non-chef food preparation occupation increases this probability by 2 percentage points. These effects are somewhat smaller in magnitude than those we estimate when we do not include our preferred set of controls. In contrast to headache remedies, we do not find any clear effect of college education. Column (4) shows that non-health science majors and health majors are not statistically different from other college graduates. Column (5) shows that the coefficient on being a chef goes largely unchanged when we focus on shoppers who are not currently employed. The coefficient on being a non-chef food preparer falls and becomes statistically insignificant, but its confidence interval includes the magnitude of our preferred estimate. These findings suggest that the effects we estimate are not driven by mechanical effects of employment in the food industry.

4.3 Evidence on Domain Specificity

We find that health experts purchase more store-brand health products and that food experts purchase more store-brand food products. A natural follow-up question is whether experts' knowledge is transferable outside of their domain of expertise. Perhaps pharmacists' understanding of the equivalence of national-brand and store-brand headache remedies leads them to also recognize the likely equivalence of national-brand and store-brand baking soda. Or perhaps their understanding does not translate beyond the categories with which they are directly familiar.

Table 5 presents evidence on domain specificity. The first two columns look at the effect of healthcare expertise on pantry staple purchases. Column (1) shows that the share of headache remedy active ingredients known has no significant effect on the probability of purchasing store-brand pantry staples, with a confidence interval that rules out effects greater than 1.2 percentage points. Column (2) shows that pharmacists, physicians, and other healthcare professionals are also not significantly more likely to buy store-brand

pantry staples. The confidence intervals on the pharmacist-physician and other healthcare occupation coefficients rule out effects greater than 5.2 percentage points and 2.2 percentage points respectively. We can confidently reject the hypothesis that these effects are as large as the effects we estimate for headache remedy purchases. The evidence thus suggests that healthcare expertise does not translate to behavior outside the health domain, consistent with past evidence on the domain specificity of expertise (Levitt et al. 2010).

The final column of table 5 looks at the effect of food preparation expertise on headache remedy purchases. Here, we do see some evidence of transferability: controlling for income and other demographics, chefs are a statistically significant 11 percentage points more likely to buy store-brand headache remedies than other consumers. There is no significant effect for food preparers other than chefs.

5 Cross-category Comparisons

5.1 Health Products

We turn next to analyzing a broad set of health products. We restrict attention to the 6 headache remedy comparables that we study above, and 44 additional comparables for which we observe at least $5,000$ purchases by households with non-missing values of our demographic controls. These include other medications such as cold remedies, first aid products such as bandages, and miscellaneous products such as vitamins and contact lens solution. Non-painkiller health categories account for \$8.94 billion of expenditure per year. Store-brand purchases account for 57 percent of volume. Store-brand prices are half of national-brand prices on average.

For each comparable, we run one regression to estimate the effect of knowing headache remedy active ingredients (using the specification in column (4) of table 2) and one to estimate the effect of being a pharmacist or physician (using the specification in column (3) of table 3). Figures 6 and 7 present coefficients on these information proxies along with 95 percent confidence intervals. We present analogous plots for the coefficients on college education and other healthcare occupation in the online appendix. In order to test joint hypotheses about the coefficients in these plots, we estimate our full set of regression models on 20 bootstrap replicates. In each replicate we draw a random subset of households with replacement. For the remainder of the paper, all bootstrap inference will be based on these 20 replicates.[36]

Figure 6 shows that the coefficient on active ingredient knowledge is positive in 43 out of 50 cases. The share of coefficient estimates that are positive is thus 0.86, which has a bootstrap standard error of 0.05,

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[36]We use 20 replicates instead of a larger number due to computational costs. The online appendix compares the standard errors on our key regression coefficients from our 20 replicates to those obtained from a more intensive bootstrap with 200 replicates, for a random subset of 20 comparables.

and is therefore highly statistically distinguishable from the null hypothesis of no effect (half of coefficients positive). Consistent with the evidence on domain specificity that we present above, if we estimate analogous models for non-health comparables, the coefficient on active ingredient knowledge is positive in only 168 out of 282 cases, which is much closer to the null hypothesis and highly statistically distinguishable from the number for health categories. Figure 8 illustrates the contrast visually, plotting the distribution of t-statistics separately for health and non-health comparables.

The differences among the coefficients in figure 6 are instructive. The coefficients tend to be larger and more significant for medications and relatively smaller for first aid and eye care products, suggesting that in the latter group informed shoppers perceive true quality differences. Indeed, contact lens solutions are the only healthcare product we have identified where some medical professionals recommend patients buy national brands due to quality concerns with store brands (Secor 2002). In the online appendix, we show that the estimated effects of most information proxies tend to be larger (though not statistically significantly so) in comparables in which *Consumer Reports* considers store brands and national brands to be equivalent. We also examine whether the effect of information is greater in the comparables for which the price gap between national and store brands is greatest, and find only a weak association. Finally, we show that the effect of information tends to be greater in more advertising-intensive comparables, consistent with the idea that perceptions of product quality by the uninformed may be driven by advertising on the part of national-brand manufacturers.

Figure 7 presents estimates of the effect of being a pharmacist or physician; estimates of the effect of being in another healthcare occupation are presented in the online appendix. We see broadly similar patterns to the coefficients on active ingredient knowledge, though with somewhat less precision. The effect of being a pharmacist or physician is positive in share 0.68 of cases (bootstrap standard error = 0.05), and the effect of being in another healthcare occupation is positive in share 0.86 of cases (bootstrap standard error = 0.04). In the online appendix we present plots analogous to figure 8 for the coefficients on the pharmacist/physician indicator and the other healthcare occupation indicator.

It is important to stress that figure 6 shows the relationship between store-brand purchase and knowledge of *headache remedy* active ingredients; we do not have direct measures of knowledge for non-headache-remedy comparables. We might therefore expect this knowledge proxy to be most strongly related to store-brand purchases in headache remedies and similar categories, even if the true effects of information are no greater in such categories. Our cross-category analysis of occupational effects in figure 7 and the online appendix is useful in part because the effects of occupation are not subject to this type of bias.

5.2 Food and Drink Products

Next we consider the remaining food and drink comparables in our data. We restrict attention to the 6 pantry staples that we study above, plus 235 additional comparables for which we observe at least 5,000 purchases by households with non-missing values of our demographic controls. These comprise a broad cross-section of supermarket products, from milk and eggs, to carbonated beverages, to ready-to-eat cereal. Excluding pantry staples, these categories account for $123 billion of expenditure. Store-brand purchases account for 43 percent of volume. On average, the price-per-equivalent-volume for store brands is 70 percent of that for national brands.

For each comparable, we run a separate regression to estimate the effect of working as a chef or other food preparer on store-brand purchases (using the specification in column (3) of table 4). Figure 9 summarizes the estimated coefficients and 95 percent confidence intervals. Rather than try to present all coefficients in a single figure, we aggregate comparables other than pantry staples into what Nielsen calls "product groups," weighting the individual comparables by precision and computing the aggregate confidence interval as if the individual coefficients are statistically independent. Thus, for example, the comparables for cola, diet cola, lemon-lime soda, and so forth are combined into the Nielsen product group "carbonated beverages."

The estimated effects of knowledge on store-brand purchases in these categories are weaker than what we saw for health products. The coefficients on working as a chef are positive for 148 comparables and negative for 93. The share of coefficient estimates that are positive is thus 0.61, with a bootstrap standard error of 0.04. The coefficients that are individually statistically significant are generally small in magnitude. The pantry staples categories stand out as having among the most positive and significant coefficients: granulated sugar has the third largest coefficient in the figure, and three of the top six coefficients are pantry staples. In the online appendix we present plots analogous to figure 9 for working in other food preparation occupations and for having a college education.

6 Aggregate Effects of Consumer Information

In this section we add structure to the stylized model in section 3. We estimate the model using a combination of the coefficients from the preceding analysis and additional data moments. We then compute the effect of consumer information on the distribution of consumer and producer surplus, and on prices and market shares.

The purpose of this analysis is twofold. First, we wish to aggregate the coefficients estimated in section

5 to learn how expenditures, market shares, and profits would change in the drug store and the grocery store if all households behaved like expert shoppers. This aggregation does not rely on details of the model: it amounts to an expenditure-weighted aggregation of the coefficients from our linear probability models (e.g., those presented in figure 7), along with information on retail and wholesale prices.

Second, we wish to predict how consumer welfare and firm pricing would change in a world of informed shoppers. Our predictions are contingent on a set of strong parametric, symmetry, and conduct assumptions. These assumptions allow us to solve the model in closed form for a large set of product categories, and to show transparently how the various empirical moments determine our estimates. Because the resulting model is highly stylized, our welfare and pricing results should be taken more as suggestive illustrations of the economic forces at work than as realistic empirical predictions.

6.1 Model

For each comparable, consider a market with R retailers indexed by r and households indexed by i. Each retailer sells a store brand with price $p(0,r)$ and a national brand with price $p(1,r)$. Each household must make a single purchase from the choice set $\{0,1\} \times \{1,...,R\}$. Both the store brand and the national brand are manufactured at constant marginal cost c.

Each retailer sets the price of, and captures all profits from, its own store brand. A single manufacturer captures all profits from the sale of the national brand and sets the price of this brand at each retailer. The assumption that the manufacturer sets the final retail price means that our model does not exhibit double-marginalization effects. We view this as an approximation to a setting in which the manufacturer has a rich set of instruments (wholesale prices, slotting fees, promotional allowances, resale price maintenance, etc.) with which to influence both the final price and the distribution of profits between the manufacturer and the retailer.[37] We treat advertising and other marketing costs incurred by the manufacturer as a sunk cost in the sense of Shaked and Sutton (1987) and Sutton (1989), and we assume these costs are chosen at a prior stage that we do not model.

The market consists of a large number of uninformed households—which we define as consumers who are not pharmacists or physicians for health products and consumers who are not chefs for food products— as well as a small number of informed households. We assume the latter are few enough that firms ignore them in making pricing decisions, and we do not include them in our welfare calculations.

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[37]See the discussion of vertical control in O'Brien and Shaffer (1992) and Shaffer (1991).

Each household maximizes utility $u_i(b,r)$ given by

$$u_i(b,r) = v_i(b) - p(b,r) - \tau_i(r), \tag{2}$$

where $b \in \{0,1\}$ is an indicator for purchasing the national brand, $v_i(b)$ is an idiosyncratic perceived brand preference, and $\tau_i(r)$ is an idiosyncratic travel cost distributed standard type-I extreme value up to a scale parameter. Each household has a true brand preference $\tilde{v}_i(b)$.

We specify brand preferences as follows. We normalize $v_i(0) = \tilde{v}_i(0) = 0$. For each household, we let $\tilde{v}_i(1) = \lambda \xi_i$ where λ is a parameter and ξ_i is a preference shock distributed i.i.d. logistic across households. For uninformed households, $v_i(1) = \xi_i$; for informed households, $v_i(1) = \tilde{v}_i(1)$.

The parameter $\lambda \geq 0$ indicates the similarity between true and perceived brand preference for uninformed households. When $\lambda = 1$, perceived and true brand preference agree; when $\lambda = 0$, national and store brand are truly identical but are perceived to be different.

Throughout our analysis, we define consumer welfare with respect to true brand preference. That is, we define the consumer surplus of a household that buys brand b at retailer r as $\tilde{v}_i(b) - p(b,r) - \tau_i(r)$. We define total consumer surplus as the sum of consumer surplus across all households, and we define total surplus as the sum of total consumer surplus and the total variable profits of the manufacturer and retailers.

The game proceeds in three stages. First, the manufacturer and retailers simultaneously announce all prices $p(b,r)$. Second, each household learns its travel cost $\tau_i(r)$ and chooses which retailer r to visit. Third, each household learns its perceived brand preference $v_i(b)$ and chooses which brand b to purchase. We restrict our attention to a symmetric equilibrium in which $p(0,r) = p(0)$, and hence $p(1,r) = p(1)$, for each retailer r.

6.2 Estimation

Estimation is in closed form. Here we outline the key steps; an appendix provides additional details.

We match $p(0)$ and $p(1)$ to the average store-brand and national-brand prices, respectively, and we choose c to match the median retail margin of store brands. We choose the scale of $\tau_i(r)$ to match the retailer's markup on the store brand: greater dispersion in $\tau_i(r)$ implies less competition among retailers and hence greater retail margins. Similarly, we choose the scale of ξ_i to match the manufacturer's markup on the national brand. Given scale parameters, we can then choose the location of ξ_i to match the overall market share of the national brand: a high market share for the national brand implies a high mean value of ξ_i.

Having pinned down the preferences of the uninformed, we choose λ to match the difference in store-brand purchase probability between informed and uninformed consumers shown in figures 7 and 9. When informed households purchase more store brand than uninformed households, $\lambda < 1$. When informed household purchase more national brands than uninformed households, $\lambda > 1$.

The online appendix presents point estimates for all parameters for all comparables, with bootstrapped standard errors.

6.3   Results

Tables 6 and 7 present summaries of our findings, aggregated across groups of comparables, for health and food products, respectively. For each set of products we present the change relative to baseline from two counterfactuals in which households choose according to true rather than perceived brand preference. In the first counterfactual, prices are held constant at observed levels; in the second, prices adjust to reflect the change in consumer demand. We measure changes in consumer expenditure and surplus, and changes in retailer and manufacturer profit, relative to baseline expenditure levels. Tables 6 and 7 use our estimated parameter values. As a benchmark, the online appendix presents analogous results in which we impose $\lambda = 0$ regardless of the estimated λ.

The left panel of table 6 presents results for headache remedies. Holding prices constant at baseline levels, if all consumers became as informed as pharmacists or physicians, the market share of national-brand headache remedies would fall by half, total expenditure on headache remedies would fall by 14 percent, and consumer surplus would increase by 4 percent relative to baseline expenditure. The national-brand manufacturer would lose profits equivalent to 19 percent of baseline expenditure, and retailers would gain profits equivalent to 5 percent. Note that total surplus falls even though we evaluate consumer welfare with respect to true preferences. The reason is that while manufacturing costs are equal across brands, prices are not. Because even experts perceive some small differences among brands ($\lambda > 0$), shifting purchases towards store-brands entails some loss of social efficiency. To illustrate this intuition, the online appendix shows that the change in total surplus gets smaller as national-brand prices approach store-brand prices.

Allowing prices to adjust softens the blow for the national-brand manufacturer by allowing the manufacturer to lower the relative price of the national brand. This harms retailers but increases the gains to the consumer. Because prices come to better reflect manufacturing costs, total surplus rises relative to the case in which prices are held constant, and there is no aggregate efficiency loss relative to baseline. In addition, calculations not reported in the table show that informed households benefit from making all households informed, because prices fall for both national-brand and store-brand goods.

The right panel of table 6 shows that for other health categories we find effects that are similar direction-ally to those for headache remedies, smaller in magnitude, and still economically significant. Allowing for price adjustment, consumers would gain surplus equivalent to 4 percent of baseline expenditure in health cat-egories other than headache remedies, were they to choose according to their true preferences. Additional results presented in the online appendix show that much of this gain would come from (non-headache-remedy) medication categories.

Table 7 examines food and drink categories. Here, the small price differences between national and store brands and the relatively modest effects of information combine to imply fairly small impacts. The greatest effect is found in pantry staples, where allowing for both price adjustment and greater consumer information would improve consumer welfare by an amount equal to 3 percent of baseline expenditure.

The calculations in tables 6 and 7 imply that, at current prices, the average household would gain $7.92 per year in consumer surplus from being as informed as a pharmacist or physician when making health-related purchases and as informed as a chef when making food purchases. Put differently, if information is costly to acquire, households would optimally choose to be as informed as an expert if the cost of doing so were less than $7.92 and to remain uninformed if the cost were greater than $7.92. Of course, these calculations consider only the benefits to information in the comparables that we study; there may well be benefits to expert information in other consumer domains (e.g., decisions about elective surgical procedures).

7 Conclusions

Across a range of products we find strong evidence that more informed shoppers buy more store brands and fewer national brands. Consumer information plays a large quantitative role in health categories, where our estimates imply that expenditures and market shares would change significantly if all households behaved like expert shoppers. By contrast, the role of consumer information is smaller in food and drink categories, where our estimates suggest much smaller gaps between expert and non-expert shopping behavior.

We do not perform any quantitative policy evaluation in the paper. However, we think our findings and methods may be relevant to several active policy areas. One such area is the regulation of "copycat" products that are designed to look like other brands. Regulators, especially in Europe, have considered the possibility that store-brand products with such "copycat packaging" might "lead consumers to think that the [store-brand] product is...of similar quality" to the national brand (UK Competition Commission 2008).[38] Our findings imply that, at least in some product categories, consumers exhibit the opposite bias, believing

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[38]See also section 2.4.4 of the European Commission's Unfair Commercial Practices Guidance (European Commission 2014).

that national brands are better than store brands when in fact they are not. In those categories, "copycat" packaging could raise consumer welfare by signaling that different brands are of similar quality.

A second area of potential policy relevance is the regulation of deceptive advertising. The Federal Trade Commission evaluates claims of deceptive advertising on whether the advertising is indeed deceptive and on whether the deception is "material," for example to the consumer's purchase decision. A common methodology for establishing deceptiveness is a "copy test," in which consumers are shown the advertisements in question and asked to interpret them (see, e.g., Federal Trade Commission 1999). A common methodology for establishing materiality is to survey consumers to ask what factors influence their decisions (Richards and Preston 1992). Our paper suggests comparing the behavioral response of experts and non-experts as a possible choice-based approach to quantifying the harm from a potentially deceptive advertising claim or campaign. If experts respond differently than non-experts, that may be taken as consistent with misinformation; our model suggests one way in which to quantify the costs of that misinformation to non-expert consumers.

In considering these and other policy implications it is worth stressing that our study is limited to examining the effects of information on quantities and prices. If consumers were to become more informed, markets would adjust on other margins as well. In particular, a more informed population of consumers might change whether and how much firms choose to advertise their products, as well as which products are introduced to the market. Taking account of these forms of dynamic adjustment, and examining their implications for welfare, is an important priority for future work.

Appendix

Details of Model Estimation and Computation

We estimate parameters separately for each comparable product group. Let the brand preference shock ξ_i be distributed logistic with location parameter μ and scale parameter σ_{brand}.[39] Define σ_{retail} so that $\tau_i(r)/\sigma_{\text{retail}}$ is distributed standard type I extreme value. The parameters to be estimated are $\{\mu, \sigma_{\text{brand}}, \sigma_{\text{retail}}, R, \lambda\}$.

Let S be the population market share of the store brand for uninformed households. From the properties of the logistic distribution, it is immediate that

$$S = \text{logit}^{-1}\left((\Delta p - \mu)/\sigma_{\text{brand}}\right), \tag{A1}$$

where $\Delta p \equiv p(1) - p(0)$ and $\text{logit}^{-1}(x) = (1 + \exp(-x))^{-1}$.

Begin with estimation of μ and σ_{brand}. It is possible to show that in a symmetric interior equilibrium the manufacturer's first-order condition is

$$p(1) - c = (1 - S)/\frac{dS}{dp(1)}, \tag{A2}$$

where

$$\frac{dS}{dp(1)} = \frac{S(1-S)}{\sigma_{\text{brand}}}. \tag{A3}$$

Given $p(0)$, $p(1)$, and c, equations (A1), (A2), and (A3) imply unique values of μ and σ_{brand} for a given S. We estimate μ and σ_{brand} by substituting the sample analogue of S into the resulting expressions.

Turn next to estimation of σ_{retail} and R. These are not separately identified but for our purposes it is sufficient to identify $\tilde{\sigma}_{\text{retail}} \equiv \frac{R}{R-1}\sigma_{\text{retail}}$. To do this we observe that in a symmetric interior equilibrium the price of the store brand must satisfy

$$p(0) - c = \left[\frac{S}{\tilde{\sigma}_{\text{retail}}} + \frac{dS}{dp(1)}\frac{1}{S}\right]^{-1}. \tag{A4}$$

Given $p(0)$, $p(1)$, c, equations (A2) and (A4) define a unique $\tilde{\sigma}_{\text{retail}}$ as a function of S. We estimate $\tilde{\sigma}_{\text{retail}}$ by substituting the sample analogue of S into the resulting expression.

The final parameter to estimate is λ. Let S_λ be the population market share of the store brand for

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[39]With this parametrization, the mean of ξ_i is μ and the variance is $\pi^2\sigma_{\text{brand}}^2/3$.

informed households:

$$S_\lambda \quad = \quad \text{logit}^{-1}\left((\Delta p/\lambda - \mu)/\sigma_{\text{brand}}\right). \tag{A5}$$

It follows that:

$$\lambda = \frac{\Delta p}{\sigma_{\text{brand}}\left(\text{logit}\left(S_\lambda\right) - \text{logit}\left(S\right)\right) + \Delta p}. \tag{A6}$$

We estimate λ by substituting sample analogues of S and S_λ into this expression.

We use the linear probability models reported in figures 7 (for health categories) and 9 (for food categories) to define sample analogues of S_λ and S for each comparable. For a given comparable, denote these sample analogues by $\hat{S}_\lambda$ and $\hat{S}$, respectively. We define an expert to be a pharmacist or physician for health categories and a chef for non-health categories. We define $\hat{S}_\lambda$ to be the mean predicted probability of choosing store brand if each purchaser i were an expert with the average expert's level of education and the purchaser's own demographics X_i and choice environment Z_i. We define $\hat{S}$ so that the average of $\hat{S}_\lambda$ and $\hat{S}$, weighted by the sample shares of experts and non-experts, is equal to the overall share choosing store brand.

A few exceptional cases are worth noting. When, for a given comparable, the data described in section 2.5 do not include the store-brand retail margin or imply a negative store-brand retail margin, we impute the store-brand retail margin as the expenditure-weighted average store-brand retail margin across other comparables in the same group (health/food). When, for a given comparable, the linear probability model reported in figure 7 (for health categories) or 9 (for food categories) implies that $\hat{S}_\lambda \geq 1$, we impute $\lambda = 0$. When the linear probability model implies that $\hat{S}_\lambda \leq 0$, or when no value of $\lambda \in \left[0, \overline{\lambda}\right]$ explains $\hat{S}_\lambda$, we set λ equal to an upper bound $\overline{\lambda}$. We use the threshold $\overline{\lambda} = 3$ in our estimates. Finally, when no value of $\tilde{\sigma}_{\text{retail}}$ solves equation (A4), we assume in computing counterfactuals that prices are fixed at $p(0)$ and $p(1)$. We summarize the frequency of these cases in the online appendix.

To compute counterfactual prices under informed choice, we solve equations (A2) and (A4) numerically assuming that demand is governed by informed rather than uninformed preferences. Exact expressions for the change in consumer welfare under informed choice are readily derived from the assumed preference structure.[40]

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[40]Fixing baseline prices, for $\lambda \leq 1$ the gain to the average uninformed consumer from choosing according to informed preferences is given by:

$$\int_{\Delta p}^{\Delta p/\lambda} (\Delta p - \lambda \xi_i)\, dF(\xi_i), \tag{A7}$$

where $F()$ is the CDF of the distribution of ξ_i. This integral exists in closed form, as does the analogue for the case of $\lambda > 1$.

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Table 1: Summary statistics

	Total expenditure ($bn / year)	Store-brand share (volume)	Store-brand share ($)	Price ratio (store brand / national brand)
Headache remedies				
Acetaminophen gelcaps	$0.39	0.51	0.38	0.58
Ibuprofen gelcaps	$0.50	0.29	0.22	0.69
Acetaminophen tablets	$0.44	0.81	0.60	0.36
Aspirin tablets	$0.24	0.75	0.40	0.22
Ibuprofen tablets	$0.94	0.81	0.61	0.36
Naproxen sodium tablets	$0.37	0.57	0.44	0.61
Total (6)	$2.88	0.74	0.53	0.40
Other health products, all (82)	$10.87	0.58	0.47	0.54
Other health products, regression sample (44)	$8.94	0.57	0.46	0.55
Pantry staples				
Baking soda	$0.14	0.33	0.27	0.75
Salt (iodized)	$0.07	0.53	0.47	0.76
Salt (plain)	$0.04	0.47	0.40	0.75
Sugar (brown)	$0.17	0.70	0.65	0.81
Sugar (granulated)	$1.27	0.60	0.59	0.92
Sugar (powdered)	$0.13	0.72	0.70	0.88
Total (6)	$1.81	0.60	0.57	0.92
Other food & drink products, all (256)	$134.90	0.39	0.33	0.71
Other food & drink products, regression sample (235)	$122.61	0.43	0.37	0.70
Remaining products, all (70)	$45.05	0.26	0.20	0.58
Remaining products, regression sample (41)	$31.81	0.34	0.26	0.68

Notes: Total expenditure is 2008 annual expenditure in all grocery, drug, and mass merchandise stores in the US, estimated as described in section 2.4. Store-brand share (volume) is the share of equivalent quantity units (pills for headache remedies, pounds for pantry staples) in each comparable devoted to store brands in our 2004–2011 sample of the Nielsen Homescan Panel. Store-brand share ($) is the share of expenditure devoted to store brands in our 2004–2011 sample of the Nielsen Homescan Panel. Price ratio is the average price per equivalent quantity unit observed in the 2008 Nielsen RMS data for store brands divided by the analogous average price for national brands. Rows for "headache remedies" and "pantry staples" each correspond to a single comparable product group. Rows for "other health products," "other food & drink products," and "remaining products" aggregate over multiple comparable product groups, with the number of such groups shown in parentheses. Rows for "all" refer to the universe of all comparables as defined in section 2.3. Rows for "regression sample" refer to the subset of comparables analyzed in section 5. In columns two through four, these aggregates average over comparable product groups weighting by expenditure, except for headache remedies, where we weight by number of pills.

Table 2: Knowledge and headache remedy purchases

Dependent variable: Purchase is a store brand

Primary shopper characteristics:	(1)	(2)	(3)	(4)	(5)
College education	0.0094	0.0206	0.0212	0.0255	0.0214
	(0.0072)	(0.0074)	(0.0075)	(0.0073)	(0.0068)
Share of active ingredients known	0.1792	0.1805	0.1805	0.1898	0.1463
	(0.0111)	(0.0112)	(0.0111)	(0.0108)	(0.0105)
Log(household income)		-0.0284			
		(0.0063)			
Believe store brands are "just as safe"					0.2058
					(0.0070)
Demographic controls?	X	X	X	X	X
Market & quarter fixed effects?	X	X	X		
Income category fixed effects?			X	X	X
Market-chain-quarter fixed effects?				X	X
Sample	Second survey wave	Second survey wave	Second survey wave	Second survey wave	Second survey wave
Mean of dependent variable	0.7392	0.7392	0.7392	0.7392	0.7392
R^2	0.1331	0.1351	0.1365	0.3561	0.3934
Number of households	26530	26530	26530	26530	26530
Number of purchase occasions	195268	195268	195268	195268	195268

Notes: Unit of observation is a purchase of a headache remedy by a household. Observations are weighted by equivalent volume (number of pills). Standard errors in parentheses are clustered by household. Household income is a categorical measure with 19 possible values. In column (2) we impute each category at its midpoint and include indicators for top-coded values. In columns (3) through (5) we include separate indicators for each category. Demographic controls are indicators for categories of race, age, household composition, and housing ownership. "Believe store brands are 'just as safe'" means the primary shopper chose "agree" (1) on a 1-7 agree/disagree scale in response to the statement "Store-brand products for headache remedies/pain relievers are just as safe as the brand name products." All models include fixed effects for the comparable product group.

Table 3: Occupation and headache remedy purchases

Dependent variable: Purchase is a store brand

Primary shopper characteristics:	(1)	(2)	(3)	(4)	(5)	(6)
College education	0.0171	0.0288	0.0351		0.0431	0.0133
	(0.0061)	(0.0064)	(0.0061)		(0.0100)	(0.0123)
Pharmacist or physician	0.1527	0.1683	0.1529	0.1667	0.1445	0.0304
	(0.0296)	(0.0294)	(0.0295)	(0.0380)	(0.0493)	(0.0379)
Other healthcare occupation	0.0792	0.0834	0.0790	0.0624	0.0489	0.0198
	(0.0099)	(0.0098)	(0.0102)	(0.0172)	(0.0224)	(0.0160)
Health major				0.0096		
				(0.0165)		
Non-health science major				0.0507		
				(0.0245)		
Demographic controls?	X	X	X	X	X	X
Market & quarter fixed effects?	X	X				
Income category fixed effects?		X	X	X	X	X
Market-chain-quarter fixed effects?			X	X	X	X
Sample	All	All	All	College major reported	Not currently employed	Second survey wave
Primary shopper survey response:						
Know all active ingredients						X
Store brands are "just as safe"						X
Mean of dependent variable	0.7424	0.7424	0.7424	0.7536	0.7390	0.8732
R^2	0.1166	0.1195	0.3037	0.4401	0.4330	0.6049
Number of households	39555	39555	39555	14190	13479	4274
Number of purchase occasions	279499	279499	279499	92020	103624	33373

Notes: Unit of observation is a purchase of a headache remedy by a household. Observations are weighted by equivalent volume (number of pills). Standard errors in parentheses are clustered by household. Occupation is defined as of the primary shopper's most recent employment spell. "Health major" and "non-health science major" refer to primary shopper's reported college major. Demographic controls are indicators for categories of race, age, household composition, and housing ownership. All models include fixed effects for the comparable product group. "Know all active ingredients" means the primary shopper correctly answered all questions about headache remedy active ingredients. "Store brands are 'just as safe'" means the primary shopper chose "agree" (1) on a 1-7 agree/disagree scale in response to the statement "Store-brand products for headache remedies/pain relievers are just as safe as the brand name products."

Table 4: Occupation and pantry staple purchases

Dependent variable: Purchase is a store brand

Primary shopper characteristics:	(1)	(2)	(3)	(4)	(5)
College education	-0.0230	-0.0060	-0.0062		-0.0023
	(0.0050)	(0.0052)	(0.0039)		(0.0063)
Chef	0.1383	0.1298	0.1175	0.2079	0.1403
	(0.0204)	(0.0197)	(0.0189)	(0.0513)	(0.0367)
Other food preparer	0.0438	0.0344	0.0227	0.0529	0.0112
	(0.0132)	(0.0127)	(0.0101)	(0.0204)	(0.0157)
Health major				0.0013	
				(0.0101)	
Non-health science major				0.0243	
				(0.0167)	
Demographic controls?	X	X	X	X	X
Market & quarter fixed effects?	X	X			
Income category fixed effects?		X	X	X	X
Market-chain-quarter fixed effects?			X	X	X
Sample	All	All	All	College major reported	Not currently employed
Mean of dependent variable	0.5987	0.5987	0.5987	0.5801	0.5931
R^2	0.0885	0.0922	0.3862	0.4453	0.4613
Number of households	44502	44502	44502	15948	15286
Number of purchase occasions	588484	588484	588484	192026	222918

Notes: Unit of observation is a purchase of a pantry staple by a household. Observations are weighted by equivalent volume (pounds). Standard errors in parentheses are clustered by household. Occupation is defined as of the primary shopper's most recent employment spell. "Health major" and "non-health science major" refer to primary shopper's reported college major. Demographic controls are indicators for categories of race, age, household composition, and housing ownership. All models include fixed effects for the comparable product group.

Table 5: Evidence on domain specificity

Dependent variable: Purchase is a store brand

Primary shopper characteristics:	(1)	(2)	(3)
College education	-0.0048	-0.0072	0.0430
	(0.0048)	(0.0039)	(0.0061)
Share of active ingredients known	-0.0012		
	(0.0067)		
Pharmacist or physician		0.0018	
		(0.0256)	
Other healthcare occupation		0.0056	
		(0.0084)	
Chef			0.1095
			(0.0340)
Other food preparer			0.0081
			(0.0168)
Products	Pantry Staples	Pantry Staples	Headache Remedies
Mean of dependent variable	0.5978	0.5987	0.7424
R^2	0.4059	0.3860	0.3017
Number of households	29561	44502	39555
Number of purchase occasions	404372	588484	279499

Notes: Unit of observation is a purchase of a pantry staple (first two columns) or headache remedy (third column) by a household. Observations are weighted by equivalent volume (pounds or number of pills). Standard errors in parentheses are clustered by household. Occupation is defined as of the primary shopper's most recent employment spell. All specifications include demographic controls, income category fixed effects, comparable product group fixed effects, and market-chain-quarter fixed effects as in column (3) of tables 3 and 4.

Table 6: Health categories purchases under full information

	Headache remedies (6)			Other health categories (44)		
	Baseline	Informed consumers at baseline prices	Informed consumers at equilibrium prices	Baseline	Informed consumers at baseline prices	Informed consumers at equilibrium prices
National-brand quantity share	0.258	0.117 (0.033)	0.286 (0.076)	0.435	0.370 (0.024)	0.506 (0.026)
National-brand price (relative to cost)	6.036	—	3.798 (0.985)	3.639	—	3.181 (0.302)
Store-brand price (relative to cost)	2.047	—	1.996 (0.105)	1.949	—	1.809 (0.073)
Change as a share of baseline expenditure:						
Manufacturer profit		-0.188 (0.047)	-0.141 (0.051)		-0.053 (0.016)	-0.011 (0.021)
Retailer profit		0.053 (0.014)	-0.010 (0.026)		0.019 (0.006)	-0.034 (0.013)
Consumer expenditure		-0.135 (0.034)	-0.151 (0.064)		-0.034 (0.010)	-0.044 (0.030)
Consumer surplus		0.038 (0.021)	0.150 (0.064)		0.033 (0.007)	0.037 (0.032)
Total surplus		-0.097 (0.025)	-0.000 (0.009)		-0.001 (0.008)	-0.007 (0.005)
Baseline consumer expenditure ($bn / year):	$2.88			$8.94		

Notes: The two panels report results for headache remedy comparables and other health comparables, respectively, with the number of comparables in parentheses. The "baseline" column reports average prices relative to estimated manufacturing costs and repeats summary information from table 1. Total expenditure are estimated 2008 totals for all grocery, drug, and mass merchandise stores in the US. Headache remedy relative prices and national-brand shares are averaged over comparable product groups weighting by equivalent units sold, while other health category relative prices and national-brand shares are averaged over comparable product groups weighting by expenditure. The "informed consumers at baseline prices" counterfactual computes the effect of all households choosing according to true rather than perceived brand preference, holding prices constant at baseline levels. The "informed consumers at equilibrium prices" counterfactual further allows prices to adjust to reflect the change in consumer demand. Standard errors in parentheses are from 20 bootstrap replications in which we draw households at random with replacement and recompute all estimates. These standard errors thus account for correlation in sampling error across comparables. See section 6 for details of model specification and estimation.

Table 7: Food and drink purchases under full information

	Pantry staples (6)			Other food and drink categories (235)		
	Baseline	Informed consumers at baseline prices	Informed consumers at equilibrium prices	Baseline	Informed consumers at baseline prices	Informed consumers at equilibrium prices
National-brand quantity share	0.404	0.311 (0.023)	0.434 (0.008)	0.575	0.565 (0.009)	0.574 (0.006)
National-brand price (relative to cost)	1.312	—	1.250 (0.013)	1.962	—	2.010 (0.039)
Store-brand price (relative to cost)	1.146	—	1.134 (0.003)	1.346	—	1.343 (0.005)
Change as a share of baseline expenditure:						
Manufacturer profit		-0.018 (0.004)	-0.016 (0.004)		-0.005 (0.005)	0.005 (0.007)
Retailer profit		0.008 (0.002)	-0.008 (0.002)		0.003 (0.002)	-0.001 (0.002)
Consumer expenditure		-0.010 (0.002)	-0.024 (0.006)		-0.002 (0.003)	0.004 (0.008)
Consumer surplus		0.002 (0.001)	0.026 (0.006)		0.004 (0.001)	-0.004 (0.010)
Total surplus		-0.008 (0.002)	0.001 (0.001)		0.002 (0.004)	0.000 (0.003)
Baseline consumer expenditure ($bn / year):	$1.81			$122.61		

Notes: The two panels report results for pantry staples comparables and other food and drink comparables, respectively, with the number of comparables in parentheses. The "baseline" column reports average prices relative to estimated manufacturing costs and repeats summary information from table 1. Total expenditure are estimated 2008 totals for all grocery, drug, and mass merchandise stores in the US. Relative prices and national-brand shares are averaged over comparable product groups weighting by expenditure. The "informed consumers at baseline prices" counterfactual computes the effect of all households choosing according to true rather than perceived brand preference, holding prices constant at baseline levels. The "informed consumers at equilibrium prices" counterfactual further allows prices to adjust to reflect the change in consumer demand. Standard errors in parentheses are from 20 bootstrap replications in which we draw households at random with replacement and recompute all estimates. These standard errors thus account for correlation in sampling error across comparables. See section 6 for details of model specification and estimation.
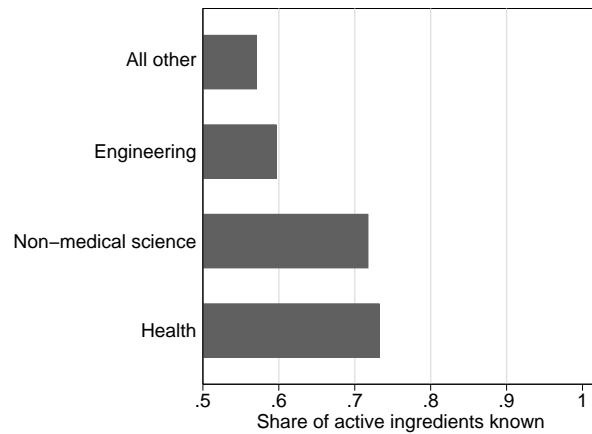
43

Figure 1: Product knowledge, headache remedies

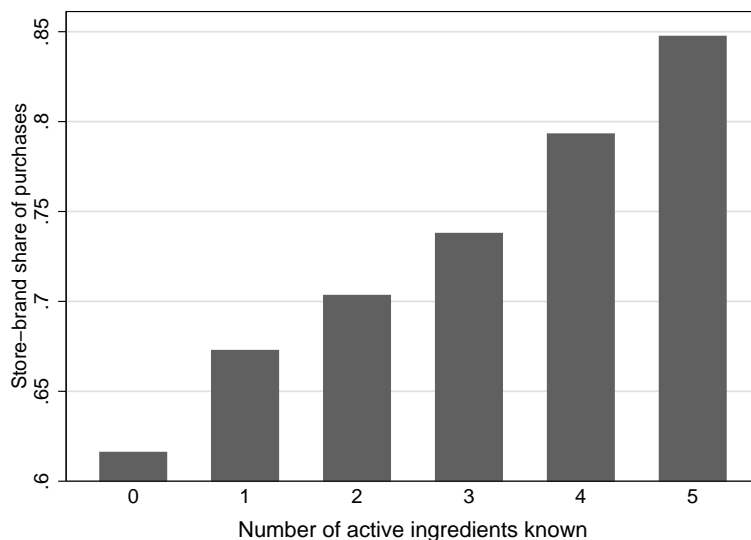*Panel A: Schooling*
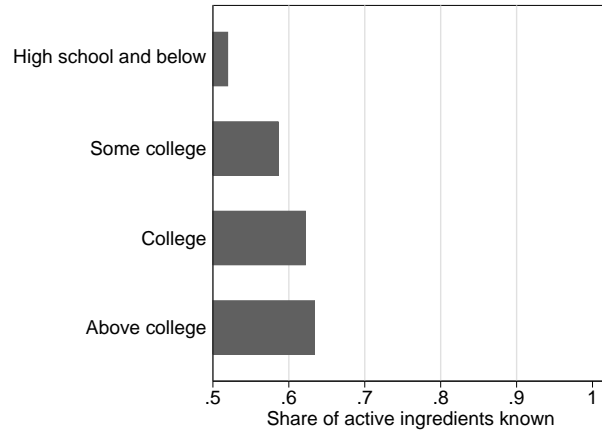
Panel B: Occupation
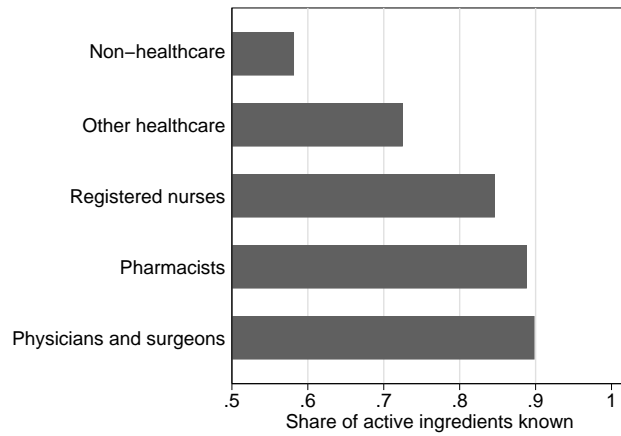

Panel C: College major

Notes: Figure shows the mean share of headache remedy active ingredients correctly identified by each group of respondents in the 2011 PanelViews survey.

Figure 2: Store-brand purchases and knowledge, headache remedies

Notes: Horizontal axis shows the number of headache remedy active ingredients correctly identified in the 2011 PanelViews survey. The bars show the store-brand share of headache remedies for households in each category, weighted by equivalent volume (number of pills). Sample is restricted to panelists who answered all five active ingredient questions.

Figure 3: Store-brand purchases and education, headache remedies
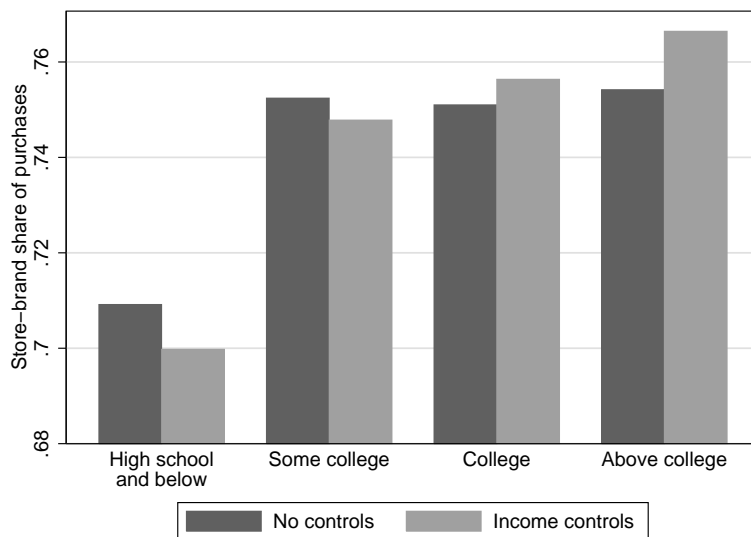
Notes: Bars labeled "no controls" show the store-brand share of headache remedy purchases for households in each education category, weighted by equivalent volume (number of pills). Bars labeled "income controls" show the predicted store-brand share in each education category from a regression on indicators for education categories and 19 household income categories, with the predicted values computed at the means of the covariates.

Figure 4: Store-brand purchases and occupation, headache remedies
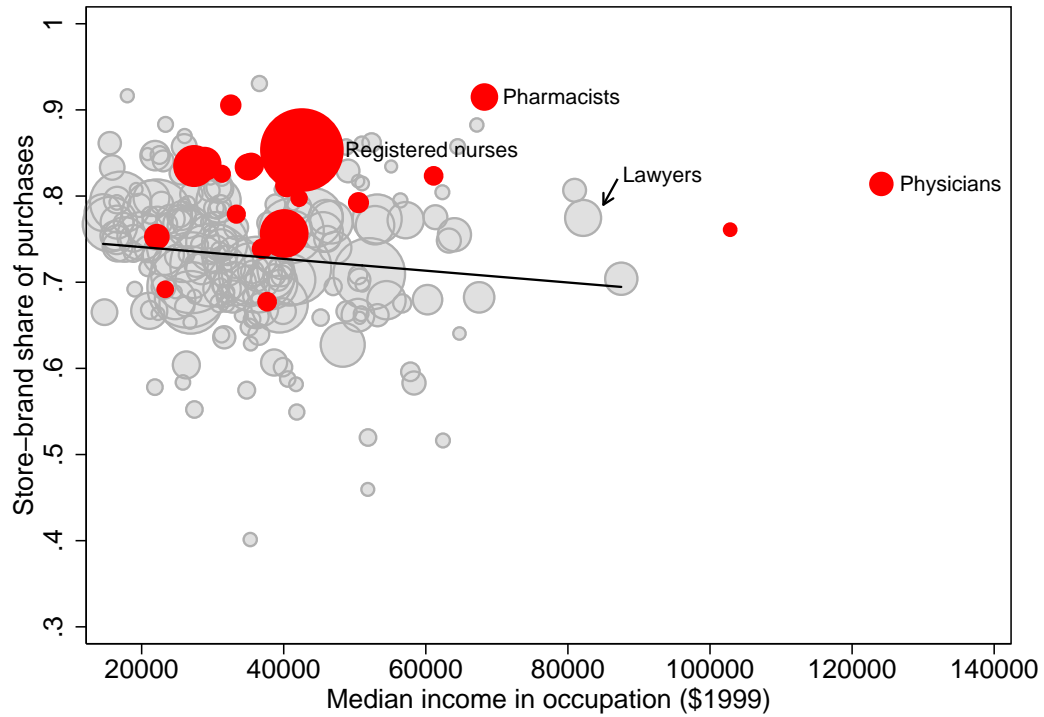
Notes: Figure shows store-brand share of headache remedy purchases by occupation (y-axis) and median earnings for full-time full-year workers in 1999 by occupation (x-axis), weighted by equivalent volume (number of pills). Filled (colored) circles represent healthcare occupations. Occupation weights are given by the number of households whose primary shopper has the given occupation in our sample (occupations with fewer than 25 such households are excluded from the figure). The area of each circle is proportional to the occupation weights, with different scale for healthcare and non-healthcare occupations. The line is the prediction from an OLS regression of store-brand share of purchase volume on median earnings excluding healthcare occupations and weighting each occupation by the occupation weights.

Figure 5: Store-brand purchases and occupation, pantry staples
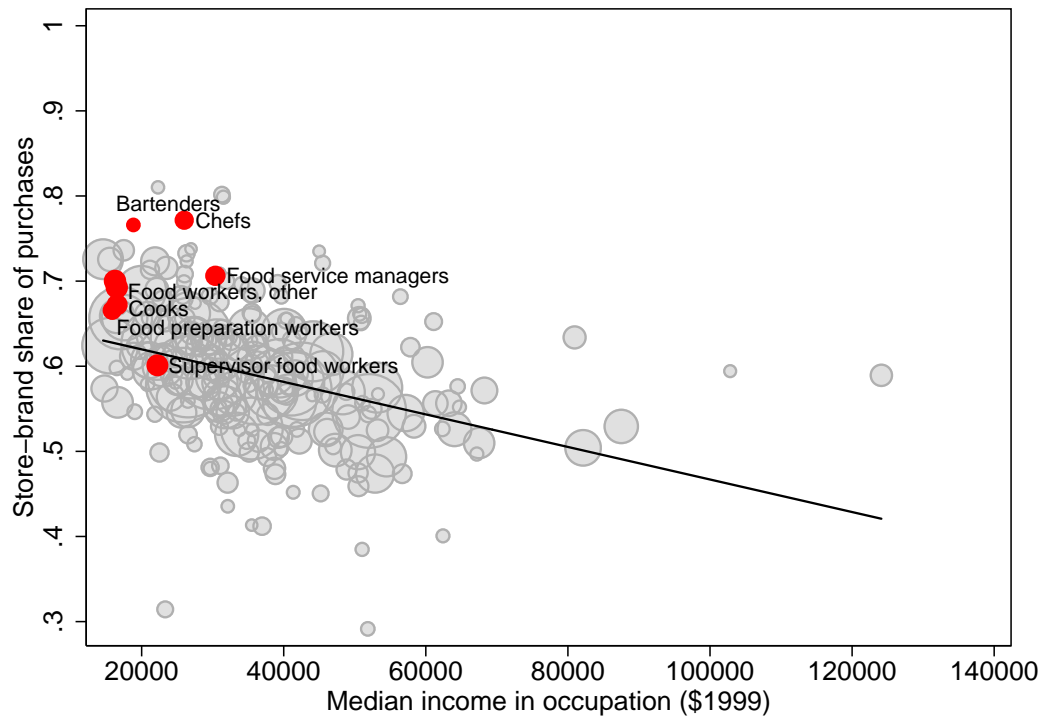
Notes: Figure shows store-brand share of pantry staple purchases by occupation (y-axis) and median earnings for full-time full-year workers in 1999 by occupation (x-axis), weighted by equivalent volume (pounds). Filled (colored) circles represent food preparer occupations. Occupation weights are given by the number of households whose primary shopper has the given occupation in our sample (occupations with fewer than 25 such households are excluded from the figure). The area of each circle is proportional to the occupation weights, with different scale for food preparer and non-food-preparer occupations. The line is the prediction from an OLS regression of store-brand share of purchase volume on median earnings excluding food preparer occupations and weighting each occupation by the occupation weights.

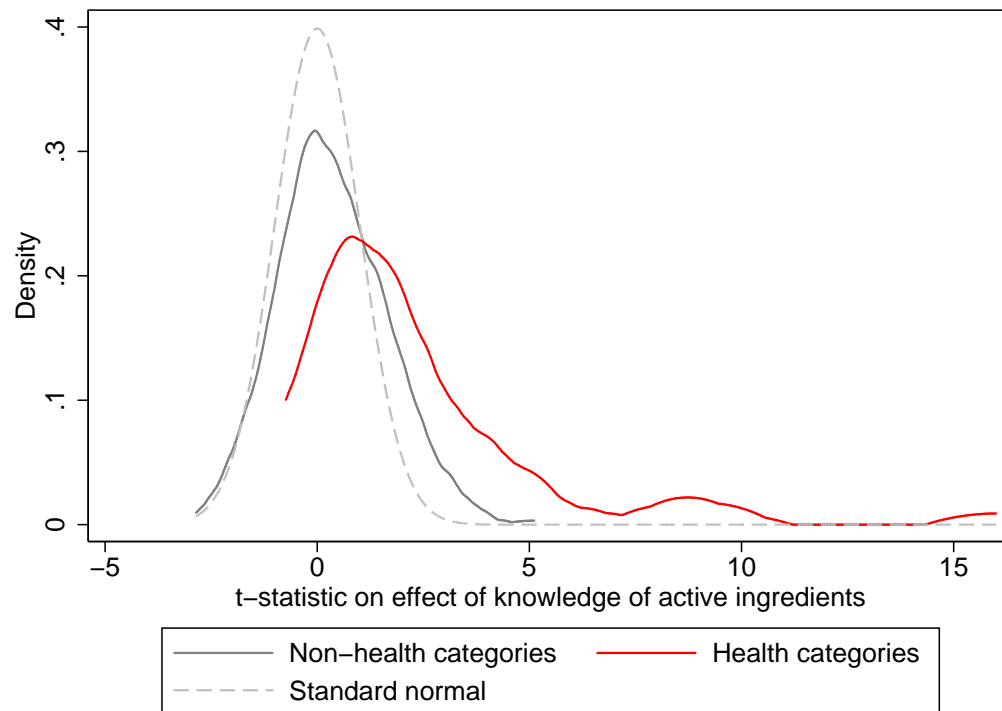Figure 6: Active ingredient knowledge coefficients
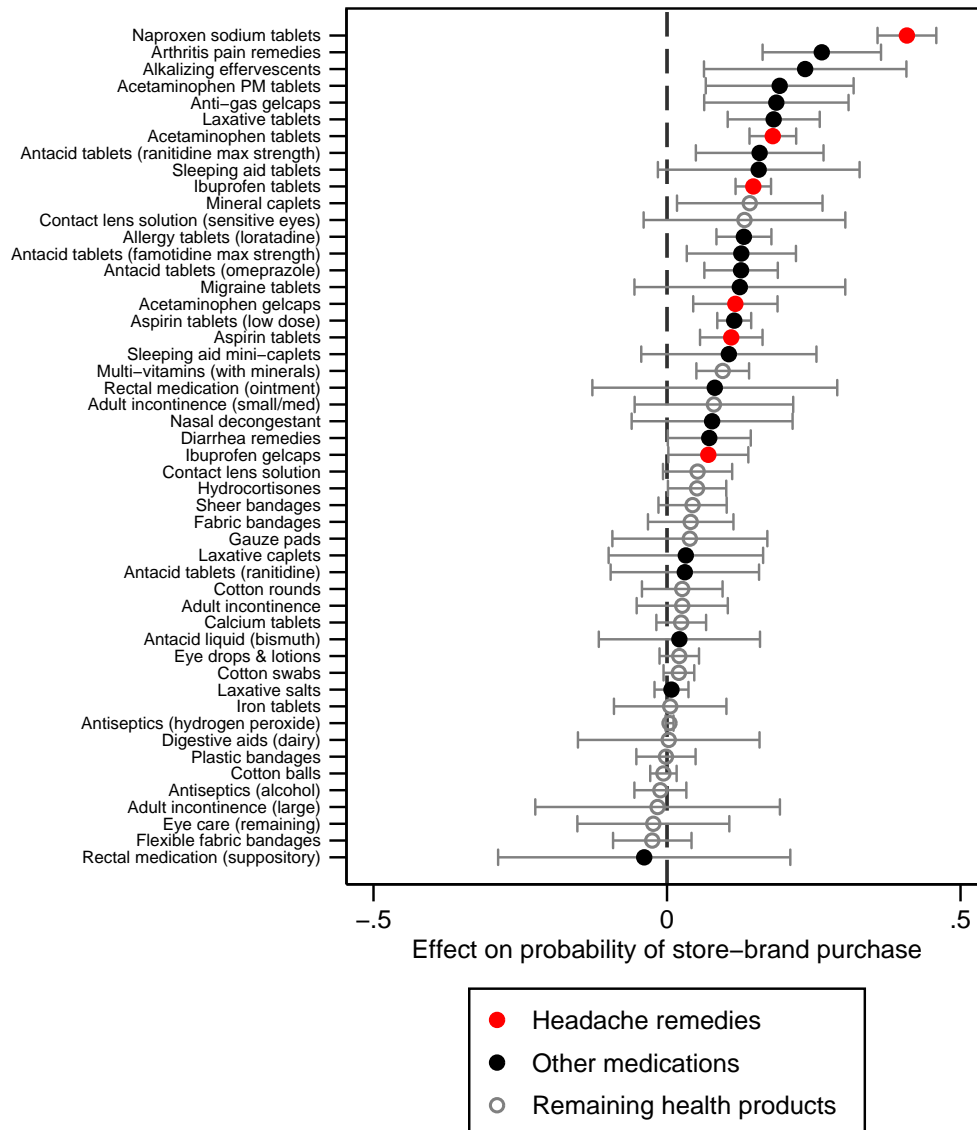
Notes: Figure plots coefficients and 95 percent confidence intervals on "share of active ingredients known" for each health-related comparable product group from a regression following the specification of table 2 column (4).

Figure 7: Pharmacist / physician occupation coefficients
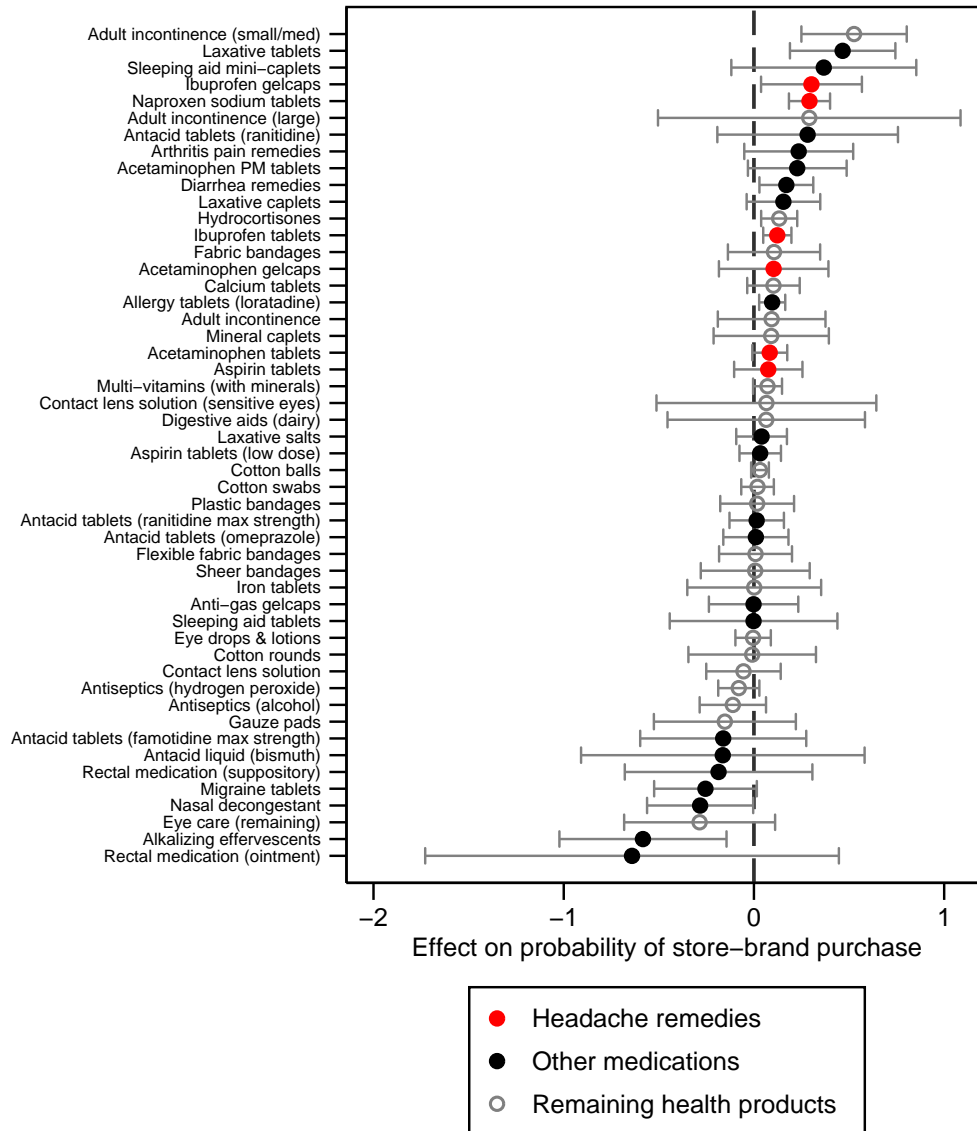
Notes: Figure plots coefficients and 95 percent confidence intervals on "pharmacist or physician" for each health-related comparable product group from a regression following the specification of table 3 column (3).

Figure 8: Active ingredient knowledge coefficients, health vs. non-health products

Notes: Figure plots the distribution of *t*-statistics on "share of active ingredients known" for all health-related and non-health-related comparable products groups from a regression following the specification of table 2 column (4). Distribution is estimated using an Epanechnikov kernel with optimal bandwidth. The standard normal density is plotted with dashed lines.

Figure 9: Chef coefficients
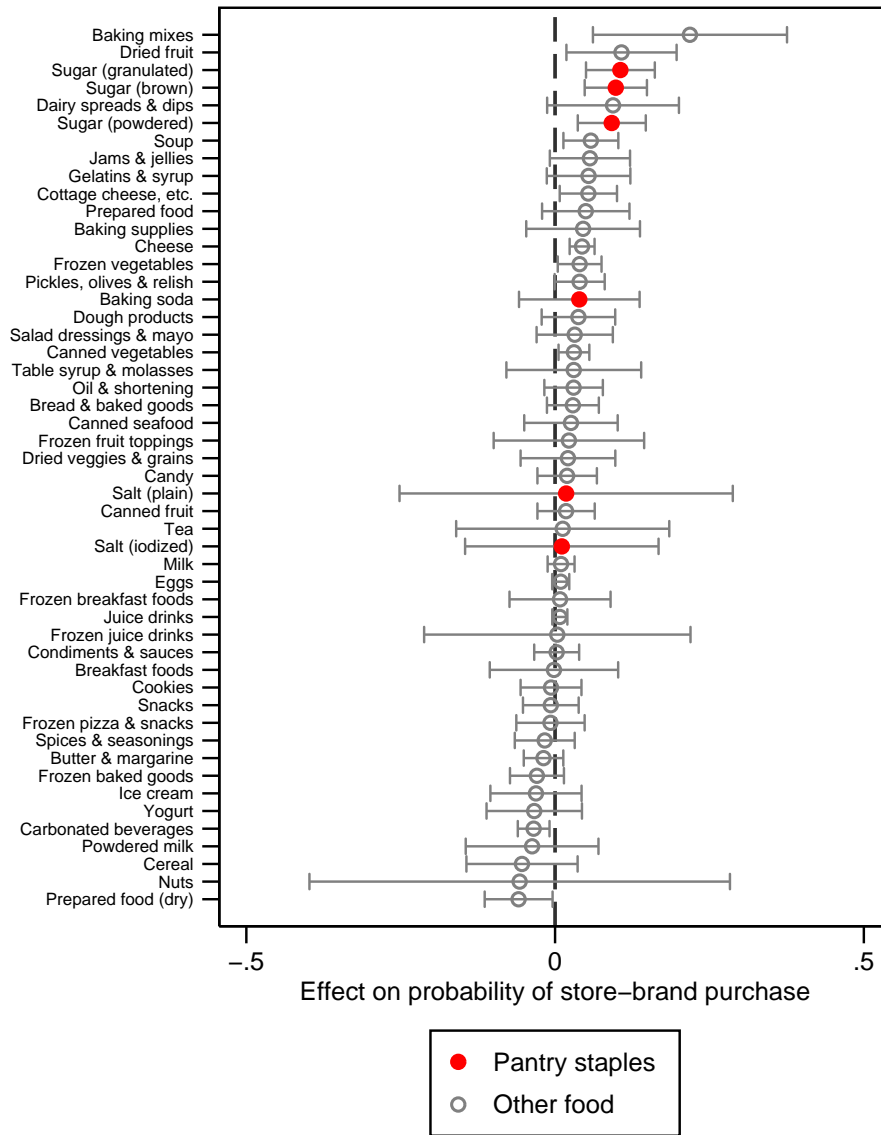
Notes: Figure plots coefficients and 95 percent confidence intervals on "chef" for each food and drink category. Coefficients are estimated separately for each comparable in a regression following the specification of table 4 column (3). Coefficients for pantry staples are plotted individually by comparable. We aggregate coefficients for all other comparables to the Nielsen product group level, reporting the precision-weighted mean of the estimated coefficients and constructing the confidence intervals based on the harmonic mean of the estimated variances.

Appendix Table 1: Knowledge and headache remedy purchases, robustness

Dependent variable: Purchase is a store brand

		Headache remedies			Pantry staples
		Share of active ingredients coefficient	College education coefficient	Pharmacist / physician coefficient	Chef coefficient
(1)	Baseline	0.1898 (0.0108)	0.0351 (0.0061)	0.1529 (0.0295)	0.1175 (0.0189)
(2)	Control for market-chain-week	0.2038 (0.0142)	0.0316 (0.0076)	0.1888 (0.0379)	0.1118 (0.0220)
(3)	Control for market-chain-store-quarter	0.2067 (0.0174)	0.0325 (0.0095)	0.1137 (0.0530)	0.1101 (0.0259)
(4)	Control for market-chain-store-week	0.2305 (0.0294)	0.0290 (0.0146)	0.1904 (0.0849)	0.0995 (0.0463)
(5)	Control for average annual purchase volume	0.1828 (0.0109)	0.0371 (0.0062)	0.1438 (0.0293)	0.1066 (0.0189)
(6)	Control for average annual grocery spending	0.1924 (0.0108)	0.0319 (0.0061)	0.1534 (0.0285)	0.1195 (0.0191)
(7)	Control for median occupational income	0.1905 (0.0108)	0.0350 (0.0063)	0.1528 (0.0319)	0.1147 (0.0189)
(8)	Condition sample on item size availability	0.1786 (0.0122)	0.0404 (0.0066)	0.1375 (0.0384)	0.0998 (0.0215)
(9)	Condition sample on item size availability and control for item size	0.1691 (0.0118)	0.0366 (0.0064)	0.1349 (0.0376)	0.0974 (0.0204)
(10)	Weight observations by Nielsen projection factor	0.1879 (0.0137)	0.0532 (0.0085)	0.1180 (0.0334)	0.1092 (0.0242)
(11)	Impute characteristics of actual shopper	0.1969 (0.0110)	0.0405 (0.0068)	0.1578 (0.0332)	0.1256 (0.0224)
(12)	Logit controlling for market and quarter	0.2119 (0.0100)	0.0327 (0.0062)	0.2240 (0.0461)	0.1290 (0.0210)

Notes: Each row gives (i) the coefficient on "share of active ingredients known" from a specification analogous to table 2 column (4); (ii) the coefficient on "college education" from a specification analogous to table 3 column (3); (iii) the coefficient on "pharmacist or physician" from a specification analogous to table 3 column (3); and (iv) the coefficient on "chef" from a specification analogous to table 4 column (3). Row (1) repeats the results from our main specifications. Row (2) is the same as the baseline but replaces market-chain-quarter fixed effects with market-chain-week fixed effects. Row (3) is the same as the baseline but replaces market-chain-quarter fixed effects with market-chain-store-quarter fixed effects. Row (4) is the same as the baseline but replaces market-chain-quarter fixed effects with market-chain-store-week fixed effects. Row (5) is the same as the baseline but adds a control for the average annual volume of headache remedies (columns 1-3) and pantry staples (column 4) purchased by the household. Row (6) is the same as the baseline but adds a control for the household's average annual grocery spending. Row (7) is the same as the baseline but adds a control for the median income of the occupation of the primary shopper. Row (8) is the same as the baseline but restricts attention to transactions such that at least one comparable national-brand purchase and at least one comparable store-brand purchase are observed in the Homescan data in the same retail chain, quarter, and item size as the given transaction. Row (9) is the same as row (8) but replaces comparable product group fixed effects with comparable product group-item size fixed effects. Row (10) is the same as the baseline but weights observations by the Nielsen projection factor. Row (11) is the same as the baseline but imputes characteristics of the actual shopper by assuming that the primary shopper is the actual shopper when there is no secondary shopper and that the primary shopper is the actual shopper 74 percent of the time when there is a secondary shopper; see the online appendix for details. Row (12) is the same as the baseline but replaces the linear probability model with a logit model and the market-chain-quarter fixed effects with market and quarter fixed effects; observations are not weighted and reported coefficients are average marginal effects.

Appendix Figure 1: Physical attribute choice and occupation, headache remedies
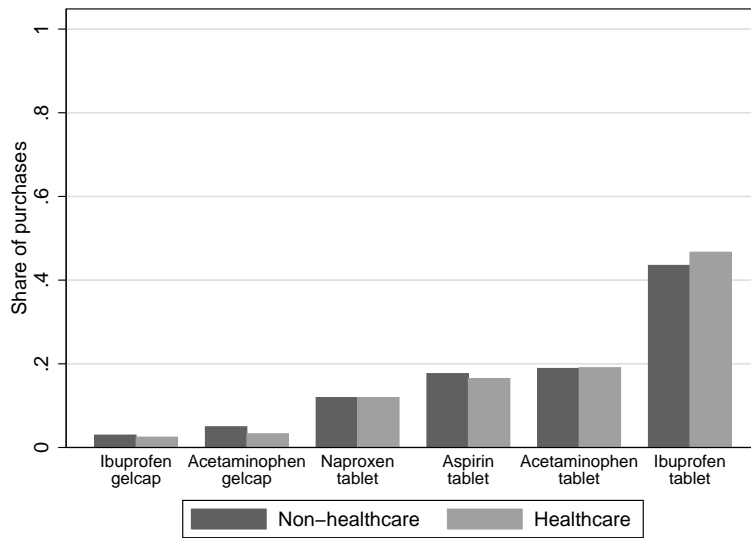
Notes: Share of purchases is computed from a set of linear probability models of the likelihood of purchasing the given product. Bars labeled "healthcare" show the predicted probability from the given model for purchases made by households whose primary shopper is in a healthcare occupation. Bars labeled "non-healthcare" show the predicted probability for the same purchases under the counterfactual in which the household's primary shopper is not in a healthcare occupation. Each linear probability model's unit of observation is a purchase occasion. Observations are weighted by equivalent volume (number of pills). All specifications include an indicator for college completion, demographic controls, income category fixed effects, and market-chain-quarter fixed effects. Demographic controls are dummies for categories of race, age, household composition, and housing ownership. Predicted probabilities set the market-chain-quarter fixed effect so that the mean predicted probability is equal to the empirical share. See the online appendix for a supporting table with additional details.