Selective Bargain Hunting. A Concise Test of Rational Consumer Search*

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November 5, 2020

Abstract

A model of time-allocation between work, leisure, and price-search predicts that rational consumers pay relatively low prices for their preferred goods. Using scanner data, we confirm empirically the implication that consumers find better prices for items (defined by scanner codes, such as a 12-pack of Pepsi) within categories (such as carbonated drinks) of which they consume relatively more. This provides direct evidence that consumers face constraints on time and/or attention, and that they rationally allocate these scarce resources to optimize welfare.

JEL classification: E21, D12.

Keywords: Consumption, consumer search, time use, bargain hunting, rational inattention.

LEE, LONG, LUENGO-PRADO & SORENSEN: SELECTIVE BARGAIN HUNTING

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We thank two anonymous referees and the editor for insightful comments and suggestions. The content is solely the responsibility of the authors and does not represent the views of the Federal Reserve Bank of Boston or the Federal Reserve System, nor Barclays and/or its affiliates.

1 Introduction

A rational consumer trades off the value of time and effort spent on finding lower prices with the value of time and effort spent on other pursuits. We conduct a simple test of rational bargain hunting/price-search: A consumer who frequently drinks soda but seldom drinks beer should rationally put more effort into finding low prices for soda than finding low prices for beer. Using detailed shopping information from the IRI Academic Dataset, we confirm this prediction. Our results are relevant for understanding consumer rationality: That consumers search relatively more for lower prices of items in desired categories provides direct evidence that consumers face constraints on time and/or attention, and that they rationally allocate these scarce resources to optimize welfare. Our findings are also relevant for optimal store pricing and for understanding how consumers can efficiently self-insure by strategically finding lower prices following employment or retirement shocks.

The IRI dataset records the purchases made by a panel of households over an 11-year period at a selection of stores in Eau Claire, Wisconsin, and Pittsfield, Massachusetts. The prices are recorded for items at the UPC (scanner-code) level, which constitutes the finest possible definition of a good. For each transaction, both the price of the item and the quantity purchased are reported, and we relate the price a consumer pays for each item in a given month to the average price paid by all consumers during the same month for the same item. The items are organized by IRI into categories of similar items (e.g., beer, soda, laundry detergent), across which consumers rarely substitute. We hypothesize that consumers with a relatively high preference for say, soda, search for low prices of soda more than they search for low prices of items in categories that they have a relatively low preference for. Consumers may search for sales of their preferred brand within the soda category, or substitute Pepsi for Coke when Pepsi is on sale. We do not document detailed search strategies but show that prices paid for items in desired categories are overall relatively low.

Stigler (1961), in a pioneering paper, suggests that information is scarce and consumers invest time in finding favorable prices—an activity that he labeled "search." As summarized in Kaplan and Menzio (2013), many recent papers examine price-search using scanner data under the heading of "bargain hunting." Particular attention has been paid to price-search during recessions. Aguiar et al. (2013) use the American Time Use Survey to show that households in states with higher unemployment spend relatively more time on home production and shopping. Coibion et al. (2015) use scanner data from IRI to show that consumers obtain better prices (averaged across categories) during recessions by switching to cheaper stores, although these authors consider sales across stores and do not directly consider prices paid at the consumer level as we do.[1] Nevo and Wong (2019), constructing fixed-weight consumer price indices using Nielsen Homescan data, show that during the Great Recession, consumers obtained lower prices by, among other practices, using more coupons, purchasing more items on sale, and shopping more frequently at "big box" stores.[2] Nevo and Wong (2019) also find that the return to shopping declined during

[1]Aguiar et al. (2013) show that about 30 percent of lost labor hours were reallocated toward non-market work, including shopping, during the Great Recession.

[2]Griffith et al. (2009) document four channels of saving: Purchasing items when they are on sale, buying in bulk (at lower per-unit prices), buying generic brands, and shopping at outlets.

the Great Recession, so the increased amount of search is consistent with a lower shadow value of time. The literature has also found intuitively reasonable differences in shopping behavior across individuals outside recessions. Aguiar and Hurst (2007) show that retirees spend relatively more time shopping, and Stroebel and Vavra (2014), using changes in house prices to isolate exogenous changes in wealth, find that wealthier households spend relatively less time shopping.

Chevalier and Kashyap (2019) examine purchases using the IRI data, estimate the share of purchases made at best versus average prices, and posit a model with two types of consumers: (1) "shoppers," who pay the best price possible because they chase discounts, substitute across products, and/or store goods they purchase during sale periods, and (2) "loyals," who buy only one brand and do not time purchases to coincide with sales. In this setting, it is optimal for firms to maintain a combination of constant regular prices and frequent short-lived sales.[3] Kaplan et al. (2019) use the Nielsen dataset and find that most variation in prices happens within stores rather than across stores. They construct a model with two groups of consumers: (1) "busy," who make all purchases in one store, and (2) "cool," who shop at several stores. Under their assumptions, in equilibrium, stores will charge different prices for the same items. Intuitively, busy consumers will buy expensive and less-expensive items in the same store, while consumers with more time for shopping will buy the cheaper items at each store (in their analysis, "goods" are either UPC-items or brand aggregates). Our paper is the first to document that individuals display different patterns of price-search across categories—for example, being attentive

[3] Guimaraes and Sheedy (2011) study the implications of sales for monetary policy in a general equilibrium model.

to prices, like the "cool shoppers," when buying diapers and inattentive, like the "busy loyals," when buying beer. Consumers who behave like busy loyals could literally be busy (having limited time for search) or loyal (having strong brand, or even item, preference). Our data only allow us to briefly investigate issues related to time allocation, but we document that key determinants of obtaining low prices are visiting more stores and shopping more often.

In this paper, we calculate consumers' relative expenditure in each category and show graphically that consumers pay lower prices for items in more preferred categories, which we identify as those with relatively high quantities of consumption throughout the sample. In order to gauge overall savings, we follow Aguiar and Hurst (2007) and construct for each consumer a bargain-hunting index (BHI), which measures the price that he or she paid for a consumption bundle relative to the cost of the same bundle based on average UPC prices in the same month and city. We refine the BHI to the category level and, using the category-specific BHI, show that consumers who purchase "relatively more" of a category pay less for the category-specific consumption basket than the average consumer would pay for the same basket of goods.[4] We also find, consistent with other studies, that prices paid differ substantially across consumers; in particular, retirees pay less and high-spending ("wealthy") consumers pay more for identical baskets of goods. Quantities may be endogenous to prices, so we estimate our relationships using instrumental-variable regressions. However, results from Ordinary Least Squares (OLS) are similar, indicating

[4]An individual can consume relatively more in a category than other consumers in a given period t, the individual can consume relatively more in a category than his or her consumption in other categories, or the individual can consume relatively more at time t in a category than he or she consumes on average in that category. Our results are similar for these different concepts of relativity.

that reverse causality from prices to category-level consumption is limited.

Building on earlier time-allocation models, such as those in Becker (1965), Benhabib et al. (1991), and Greenwood and Hercowitz (1991), we construct a simple static search model where consumers trade off time versus prices good-by-good. The model predicts that consumers pay relatively less for goods (which we interpret as categories) of which they purchase relatively more because they search relatively more for better prices of goods that they prefer.[5] The model also predicts that individuals with high wages pay relatively more, and that retired individuals on fixed income pay relatively less. We do not rely on time-use data in our empirical work. While our benchmark model is written in terms of a time constraint, our favored interpretation of the empirical results is that consumers obtain lower prices by expending effort more broadly defined; for example, by paying attention to sales. In the appendix, we outline a model of store price-setting which is consistent with a model where consumers search only for low prices for their preferred goods.

The rest of the paper is organized as follows: Section 2 derives a simple model of time use. Section 3 describes the data and depicts the relationship between relative category spending and prices paid for items in that category. Section 4 presents our more formal empirical results, and Section 5 concludes.

[5] It may be optimal to only search for low prices of the preferred good or not to search at all.

2 A Stylized Model of Consumer Search

We formulate a model of consumer-search across two different goods that represent the categories in our empirical analysis. Income varies across consumers as do their preferences over the two different goods and leisure. Consumers, indexed by i, face a time constraint, where leisure is residual time after searching for good(s) and working. They derive utility as summarized by the objective function:

$$\max_{Q_i^1, Q_i^2, T_i^Y, T_i^1, T_i^2} \quad \alpha_i^1 \ln Q_i^1 + \alpha_i^2 \ln Q_i^2 + \mu \ln (T - T_i^Y - T_i^1 - T_i^2 - T_i^0), \tag{1}$$

$$\text{subject to:} \qquad P_i^1 Q_i^1 + P_i^2 Q_i^2 = Y(T_i^Y), \tag{2}$$

where Q_i^1 and Q_i^2 are the purchased quantities of good 1 and good 2, and α_i^1/α_i^2 is consumer i's preference for good 1 relative to good 2, with $\alpha_i^1 + \alpha_i^2 = 1$. T_i^Y is time spent working, T_i^c $(c = 1, 2)$ is time spent searching for good (category) c, and T_i^0 is a search fixed cost incurred whenever the consumer searches for any of the goods. T is the total time endowment and $T - T_i^Y - T_i^1 - T_i^2 - T_i^0$ is leisure. Solutions with negative time in any activity are not valid, but we do not explicitly write down Kuhn-Tucker conditions for ease of exposition.

Income is a linear function of work time with wage rate W_i^1 and non-wage income W_i^0: $Y(T_i^Y) = W_i^0 + W_i^1 T_i^Y$. Time spent searching results in lower prices according to the function $P_i^c = P^h(T_i^c + \eta)^{-\beta}$, with $\beta > 0$. β determines the efficiency of search: The larger β, the more a unit of search time lowers the price paid. $P^H = P^h \eta^{-\beta}$ is the highest price charged by stores when no search occurs. The marginal effect of an additional unit of search is $\frac{dP_i^c}{dT_i^c} = -\beta P^h (T_i^c + \eta)^{-\beta-1} = -\beta P_i^c (T_i^c + \eta)^{-1}$.

The model has obvious implications for work and leisure time, derived in the online appendix, but the main implication for this study is that search time for good c increases (and thus its price decreases) with good preference, total time available, non-wage income, and search efficiency, and it decreases with the wage rate and leisure preference:

$$T_i^c = \beta \alpha_i^c \frac{T - T_i^0 + 2\eta + \frac{W_i^0}{W_i^1}}{1 + \beta + \mu} - \eta. \tag{3}$$

In our empirical work, we consider consumers' prices and quantities relative to other consumers. In order to depict the implications of the model for relative prices and quantities, we select N model-individuals with preferences α_j^1 uniformly distributed on the [0,1] interval. We calculate individual-specific prices and quantities according to their preferences as well as averages across the individuals for two different search efficiency parameters. Panel A of Figure 1 shows, for each value of α_i^1, the price paid for good 1 (left subpanel) and the quantity purchased (right subpanel) by an agent with preference value α_i^1 relative to the average. In Panel B, we plot the savings on good 1 for each consumer (indexed by the preference value) as a function of their relative quantity. Savings compares actual spending on good 1 to what this consumer would have paid, had he or she paid the average price. Specifically, we construct a bargain-hunting index for good 1:

$$BH_i^1 = 1 - \frac{P_i^1 Q_i^1}{\overline{P}^1 Q_i^1},$$

where $\overline{P}^1$ is the average price paid for good 1 across all agents, drawn with different relative preference for good 1, weighted by purchased quantities: $\overline{P}^1 = \sum_{i=1}^{N} w_i^1 P_i^1$, with $w_i^1 = Q_i^1 / \sum_{j=1}^{N} Q_j^1$. The denominator in the fraction is the money that would have been spent on good 1 if the consumer purchased the amount Q_i^1 at average prices, while the numerator is the actual expense on good 1. One minus the ratio, therefore, shows the percent savings that the consumer obtains from searching for that good. We define a relative quantity index (purchased quantity of good 1 relative to the average quantity of good 1 across all consumers) as:

$$QI_i^1 = \frac{Q_i^1}{\frac{1}{N}\sum_{j=1}^{N} Q_j^1}.$$

Figure 1, Panel B, highlights the positive (negative) relationship between savings (relative prices paid) and relative quantities purchased. We focus on relative savings/prices and relative quantities across consumers going forward and generalizations of the bargain-hunting and quantity indices will be prominent in our empirical regressions. The model implies a positive (negative) relationship between prices (the bargain hunting index) and relative quantities consumed of a given good, because consumers vary their search intensity across goods in accordance with their relative preferences.

3 Data Description and Construction of Key Variables

3.1 The IRI Academic Dataset

We use the IRI academic dataset which, as Bronnenberg et al. (2008) describe in detail, contains weekly transaction information on the purchases of groceries in 31 item categories. Our dataset spans 2001 through 2012 and includes information about purchases at the store level and at the individual level. At both levels, weekly total dollar and unit sales are collected for each UPC item. A UPC is encoded in a bar code used for scanning at the point of sale, and it contains information on very specific product attributes, such as volume, product type, brand name, package size, and even flavor or scent for some products. Products that are essentially the same but differ in size or packaging have different UPCs; for example, a bottle of Budweiser beer intended for single sale has a different UPC code than a physically identical bottle of Budweiser beer sold in a six-pack.

The store-level data contain weekly total-dollar and unit-sales information for each UPC from grocery stores and drug stores in 50 IRI markets (metropolitan areas). Most stores belong to large chains (masked), and each store has a unique identifier. The individual-level panel dataset provides price and quantity information for all transactions (where a "transaction" is a UPC-specific purchase) made by a consumer panel in two small markets (cities): Eau Claire, Wisconsin, and Pittsfield, Massachusetts. The dataset includes some demographic information about the consumers, such as age, marital status, education, income, employment status, and family size. However, these variables are collected sporadically, reported only for discrete categories, and not consistently coded over time, so we include only a dummy for 65-plus years of age in our regressions.[6] Prices are linked to the store-panel data for purchases from the stores in the IRI store dataset. When IRI does not receive store data directly because the store is not in the set of stores followed, consumers record prices using an electronic wand.

The IRI dataset also includes a supplemental "trips file," which provides information on when (week) and where (store number) each panelist went shopping, as well as the amount of money spent while shopping. We calculate the total number of trips each panelist made to stores in a given period and the number of stores visited. We mainly use the individual-level transaction data, but we use price information from the store-level dataset to calculate average market prices by UPC.

We exclude the years 2001 and 2002 due to incomplete information and inconsistencies with later years, and we exclude "soup" purchases due to unrealistic price variation for this category—the exclusion of these years and this product category does not significantly affect our results. The store-level dataset is available for cities other than Eau Claire and Pittsfield, but we only make use of the data for these two markets because they can be linked to the consumer panel. For regressions on overall expenditure, we drop panelist $\times$ month observations if the panelist's expenditure in the month is less than \$5. For regressions on category expenditure, we drop the panelist $\times$ month $\times$ category cell if the panelist's expenditure in the month is less than \$2 for that category.[7]

[6] Our main qualitative results are not sensitive to inclusion of panelist fixed effects, which control for all non-time-varying consumer characteristics, so it is unlikely that including this information would alter our conclusions.

[7] IRI includes only respondents who make at least one transaction in each of the 13 four-week periods in each year. (The documentation does not make this more precise.)

The appendix gives more details about the consumer panel, including the brackets in which income, age, and education are reported. Table A.1 displays summary statistics for the panelists in January 2007. Average education is 13.8 years, and average age is 55 years. Individuals in our sample are between 21 and 70 years old. Average income is roughly $52,500 with a standard deviation of $36,600 (this calculated standard deviation is likely lower than the actual standard deviation because income is reported in brackets). About a third of the sample is over 65 and average expenditure is about $80 a month.

Compared with the Panel Study of Income Dynamics (PSID), a representative sample of the United States (for which we do not tabulate the numbers), the IRI panelists in 2007 are somewhat older (the average age of a PSID household head is 50), poorer (average income in the PSID is $67,000), and similarly educated (the average number of years of education completed in the PSID is 13.1). In the PSID, the average food-at-home expenditure in 2007 is roughly $4,400 a year. Using that number as an approximation of average food consumption for our sample, it implies that spending on categories in the panel IRI dataset covers 22 to 28 percent of food-at-home expenditure.[8]

3.2 Average Prices and Quantity Indices

Our main focus is on selective bargain hunting; that is, whether consumers devote relatively more time to find lower prices of goods they prefer, as our model predicts. Focusing on the relationship between prices and quantities at the UPC level is complicated by the

[8]The lower number does not adjust for income differences in the two samples, whereas the higher number does.

endogeneity of quantities at this level and by a large number of zeroes, as most households purchase just a few different UPC items in a given period. We therefore study how consumers' total purchases at the category level associate with the prices paid for (UPC) items in those categories. Categories are defined by IRI as groups of similar items which are listed in Figure 2, but two examples are (non-alcoholic) carbonated beverages ("soda") and beer.[9]

Similarly to Aguiar and Hurst (2007), we define the average price of a UPC item u, in a given market m, and month t, as a quantity-weighted average of the prices of all transactions k that involve that specific item. A transaction in our analysis is the purchase of a given item during a visit to a store, where one visit to a store usually comprises many transactions.[10] The average price of item u is

$$\overline{P}^{u,m,t} = \frac{\sum_{k \in u,m,t} Q_k^{u,m,t} P_k^{u,m,t}}{\sum_{k \in u,m,t} Q_k^{u,m,t}} ,$$

where Q_k is the quantity purchased in transaction k (involving u), and P_k is the unit price. To compute this average price, which we refer to as the store-average price, we use the store-level dataset which includes all transactions in all IRI stores in each market.

The choice of a time-horizon of one month is arbitrary. We aggregate our variables over a month in order to avoid a large number of zero purchases at higher frequencies,

[9]We could construct groups of UPCs ourselves, but there is no obvious way of doing this and an arbitrary choice of categories would open up the scope for data mining; we therefore use the categories defined by IRI.

[10]For example, a purchase of three toothbrushes and a toothpaste tube is at least two transactions. It would be four transactions if the toothbrushes were all different brands, and even if the toothbrushes were of the same brand, there would be three transactions in total, if the consumer bought a single toothbrush and a two-pack.

which might result in less precise estimates. Some goods can be easily stored for a month, allowing consumers to time their purchases independent of consumption, while others cannot be stored for more than a few days. Our results are qualitatively robust to whether we average prices over a month, a week, or a quarter. To keep it simple, we relate (average) prices to quantities purchased during the same period of time, a month.[11]

We study the relationship between relative prices paid on items within a category and the relative quantities bought overall in the category. We construct indices of relative quantities purchased by category as follows.[12] First, we calculate total consumption of consumer i in category c in period t at average prices as

$$\text{Qcat}_{i,t}^{c} = \sum_{k,u(k)\in c} \overline{P}^{u(k),m,t} \times Q_{i,k}^{u(k),t}, \tag{4}$$

where k is an index for transactions, $u(k)$ is the UPC of transaction k, and $Q_{i,k}^{u(k),t}$ is the quantity purchased by consumer i in transaction k (involving u). The price weights reflect differences in quantity and quality (broadly defined), so purchases of larger amounts of more expensive UPCs have greater weights than purchases of larger amounts of less expensive UPCs.

We construct a time-varying category-level quantity index for a consumer i in period

[11]One may relate, say, paid prices to average weekly prices and aggregate purchased amounts to the quarterly level, as we did in an earlier version of this paper. The qualitative conclusions are similar, but we prefer to limit confusion by aggregating quantities over a month to match the averaging frequency for prices. Results are similar when using quarterly frequencies to both aggregate quantities and to calculate average prices. See the online appendix.

[12]The alternative of using budget shares is not feasible with our data because many other goods and services purchased are not observed.

t, computed as the value of his or her transactions in a given category relative to the average value across consumers of transactions in the same category:

$$\mathrm{QI}_{i,t}^{c} = \frac{\mathrm{Qcat}_{i,t}^{c}}{\sum_{j \in J_t^m} \mathrm{Qcat}_{j,t}^{c} / \# J_t^m}, \tag{5}$$

where J_t^m is the set of consumers in market m at period t, and $\# J_t^m$ is the number of consumers.

Two individuals with similar values of the QI index may differ in that one systematically buys fewer, but more expensive UPCs than the other. In either event, these consumers will have an incentive to search for better prices within categories with a high value of the quantity index.[13] Panel A of Figure 2 illustrates that there is substantial variation in the quantity index (winsorized at the top and bottom 1 percent) by category. Categories are ordered by their interquartile range in this figure, and by construction, the mean for the quantity index for each category is roughly 1.

The QI gives higher weight to more expensive UPCs, which is not necessarily a problem. However, to explore the robustness of our results to potential biases arising from the price weights, we also construct an equal-weight QI that we refer to as the naive QI. This measure is based on the total count of UPCs purchased in a given month by category

[13] Neiman and Vavra (2019) document that consumers increasingly concentrate their consumption on individual-specific items. Our quantity index is robust to such changes as it is invariant to concentration within categories. Neiman and Vavra (2019) construct a model where tastes for individual goods vary across consumers, while there is a utility cost of consuming a large number of goods. Conceivably, such costs might be rationalized by search costs.

relative to the average count across all consumers. In particular,

$$\text{Naive QI}^c_{i,t} = \frac{\sum_{k,u(k)\in c} Q^{u(k),t}_{i,k}}{\sum_{j\in J^m_t}\sum_{k,u(k)\in c} Q^{u(k),t}_{j,k}/\#J^m_t}\,, \tag{6}$$

which is the sum of items purchased in category c by consumer i relative to the average of that statistic over all consumers in the market.

We make use of the average QI calculated as $\overline{\text{QI}}^c_{i,t} = \frac{1}{T_i}\Sigma^{T_i}_{t=1}\text{QI}^c_{i,t}$, where T_i is the number of months a consumer i is in the sample. We also calculate the average excluding the current period as $\overline{\text{QI}}^c_{i,t-} = \frac{1}{T_i-1}\Sigma^{T_i}_{s=1,s\neq t}\text{QI}^c_{i,s}$ to use as an instrument for the current QI in IV-regressions. Average Naive QI indices labelled Naive $\overline{\text{QI}}^c_{i,t}$ and Naive $\overline{\text{QI}}^c_{i,t-}$ are calculated similarly.

3.3 The Relationship between the Quantity Index and Relative Prices: A Graphical Depiction

We plot relative prices paid within categories against relative quantities consumed as measured by the category-level quantity indices (QI). We use binned scatter graphs, where we plot consumers' relative prices by item against (average) $\overline{\text{QI}}$ for the category the item belongs to. Relative prices are defined for each item u purchased by consumer i in period t as the price the consumer pays for that item (averaged over the transactions of the consumer involving item u in that month) relative to the store-average price for the same item that month in the consumer's market, $r^{u,m}_{i,t} = P^{u,m,t}_i/\overline{P}^{u,m,t}$. Before plotting relative prices against $\overline{\text{QI}}$, we absorb fixed effects for the consumer and the category. $\overline{\text{QI}}$ is sorted and collected into 20 quantiles on the x-axis and relative prices are averaged over the observations in each quantile-cell of $\overline{\text{QI}}$ on the y-axis.[14] The left panel of Figure 3 shows a clear negative relationship between the relative prices paid for items purchased and relative consumption in the category. The right panel of Figure 3 shows a similar negative relationship between the relative prices paid and relative consumption the category as measured using the naive $\overline{\text{QI}}$. Overall, higher spending on a category is clearly associated with lower prices for UPC items in that category.[15]

3.4 Bargain Hunting Indices

We follow Aguiar and Hurst (2007) and define an overall bargain-hunting index, $\text{BHI}_{i,t}$, for consumer i in period t as the amount a consumer saves for the products he or she buys relative to the cost of the exact same products at average prices in the same month and market. This is the ratio of actual expenditure to hypothetical expenditure evaluated at average prices where average prices are computed at the weekly level. The bargain-hunting index is computed as follows:

$$\text{BHI}_{i,t} = \left(1 - \frac{\sum_{k=1}^{N_i^t} P_{i,k}^{u(k),m,t} \times Q_{i,k}^{u(k),m,t}}{\sum_{k=1}^{N_i^t} \overline{P}^{u(k),m,t} \times Q_{i,k}^{u(k),m,t}}\right) \times 100\,, \tag{7}$$

where i is a consumer who purchases products in market m, k is a transaction of consumer i, $u(k)$ is the UPC of the transaction, and we aggregate expenditure to the monthly

[14]This is a fairly standard approach and we use the “binscatter” routine in Stata for this purpose. The QI has been demeaned by category to have mean zero in this graph.

[15]Using the time-varying QIs results in qualitatively similar pictures.

frequency t by summing over all N_i^t transactions of consumer i in month t. A consumer purchases many products and can purchase a particular product more than once a month, so the number of transactions is at least as large as the number of different goods purchased.

For each transaction, we use the exact price of the good in that transaction, $P_{i,k}^{u(k),m,t}$, to calculate actual expenditure. Given the consumer's consumption bundle, hypothetical expenditure is measured using the store-average price, $\overline{P}^{u(k),m,t}$, of the good in that transaction in the same market and month, where $u(k)$ denotes the UPC of the good purchased in transaction k. A higher BHI means saving more (paying less) relative to the store-average prices given the household's consumption bundle. This index encompasses all goods a household purchases, and the prices are compared at the UPC level. In our regressions, we multiply the bargain-hunting index by 100 and the interpretation is the percent savings that the consumer realizes by finding better than average prices.

Table A.2 in the online appendix displays the mean and standard deviation of the BHI (along with summary statistics for other variables used in the regressions). The average BHI is 7.5 percent, which means that panelists save 7.5 percent on average by finding better-than-average prices. The average price for each UPC is calculated outside the panelist sample and includes transactions by all shoppers in these markets; a positive average could reflect that panelists in our sample are, on average, older than the typical population.[16] It is also possible that stores outside the IRI store sample are on average

[16] The un-weighted average over a set of consumers can also deviate from the quantity weighted average for the same consumers when quantities vary across consumers.

cheaper. Going forward, we demean the BHI to 0 each period.[17]

To study our main hypothesis, we use a modified version of the bargain-hunting index defined at the category level (for each consumer and time period). Let c denote a category. A category-level BHI for a given consumer i in period t, $\text{BHI}_{i,t}^{c}$, is computed similarly to the overall BHI, except that only transactions involving products in a given category are added up:

$$\text{BHI}_{i,t}^{c} = \left(1 - \frac{\sum_{k,u(k)\in c} P_{i,k}^{u(k),m,t} \times Q_{i,k}^{u(k),m,t}}{\sum_{k,u(k)\in c} \overline{P}^{u(k),m,t} \times Q_{i,k}^{u(k),m,t}}\right) \times 100\,. \tag{8}$$

Figure 2, Panel B, presents a box plot of the BHI by category, illustrating the range of prices paid, and thus consumers' potential for saving from searching, which varies by category.[18] In the graph, IRI's categories are ordered by the interquartile range of the category-specific BHIs. For example, the interquartile range for beer is 1/11th of that for laundry detergent (2.63 percent versus 28.92 percent). This significant difference is likely due to very disparate pricing strategies employed by retailers and/or producers of the two products; nevertheless, there is price variation for identical UPCs within all product categories, implying potential gains from price-search.

To explore whether consumers save from visiting certain stores or from timing of purchases, we compute for each consumer an alternative "store BHI," $\text{BHI}_{i,t}^{c,s}$, that computes the value of consumer i's basket using the average price, $\overline{P}_{s}^{u,m,t}$, of each UPC in a given month *in the store*, s, where the item was purchased. To compute this average price, we

[17]Demeaning is not strictly necessary in our regression analysis, because we include period (year × month) fixed effects.

[18]The category names are intuitive, except maybe the category "blades," which is mainly made up of cartridges for shavers.

use the store-level dataset.[19] The exact expression for the store (category-level) bargain-hunting index is

$$\mathrm{BHI}_{i,t}^{c,s} = \left(1 - \frac{\sum_{k,u(k)\in c} \overline{P}_s^{u(k),m,t} \times Q_{i,k}^{u(k),m,t}}{\sum_{k,u(k)\in c} \overline{P}^{u(k),m,t} \times Q_{i,k}^{u(k),m,t}}\right) \times 100. \tag{9}$$

The store bargain-hunting index replaces the numerator (the amount paid for the purchased basket) in the bargain-hunting index with the counterfactual amount that the consumer would have paid for the purchased basket, had he or she paid the average price (in that month) in the store in which each good was purchased. This index is informative about whether the consumer obtains lower prices by shopping in stores where the desired goods are relatively cheap with the discrepancy to the regular bargain-hunting index explained by timing of purchases within stores. If the BHI for a consumer is lower than the store BHI, the consumer has, on average, purchased goods at times of the month when the prices of the goods were lower than store-specific monthly average prices. Figure A.5 in the appendix compares the original BHI to the store BHI using histograms. The correlation between the two indices is 0.52, and the histograms suggest gains from both store selection and the timing of purchases (with the latter being quite important).

[19] This exercise is performed using data from 2003 through 2007, because store identifiers in the store-level dataset are not fully consistent with identifiers in the panelist dataset after 2007. Also, goods purchased at stores outside the IRI sample are not included in the index.

4 Regression Results

In this section, we first report regressions similar to those in the bargain-hunting literature and establish that our data does not deliver deviating results along the dimensions where we can compare to previous work. Then, we focus on category-specific regressions, the main contribution of our paper.

Replicating Previous Findings

Table 1 reports results from regressions of the form

$$\mathrm{BHI}_{i,t} = \mu_i + \gamma_{m,t} + X_{i,t}\,\alpha + \epsilon_{i,t}\,, \tag{10}$$

where $\mathrm{BHI}_{i,t}$ is the overall bargain-hunting index for individual i in month t, μ_i is an individual fixed effect included in only some of the specifications, $\gamma_{m,t}$ is a market $\times$ month fixed effect, and X is a vector of regressors: A dummy for age 65 and older, the logarithm of expenditure (our proxy for labor income), the number of shopping trips, and the number of different stores visited each month to study possible channels for bargain-hunting savings. The number of shopping trips and the number of different stores visited are not included in all regressions, as they are likely to be endogenous, but these variables are informative about how consumers save. Aguiar and Hurst (2007) use a similar specification, although they do not include the number of stores visited.

The left panel of Table 1 shows results for regressions without individual fixed effects.

The results in column (1), when only expenditure and age (besides market × month fixed effects) are included, confirm previous results that higher-spending consumers pay relatively more (with an elasticity of –0.62), and that consumers 65 and older pay relatively less (with average savings of 0.71 percent). This is consistent with the model's interpretation that high-wage workers elect to search less because of their higher value of time, while older individuals search more because of their lower value of time.

In columns (2)–(4), we include the number of different stores visited in a month and the number of shopping trips as direct measures of search effort. These variables are not necessarily exogenous—one might imagine some stores having frequent sales, which makes consumers take more trips to the store and obtain lower prices—but we include them because they are informative of the mechanism by which consumers obtain bargains.[20] The number of stores visited in a given month predicts lower prices paid robustly and with high statistical significance. The economic interpretation of the coefficient to this variable in column (2) is that consumers who visit one more store each month pay 0.77 percent less for their consumption basket than they would have paid at average prices. The inclusion of the number of stores visited increases the R-squared from 0.01 to 0.04, so this variable has much greater explanatory power than do age and expenditure (although this likely reflects that the age dummy is somewhat imprecisely correlated with retirement, and it may be that retired people save more by visiting more stores).

Including the number of shopping trips, in column (3), while omitting the number of stores visited, gives a highly significant coefficient for trips of 0.19 with an R-squared of

[20]Conceivably, monthly expenditure is endogenous but the results of interest are not sensitive to the inclusion of this variable.

0.02. However, including the number of shopping trips together with the number of stores visited, in column (4), lowers the coefficient to the number of shopping trips significantly, while the coefficient to the number of stores visited is quite similar across columns. Clearly, it is the number of stores visited, rather than the number of trips, that is associated with lower prices although, according to column (4), one more trip (controlling for number of stores visited) still lowers the average price paid by 0.05 percent.[21]

In the right panel of Table 1, we include individual fixed effects. The R-squared jumps to 0.25, so it appears that some consumers are consistently "shoppers," while others are "loyals" (in the parlance of Chevalier and Kashyap, 2019).[22] Expenditure and age are still significant. The coefficient on age is smaller, as it is now identified only from consumers who turn 65 during the sample period. The number of stores visited remains significant, but with individual fixed effects, the coefficient drops to 0.22 in column (8). This indicates that some consumers consistently shop at many stores and these consumers may be more informed, obtaining bigger savings from multi-store shopping. The number of trips and the number of stores visited do not add much to the explanatory power of the regressors when individual fixed effects are included.

[21]This is consistent with the findings of Kaplan et al. (2019), that some stores are cheaper for some goods but not for others.

[22]Our results are not informative about whether some consumers are inherently looking for deals, whether they live close to an inexpensive store, or whether they are impacted by other unmeasured features, so we interpret those terms broadly.

Category-Specific Regressions

The main innovation of this paper is that it examines the relationship between quantities and prices by category. We measure quantities at the category level, but price comparisons are at the UPC level (prices paid by the consumer relative to average UPC-level prices across consumers). The bargain-hunting index measures the savings obtained by consumer i by paying below-average prices for (UPC) items u in category c. The index is unit free and measures savings from search in percentages that are comparable across categories and households. The data form a panel indexed by individual $\times$ category $\times$ time (as before, i denotes individual, c category, and t month). The panel is highly unbalanced, as a large number of consumers do not make purchases in each category each month (such cells are excluded from the sample). Our main regression is

$$\mathrm{BHI}^c_{i,t} = \nu_c + \gamma_{m,t} + \mu_i + \beta\,\mathrm{QI}^c_{i,t} + X_{i,t}\,\alpha + \epsilon_{i,c,t}\,, \tag{11}$$

which allows for category, ν_c, and market $\times$ time fixed effects, $\gamma_{m,t}$. μ_i is a consumer fixed effect and we show results with and without this fixed effect. The focus of our paper is on the coefficient β; in particular, our hypothesis is that β is positive, implying that consumers save relatively more in categories of which they purchase relatively more.

We complement this category-specific BHI regression by first showing regressions of UPC percent savings for items in a given category on the average QI (excluding t) for that category, corresponding closely to Figure 3. UPC percent savings, $\mathrm{s}^{u,m}_{i,t}$, is defined as $(1 - \mathrm{r}^{u,m}_{i,t}) \times 100$, where $\mathrm{r}^{u,m}_{i,t}$ is consumer i's price of item u relative to the store-average price, and we use the regression specification

$$\mathrm{s}_{i,t}^{u,m} = \nu_c + \gamma_{m,t} + \mu_i + \beta\,\overline{\mathrm{QI}}_{i,t-}^{c} + X_{i,t}\,\alpha + \epsilon_{i,u,t}\,. \tag{12}$$

Leaving out period t on the average QI limits the scope for reverse causality. However, our more important identifying assumption is that consumers do not switch their average consumption from, say, beer to soap, in response to a period t low price of soap. We consider this a reduced form regression and we will also use $\overline{\mathrm{QI}}_{i,t-}^{c}$ as an instrument in our bargain-hunting regressions. The instrument is time-varying, but for simplicity we refer to it as the average category-specific quantity index.

The β-coefficient on the quantity index (ignoring the controls, which are not of importance for this issue) is identified from deviations from the fixed effects included. Including a market $\times$ time fixed effect implies that differences between markets at any time do not contribute to identification and, because of the category fixed effect, neither do permanent differences across categories. This leaves variation across consumers, across categories for each consumer, and across time within each consumer's category. For the category bargain-hunting regressions, we display OLS and IV results without and with individual fixed effects, which absorb (average) differences between individuals.

The results presented in Table 2 show average percent savings per item in columns (1)–(3) and average percent savings for the category-baskets in columns (4)–(6) as a function of category-level quantities. The purpose of showing both is that savings per item involves only the prices paid and will not be affected by, say, higher quantities purchased of an item in response to a low price—such a pattern would not imply reverse causality as our right-hand side variables are average quantities, but it is of interest to see if prices paid are indeed lower. In all regressions, the QI-indices are standardized by category for easier interpretation. Column (1), which does not include individual fixed effects, shows that a one-standard deviation increase in quantities purchased in a category is associated with 0.93 percent lower prices (relative to average market prices) for items in that category, consistent with rational allocation of time and effort across categories. The estimated coefficients for the controls are similar for price percent savings and the bargain-hunting regressions, and for these variables we comment on all columns together. The coefficient to age is significant and similar to what was found in Table 1, while the coefficient to log-expenditure is highly significant with an elasticity between –1.03 and –1.47. These coefficients are numerically larger than those found in Table 1, which suggests that the former estimates may suffer slightly from left-out variable bias due to expenditure levels being correlated with the left-out category quantity index.[23]

Including individual fixed effects in column (2) delivers a somewhat smaller coefficient to the price ratio of 0.58, which is intuitive because some consumers are "shoppers" across the board. The inclusion of the time fixed effect increases the R-squared from 0.05 to 0.11, so differences across consumers are important. However, it is still the case that consumers who on average save more do so via more intensive price-search in preferred categories. The coefficient to category QI in column (2) is still highly significant with a t-coefficient

[23]The regressions in Table 1 involve data aggregated over the categories. Left-out variable bias in the more disaggregated regressions may well translate to the aggregate level, but we will not pursue this issue in detail.

above 10, indicating that consumers engage in selective bargain hunting depending on category preferences. The results in column (3), which uses the naive QI, are very similar, so it appears that the patterns found are not due to differences in product quality or sizes within categories. Having verified that prices correlate with average category spending, we focus on the effect of the QI on the bargain-hunting index from here on.

In column (4), we show the results of an OLS-regression using the time-varying quantity index and in columns (5)–(6), we show IV regressions using the average (minus t) quantity index as an instrument. The results are very similar for OLS and IV in columns (4) and (5), indicating that reverse causality is not an issue. The smaller coefficient in column (6) is due to the inclusion of the consumer fixed effect. The coefficients of the quantity index in columns (4) and (5) are 2.32 and 2.39, which are larger than the corresponding coefficient in the price-percent-saving regressions of column (1) (also without individual fixed effects). The interpretation is that consumers save a larger percentage on their baskets than just the average percentage decline in prices. This is the result of paying relatively low prices for items consumed in higher amounts—we do not attempt to determine whether within-category savings are due to opportunistic shopping or to differential search across items. The coefficient is somewhat smaller at 1.45 in column (6), which includes individual fixed effects, again consistent with persistent differences across consumers when it comes to shopping.

Robustness and Channels

Table 3 explores a few issues. In column (1), the number of trips and the number of stores visited are added to the IV specification in column (5) of Table 2. The results for these variables are similar to those of Table 1. For example, the coefficient to number of stores visited in column (1) takes a value of 0.56 compared with a value of 0.68 in column (4) of Table 1. The similarity is to be expected unless the number of stores visited is highly correlated with the category dummies (which are not defined in the regressions using the overall bargain-hunting index). Even controlling for trips and the number of stores visited, the coefficient to the quantity index is very similar to what we found in previous regressions without these controls.

When the dispersion in prices is higher, the efficiency of price search is likely to be higher. We check if our results are robust to controlling for price dispersion within each category (by market and month). We compute the coefficient of variation (CV) of the prices of each UPC in a given market and month, and average the UPC-level CVs across the UPCs in each category, creating a category-level CV.[24] We add this category-level CV as a control in our regressions as well as its interaction with the QI—the category-level CVs are standardized to have mean 0 and a standard deviation of 1 across categories for easier interpretation. Column (2) of Table 3 reveals that the quantity index has a stronger impact on prices in categories with higher price variation, consistent with search efficiency increasing with price variation. Consumers save more in categories of which

[24]A simple average of the UPC-level CVs in a given category and averages that give more weight to higher-price UPCs or UPCs that are purchased more frequently deliver similar results.

they purchase relatively larger quantities, and more so if price dispersion is larger in the category.

We also report results using the store bargain-hunting index, which is calculated under the counterfactual assumption that the consumer paid the average price in the store for each good purchased in that store. For data reasons, we are only able to calculate the store BHI pre-2008, so the regression of the first column is repeated in column (3) for this truncated sample in order to make sure that any differences in results are not simply reflecting the change in sample. (The coefficients to the quantity index in columns (1) and (3) are very similar.) In column (4), we report results from estimating

$$\mathrm{BHI}_{i,t}^{c,s} = \nu_c + \gamma_{m,t} + \beta\,\mathrm{QI}_{i,t}^{c} + X_{i,t}\,\alpha + \epsilon_{i,c,t}\,,$$

which is similar to the regression of column (1), except for the left-hand side being the store bargain-hunting index by category. The results in column (4), obtained for the store BHI, reflect the prices the consumer *would have paid* had he or she paid the average store price for the items purchased in the given month, rather than the actual price paid. Any difference to the results using the original BHI index is due to gains from the timing of purchases. The coefficient to the quantity index drops from 2.28 to 0.52, although the coefficient is extremely significant in a statistical sense. Our interpretation is that a large fraction of the savings obtained in favorite categories results from choosing the time to shop in a given store, rather than from choosing to shop in stores with consistently lower prices.[25]

[25] The results regarding the relative importance of timing is sensitive to the length of the period used.

The regression results reported in Tables 2 and 3 are pooled across categories, but pooling may mask differences across categories. As shown in Figure 2, Panel B, the BHI is significantly more compressed for some categories than for others, with almost no variation in prices paid for identical beer UPCs (on average) and little variation for cigarettes (followed by milk and sugar substitutes). Laundry detergent displays the largest variation, followed by hot dogs and frozen pizza. This is not a simple reflection of relative quantities consumed. For the quantity index, razors and ketchup/mustard show the least variation across consumers, and carbonated beverages and cigarettes the most (see Figure 2, Panel A). To test whether our results are robust across categories, we estimate the regression separately for each category. Table A.3 in the online appendix shows the regressions category-by-category and our main qualitative result is remarkably robust—the coefficient to the quantity index is positive and highly significant in almost all categories.

Discussion

Consumers find lower prices for items in their preferred categories. As Aguiar and Hurst (2007), we compare prices at the UPC level, but we ignore savings from switching between brands or even package sizes within a category. Because consumers may save by changing to less expensive brands or by buying larger packages of the same good, our findings provide a lower bound on the savings obtained by consumers. However, switching to different brands or package sizes brings a potential loss in utility that can be evaluated

If, for example, store prices were averaged over only a week, the timing would be less important than the choice of store visited because there would be less scope for within-store price variation. The interpretation of this pattern is that some consumers are able to time their purchases over intervals longer than a week.

only by using functional forms, which we abstract from in this paper.

If a consumer changed consumption within a category to more expensive brands, this would appear as an increase in the quantity index. The bargain-hunting index compares the price paid for a brand to the average price of that particular brand (or rather UPC, which is even more specific), and our model predicts that a consumer that switches to a more expensive brand will search more for a relatively low price. To the extent that this does not happen, it will play the role of measurement error and bias our coefficients towards zero.

Our consumer model assumes different a priori preferences for goods. However, one can imagine a case where a consumer has no preference for frozen dinners versus frozen pizza (two of our categories), but buys the frozen food that happens to be relatively cheaper when he or she visits the store, which would result in an inverse relationship between good prices and quantities. (This, of course, is also rational behavior on behalf of the consumer, but the store-pricing implications would differ.) We use IV-regressions for this very reason. We find very similar IV- and OLS-estimates, which indicates that causality goes from preferences to prices after aggregating to the category level. In addition, we would expect random sales to average out over a longer time period, and we, as a second indicator that most causality goes from preferences to prices, repeat the regressions in Table 3 for quarterly frequencies. The results, show in Table A.4, are very similar to those obtained at the monthly frequency, which supports the causal interpretation of the results.

5 Conclusion

We find that, consistent with a model of rational price search, consumers pay lower-than-average prices for items (such as a 12-pack of Coca-Cola) in categories (such as soda) of which they consume relatively more, and they pay higher-than-average prices for items in categories of which they consume relatively less. The empirical results provide robust support for the notion that consumers rationally search for better prices when it has a higher return.

Our results are consistent with those from models of "shoppers" versus "loyals," or "cool" versus "busy" consumers, in that we document significant variation in the prices consumers pay. In Table 4, we illustrate the magnitudes of the savings. The top quarter of consumers in the BHI distribution (the cool shoppers) pay, on average, 11.75 percent less than the average consumer, whereas consumers in the bottom quarter (the busy loyals) pay 10.21 percent more for the exact same goods. The main innovation of our work is that we depart from the assumption that some consumers pay low (high) prices across the board. For each consumer, we rank his or her purchased categories according to the quantity index and divide the goods into top-half and bottom-half categories (for this exercise, we include only consumers who purchase at least two categories).[26] We then compute separate BHIs for top-half and bottom-half categories (in terms of the quantity index). On average, consumers save 0.74 percent on the goods of which they buy more (relative to other consumers) and pay 2.28 percent more for the goods of which they buy less. Most savings accrue to consumers who find low prices across the board, although

[26] If the number of categories is not even, the top group has one more category.

these consumers clearly obtain higher savings for their most preferred goods. Consumers who on average pay the highest prices show no tendency for saving more on preferred goods though.

Overall, there is substantial heterogeneity across consumers, as previously documented. Our contribution is to study how rational consumers shop across goods and to show that consumers conduct more bargain hunting for their most desired categories. An additional implication of our model is that improvements in search efficiency, while lowering prices on average, may not result in lower price dispersion across consumers. Given that consumer preferences for a particular category differ, search efforts will still vary across categories and price dispersion may not decrease. (We illustrate this numerically in Figure A.3.)

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Table 1. The Bargain-Hunting Index for Overall Expenditure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pooled OLS				Panelist Fixed Effects			
Log. Expenditure	–0.62***	–0.81***	–1.08***	–0.91***	–0.55***	–0.66***	–0.80***	–0.78***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.03)	(0.03)	(0.03)	(0.03)
Old (65+)	0.71***	0.40***	0.34***	0.35***	0.36**	0.30*	0.32*	0.29*
	(0.12)	(0.11)	(0.11)	(0.11)	(0.17)	(0.17)	(0.17)	(0.17)
# stores visited (monthly)		0.77***		0.68***		0.32***		0.22***
		(0.03)		(0.03)		(0.02)		(0.02)
# trips (monthly)			0.19***	0.05***			0.10***	0.06***
			(0.01)	(0.01)			(0.01)	(0.01)
Month-Year × Market FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	551438	551438	551438	551438	551438	551438	551438	551438
Adj. R-squared	0.01	0.04	0.02	0.04	0.25	0.25	0.25	0.25

Notes: Regression: $\text{BHI}_{i,t} = \mu_i + \gamma_{m,t} + X_{i,t}\,\alpha + \epsilon_{i,t}$, where $\text{BHI}_{i,t}$ is the bargain-hunting index for individual i in month t, μ_i is an individual fixed effect (FE) ($\mu_i = \mu$ in the first four columns), $\gamma_{m,t}$ is a market × month FE, and X is a vector of regressors: A dummy for age 65 and older, the logarithm of total expenditure, the number of different stores visited monthly, and the total number of shopping trips in the month. Standard errors clustered by individual. *** (**) [*] significant at the 1 (5) [10] percent level.

Table 2. Rational Inattention. Savings and the Category Quantity Index

	(1)	(2)	(3)	(4)	(5)	(6)
Estimator:	OLS	OLS	OLS	OLS	IV	IV
Obs. (by time, id):	UPC	UPC	UPC	Category	Category	Category
Dep. Variable:	Pct. Sav.	Pct. Sav.	Pct. Sav.	BHI^c	BHI^c	BHI^c
Quantity Index:	$\overline{\mathrm{QI}}^c_{t-}$	$\overline{\mathrm{QI}}^c_{t-}$	Naive $\overline{\mathrm{QI}}^c_{t-}$	current QI^c_t	current QI^c_t	current QI^c_t
Instrument:					$\overline{\mathrm{QI}}^c_{t-}$	$\overline{\mathrm{QI}}^c_{t-}$
Quantity Index	0.95***	0.58***	0.58***	2.32***	2.39***	1.45***
	(0.07)	(0.04)	(0.04)	(0.02)	(0.07)	(0.04)
Log. Expenditure	–1.03***	–0.83***	–0.82***	–1.43***	–1.47***	–1.06***
	(0.05)	(0.03)	(0.03)	(0.05)	(0.04)	(0.03)
Old (65+)	0.57***	0.29*	0.29*	0.42***	0.42***	0.24*
	(0.13)	(0.16)	(0.16)	(0.11)	(0.11)	(0.14)
Mth-Yr × Mkt FE	Yes	Yes	Yes	Yes	Yes	Yes
Category FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	No	Yes	Yes	No	No	Yes
Observations	9049372	9049372	9049372	3793574	3768437	3768437
Adj. R-squared	0.05	0.11	0.11	0.02		
F-test excl. inst.					1331268	1261197

Notes: Columns (1)–(3) display regressions of the (individual, time, UPC)-level of percent savings by item c on category consumption: $\mathrm{s}^c_{i,t} = \nu_c + \gamma_{m,t} + \mu_i + \beta\overline{\mathrm{QI}}^c_{i,t-} + X_{i,t},\alpha + \epsilon_{i,u,t}$, where the quantity index is averaged over the sample period for a given individual and excludes period t. Our preferred quantity index and the naive quantity index are described in equations (5) and (6), respectively. They measure the average category c consumption of consumer i at average prices relative to other consumers (not including period t), or the number of items bought in category c by consumer i relative to other consumers (not including period t). ν_c denotes category fixed effects, $\gamma_{m,t}$ is a market × month fixed effect, μ_i is an individual fixed effect, and X ia vector of regressors. Columns (4)–(6) display regressions at the individual, time, category level of the bargain-hunting index on the quantify index: $\mathrm{BHI}^c_{i,t} = \nu_c + \gamma_{m,t} + \mu_i + \beta\mathrm{QI}^c_{i,t} + X_{i,t},\alpha + \epsilon_{i,c,t}$, where $\mathrm{BHI}^c_{i,t}$ is the category-specific bargain-hunting index for individual i in month t, and $QI^c_{i,t}$ is the quantity index described in equation (5). The quantity index, which measures whether a consumer purchases more or less of a category than the average consumer, is standardized by category (mean 0, std 1) for easier interpretation. The IV-regressions use as an instrument the average category-specific quantity index defined for observation t as $\overline{\mathrm{QI}}^c_{i,t-} = \frac{1}{T_i-1}\Sigma^{T_i}_{s=1,s\neq t}\mathrm{QI}^c_{i,t}$. Standard errors clustered by individual. *** (**) [*] significant at the 1 (5) [10] percent level.

Table 3. Rational Inattention. IV. Trips and Stores Controls. Store Index.

Dep. Variable:	(1) All Years BHI^c	(2) All Years BHI^c	(3) Pre-2008 BHI^c	(4) Pre-2008 Store BHI^c
Quantity Index	2.28***	2.30***	2.36***	0.52***
	(0.06)	(0.06)	(0.06)	(0.03)
Log. Expenditure	–1.66***	–1.67***	–1.77***	–0.60***
	(0.05)	(0.05)	(0.05)	(0.02)
Old (65+)	0.08	0.09	–0.17	–0.10**
	(0.10)	(0.10)	(0.10)	(0.05)
# stores visited (monthly)	0.56***	0.56***	0.76***	0.33***
	(0.03)	(0.03)	(0.03)	(0.01)
# trips (monthly)	0.05***	0.05***	0.05***	0.01**
	(0.01)	(0.01)	(0.01)	(0.00)
QI × Prices-CV		0.50***		
		(0.04)		
Prices-CV		–0.00		
		(0.02)		
Month-Year × Market FE	Yes	Yes	Yes	Yes
Category FE	Yes	Yes	Yes	Yes
Observations	3729149	3729149	2133968	2133968
Adj. R-squared	0.03	0.03	0.04	0.01
F-test excl. inst.	1315054	644147	799500	799500

Notes: Regression: $\text{BHI}^c_{i,t} = \nu_c + \gamma_{m,t} + \beta \text{QI}^c_{i,t} + X_{i,t}, \alpha + \epsilon_{i,c,t}$, where $\text{BHI}^c_{i,t}$ is the category-specific bargain-hunting index for individual i in month t, and ν_c denote category fixed effects. $\gamma_{m,t}$ is a market × month FE, X is a vector of regressors, and $QI^c_{i,t}$ is the quantity index described in equation (5). The quantity index, which measures whether a consumer purchases more or less of a category than the average consumer, is standardized (mean 0, sd 1) for easier interpretation. Prices-CV denotes the average of the coefficients of variation of all UPC-level prices in a given category by market and month, also standardized. In column (3), $\text{BHI}^c_{i,t}$ is replaced by a category-specific store BHI, $\text{BHI}^{c,s}_{i,t}$. All regressions are estimated by IV, using the average category-specific quantity index as an instrument, defined more precisely in the notes to Table 2. Standard errors clustered by individual. *** (**) [*] significant at the 1 (5) [10] percent level.

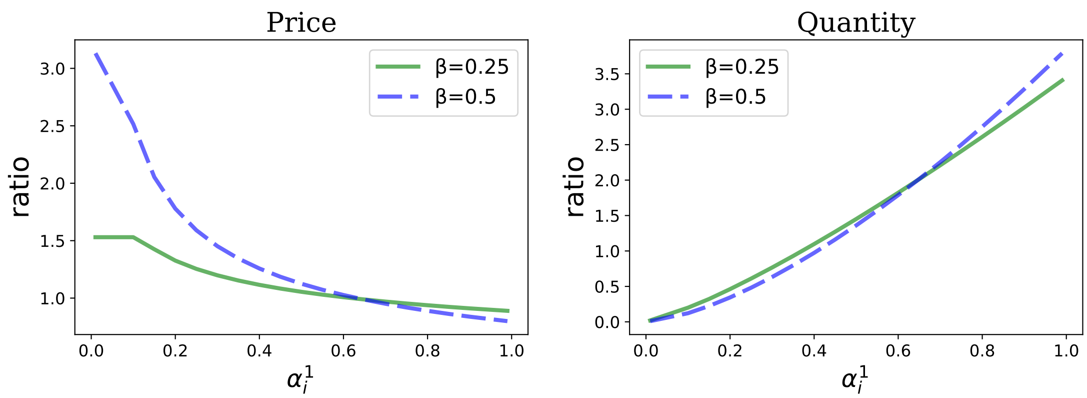
Table 4. Average Values of BHI within Quarters of its Distribution

	(1)	(2)	(3)	(4)	(5)
		Consumers Sorted by BHI			
	All	Highest Savings	2^{nd} Highest Savings	2^{nd} Lowest Savings	Lowest Savings
Percent Savings					
Total	0.00	11.75	1.88	–3.74	–10.21
More preferred categories	0.74	13.91	2.69	–3.49	–10.50
Less preferred categories	–2.28	5.17	–0.57	–4.37	–9.60

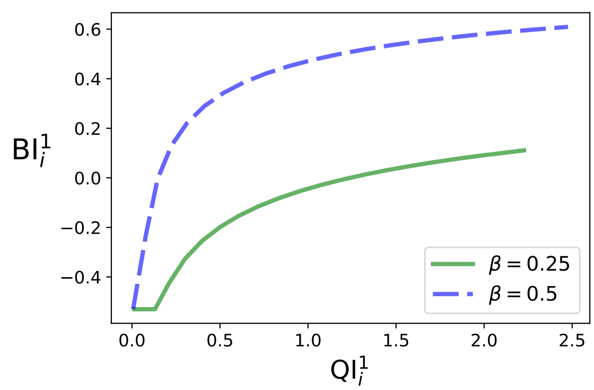
Notes: The table displays in the first row the value of the bargain hunting index (BHI), normalized to be 0 on average, and the BHI for consumers with the highest, second-highest, second-lowest, and lowest BHI. For each consumer, we rank his or her purchased categories in terms of the quantity index and divide them into top-half and bottom-half purchased categories (we include only consumers who purchase from at least two categories). We then compute two BHIs for top-half (more preferred) and bottom-half (less preferred) categories. The average values of these two BHIs are presented in the second and third rows of the table, first for all consumers in column (1), and then by quartile-group of the overall BHI in columns (2) through (5).

Figure 1. Relative Prices and Quantities in Model

Panel A: Price and Quantity Relative to Average



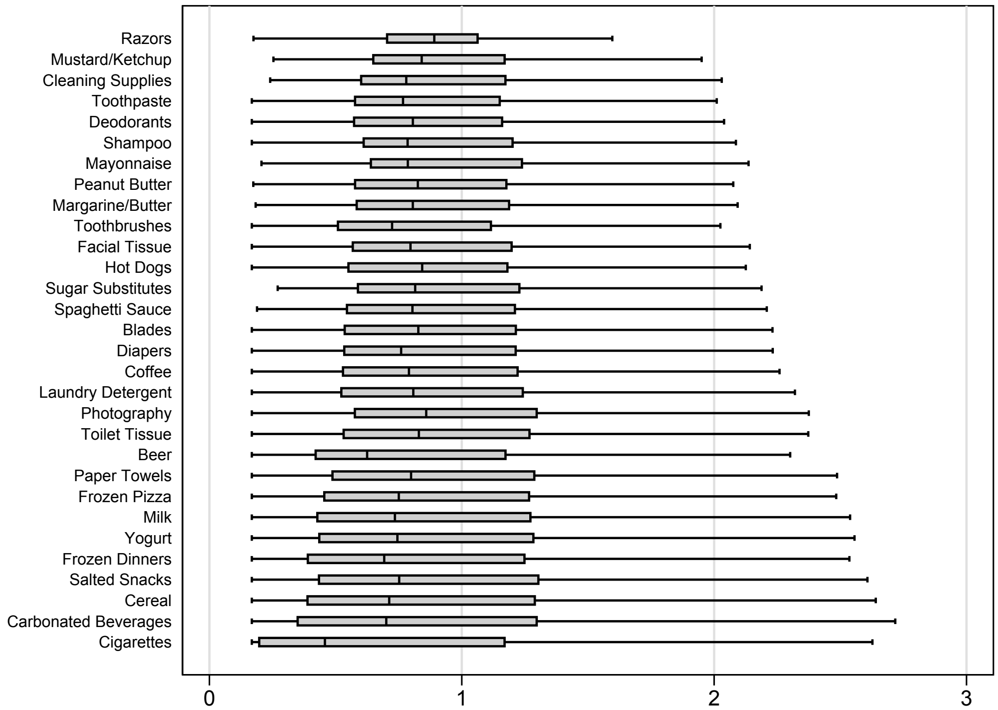
Panel B: Bargain-Hunting and Quantity Indices



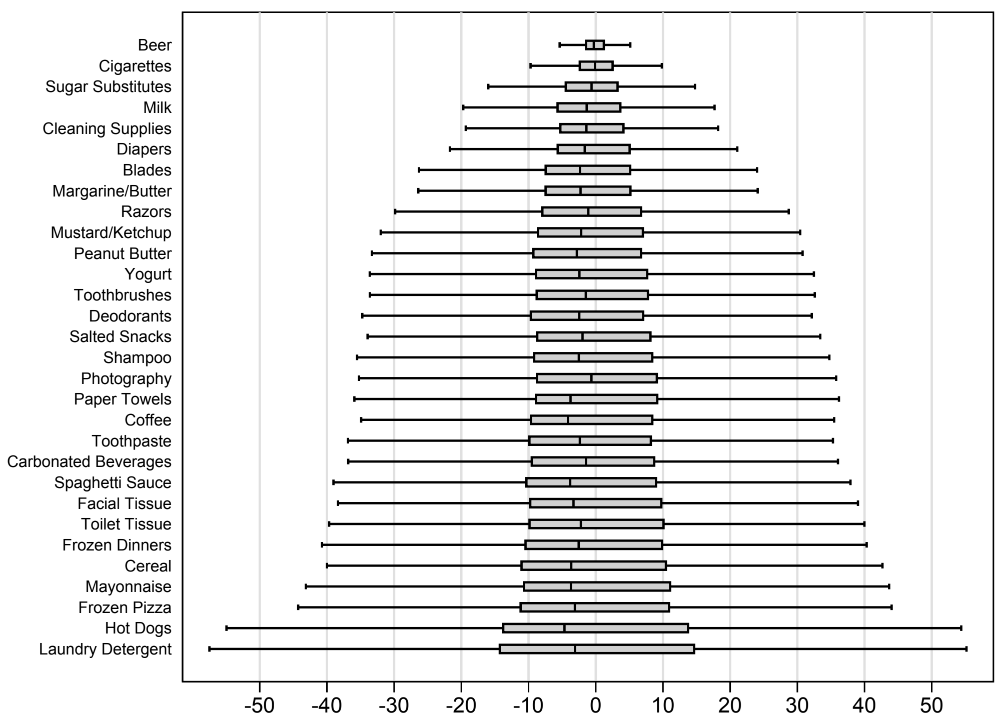
Notes: Panel A depicts the relative (to the average) prices paid and quantities consumed of good 1 for individuals with different preferences (indicated on the x-axis). Panel B depicts the bargain-hunting index, BH_i^1, for good 1 on the y-axis and the corresponding quantity index (QI_i^1) on the x-axis for the individuals in Panel A. Each point on the line represents a different individual. A higher α_i^1 results in a higher QI_i^1, as shown in Panel A. $BH_i^1 = 1 - (P_i^1 \times Q_i^1)/(\overline{P}^1 \times Q_i^1)$ and $QI_i^1 = Q_i^1/\overline{Q}^1$. We assume a uniform distribution of consumers with $\alpha_i^1 \in [0, 1]$. Search efficiency and preference for good 1 (β and α^1) vary as indicated in each subplot. The remaining model parameters are as follows: $T = 50,\ P_H = 1, \eta = 1,\ \mu = 0.5,\ W^0 = 50,\ W^1 = 5, T^0 = 5$.

Figure 2. Variation by Category

Panel A: The Quantity Index

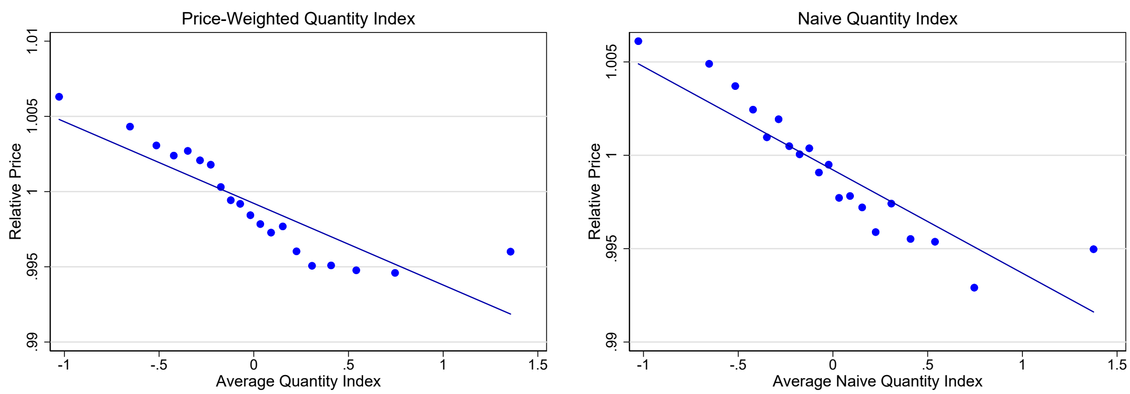


Panel B: The Bargain-Hunting Index



Notes: Product categories are defined by IRI. Panel A shows variation in the quantity index (QI) by category. The left and right borders of each category box depict the 75th and 25th percentiles of the QI for that category, while the whiskers represent upper and lower adjacent values (outside values not plotted). The categories have been sorted by the interquartile range. Panel B depicts variation in the bargain-hunting index (BHI) by category and is created analogously.

Figure 3. Relative Prices by UPC and the Category-Level Quantity Index



Notes: The figures are binned scatter plots of relative prices for the UPC items consumers purchase on their average value of the quantity index (QI) for the category the item belongs to. Relative prices are defined for each item c purchased by consumer i in period t as the average price the consumer pays for that item in a given month relative to the store-average price for the same item that month. The average QI is calculated over the period a consumer is in the sample. Before plotting relative prices against the average QI, we absorb fixed effects for the consumer and the category. The average QI is sorted and collected into 20 quantiles on the x-axis, and relative prices are averaged over the observations in each quantile-cell of the QI on the y-axis. The QI is demeaned to have mean zero, and relative prices have a mean of one. For the definitions of the price-weighted QI and the naive QI, see equations (5) and (6).

Online Appendix

Detailed Solution of the Model

We provide the details of solving the model via a standard Lagrange technique. We suppress the subscript i that denotes individuals to simplify notation. The Lagrangian is $L = \alpha^1 \ln Q^1 + \alpha^2 \ln Q^2 + \mu \ln(T - T^Y - T^1 - T^2 - T^0) + \lambda[Y(T^Y) - P^1Q^1 - P^2Q^2]$, and the first order conditions (FOCs) with respect to (wrt.) consumption are:

$$\frac{\alpha^c}{Q^c} = \lambda P^c\,;\; c = 1, 2\,. \tag{13}$$

This implies that $\frac{Q^1}{Q^2} = \frac{\alpha^1 P^2}{\alpha^2 P^1}$; that is, a higher α^1 (higher weight on good 1) increases Q^1 over Q^2. A higher relative price of good 2 has the same effect. Substituting into the budget constraint, (2), we find that expenditure shares for the two goods are constant: $P^1Q^1 = \alpha^1 Y(T^Y)$ and $P^2Q^2 = \alpha^2 Y(T^Y)$.

The FOCs of the Lagrangian wrt. T^c, $c = 1, 2$ are:

$$-\mu(T - T^Y - T^1 - T^2 - T^0)^{-1} - \lambda Q^c \frac{dP^c}{dT^c} = 0;\; c = 1, 2\,. \tag{14}$$

Combining the conditions, we find that the marginal gain from search time is equalized across goods:

$$\frac{dP^2}{dT^2} Q^2 = \frac{dP^1}{dT^1} Q^1, \quad \text{or} \quad \frac{\frac{dP^2}{dT^2}}{\frac{dP^1}{dT^1}} = \frac{Q^1}{Q^2}.$$

Given that $Q^c = \alpha^c / \lambda P^c$, from FOC (13), and that $dP^c/dT^c = P^h \beta (T^c + \eta)^{-\beta - 1}$, we can rewrite the previous expression as:

$$\frac{-\beta(T^2+\eta)^{-\beta-1}}{-\beta(T^1+\eta)^{-\beta-1}} = \frac{\alpha^1}{\alpha^2}\frac{(T^2+\eta)^{-\beta}}{(T^1+\eta)^{-\beta}} \quad \text{or} \quad \frac{T^1+\eta}{T^2+\eta} = \frac{\alpha^1}{\alpha^2}\,.$$

That is, relative time allocated to searching for goods is proportional to their relative preferability.

The FOC of the Lagrangian wrt. T^Y is $-\mu(T - T^Y - T^1 - T^2 - T^0)^{-1} + \lambda\frac{dY}{dT^Y} = 0$, and combining this FOC with FOC (14), we obtain $-Q^c\frac{dP^c}{dT^c} = \frac{dY}{dT^Y}$. That is, the marginal gain from a unit increase in shopping time is equal to the marginal loss of income.

Substituting for the price derivative, we obtain $Q^c\frac{dP^c}{dT^c} = Q^c(-\beta P^c(T^c+\eta)^{-1}) = -\beta(P^cQ^c)(T^c+\eta)^{-1}$, and as $Q^cP^c = \alpha_i^c Y(T^Y)$, we find $\beta\alpha_i^c Y(T^Y)(T^c+\eta)^{-1} = \frac{dY}{dT^Y}$ or $T^c + \eta = \beta\alpha_i^c\frac{Y(T^Y)}{\frac{dY}{dT^Y}}$, implying that $T^c = \beta\alpha_i^c\left(\frac{W^0}{W^1} + T^Y\right) - \eta$ and $T^1 + T^2 = \beta\left(\frac{W^0}{W^1} + T^Y\right) - 2\eta$. FOC (13) and the fact that $Q^cP^c = \alpha_i^c Y(T^Y)$ imply that $\lambda = 1/Y(T^Y)$. Given that $\frac{dY}{dT^Y} = W^1$ and substituting for λ, we can rewrite the FOC wrt. T^Y as:

$$\mu(T - T^Y - T^1 - T^2 - T^0)^{-1} = \frac{W^1}{W^0 + W^1T^Y}.$$

Substituting for the value of $T^1 + T^2$, we can solve for T^Y :

$$T^Y = \frac{T - T^0 + 2\eta - (\beta+\mu)\frac{W^0}{W^1}}{1+\beta+\mu}\,. \tag{15}$$

Plugging the value of T^Y into the solution for T^c, we obtain:

$$T^c = \beta\alpha^c \frac{T - T^0 + 2\eta + \frac{W^0}{W^1}}{1 + \beta + \mu} - \eta. \tag{16}$$

Leisure is

$$T - T^1 - T^2 - T^Y - T^0 = \frac{\mu}{1 + \beta + \mu} \left(T - T^0 + \frac{W^0}{W^1} + 2\eta \right).$$

Assume with no loss of generality that good 1 is the preferred good and consider a consumer who searches only for prices of good 1, because the non-negativity constraint on search time is binding for good 2. In this case, optimal work time is

$$T^Y = \frac{T - T^0 + \eta - (\beta\alpha^1 + \mu)\frac{W^0}{W^1}}{1 + \beta\alpha^1 + \mu}. \tag{17}$$

Search time for good 1 is

$$T^1 = \beta\alpha^1 \frac{T - T^0 + \eta + \frac{W^0}{W^1}}{1 + \beta\alpha^1 + \mu} - \eta,$$

and leisure time becomes

$$T - T^1 - T^Y - T^0 = \frac{\mu}{1 + \beta\alpha^1 + \mu} \left(T - T^0 + \frac{W^0}{W^1} + \eta \right).$$

Without search, consumers will pay the higher price for each good, and work and leisure time will be

$$T^Y = \frac{T - \mu\frac{W^0}{W^1}}{1+\mu}, \tag{18}$$

and

$$T - T^Y = \frac{\mu}{1+\mu}\left(T + \frac{W^0}{W^1}\right).$$

Plugging the full solutions into the utility function for various values of the parameters allows us to determine which of these discrete choices is preferred.

To illustrate the empirical implications of the model, we select certain parameter values and plot optimal search times, prices, and quantities in Figure A.1. We vary the relative preference for good 1, captured by the parameter α^1 (i subscript omitted), and the efficiency of the search function, β—the higher β, the lower the prices paid for the same level of search. All other parameters are kept constant and are detailed in the notes to the figure. Note the fixed cost of search, T^0, is set to zero in both cases.

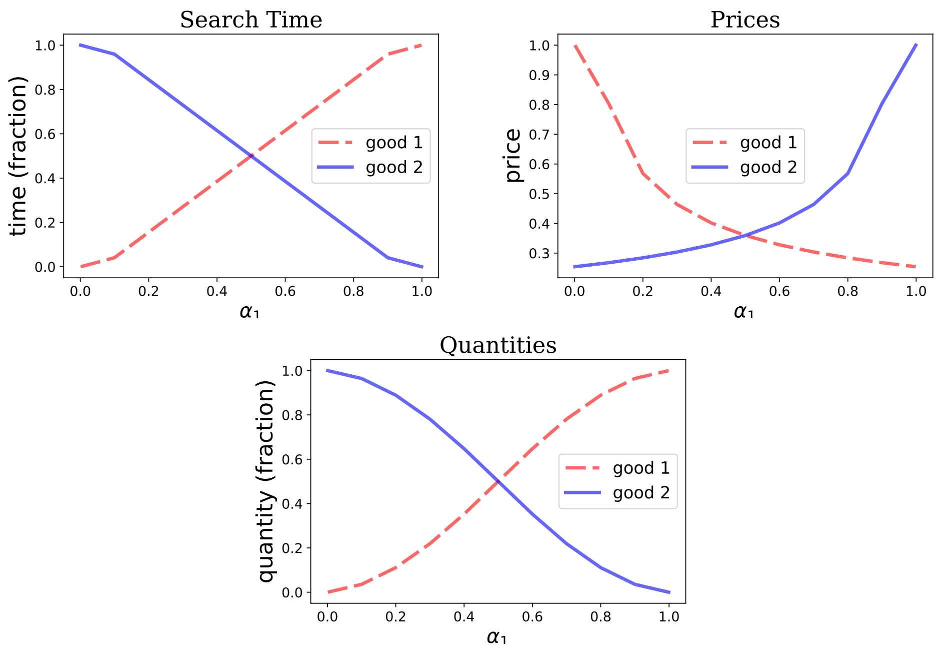
Panel A displays the case of relatively high search efficiency, $\beta = 0.5$. Search time for good 1 (2) increases (decreases) with α^1. The price paid for good 1 declines with α^1 due to the higher search intensity, and the consumer shifts the basket towards higher consumption of good 1 as his or her preference for good 1 increases. *Ceteris paribus*, the model implies an inverse relationship between the prices paid and the quantities consumed of a given good, because consumers vary their search intensity across goods in accordance with their relative preferences. We lower search efficiency in Panel B to illustrate that when search efficiency is relatively low, the consumer optimally chooses not to search for one of the goods even when the search fixed cost is zero ($\beta = 0.1$ in this case).

We highlight the importance of search fixed costs in Figure A.2. The figure depicts (restricted) utility under three scenarios, each represented by a line in the figures: (1) the consumer does not search for better prices at all, (2) the consumer searches only for his or her preferred good (that with the highest α^c), and (3) the consumer spends time to obtain better prices for both goods. The consumer will evaluate the utility under these three scenarios and rationally choose the one delivering the highest utility. In the figure, we illustrate three cases: (a) the search fixed cost is zero; (b) the search fixed cost is positive and the same when searching for one or two goods ($T^0 = 5$); and (c) the search fixed cost is higher when searching for two goods ($T^0 = 10$ vs. $T^0 = 5$). We further vary the level of search efficiency ($\beta = 0.25$ or $\beta = 0.5$) and, in all figures, the relative preferences for good 1, α^1. Consider the case where the consumer cares for both goods equally ($\alpha^1 = 0.5$, in the middle of each figure), and the search fixed cost is low and/or the search efficiency is high. In these scenarios, the consumer is better off searching for lower prices of both goods. In contrast, when fixed costs are high and search efficiency is low, the consumer optimally decides not to search at all (see the left figure of Panel C). When the consumer has differential preferences for the two goods, he or she may optimally decide to spend time searching for low prices of just one good. In this illustration, this situation occurs for extreme relative preferences in Panel B, but also if the search for a second good entails an additional fixed cost, see Panel C.

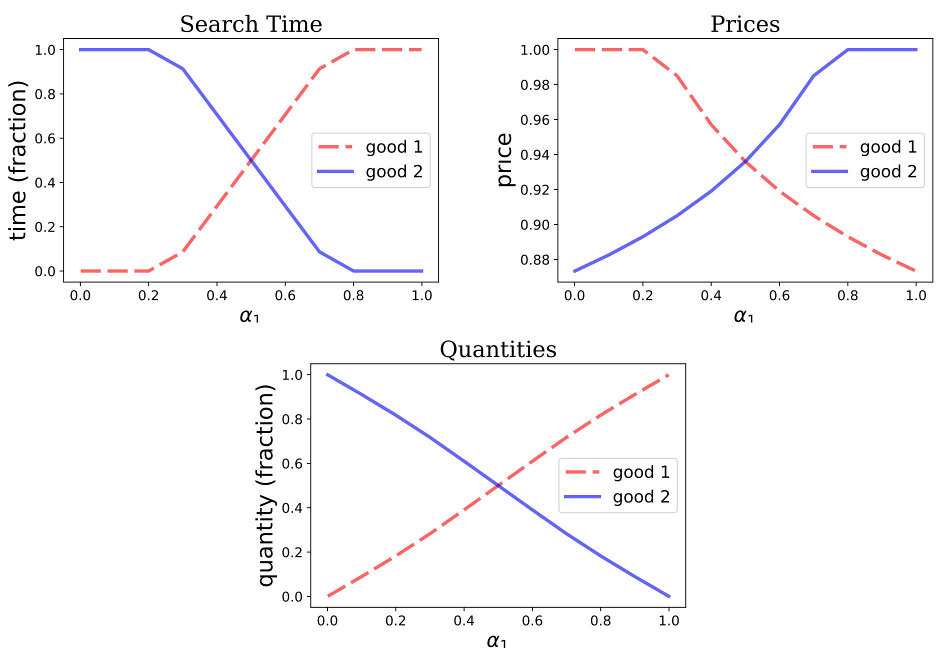
Figure A.3 illustrates one additional implication of our model: improvements in search efficiency, while lowering prices on average, may not result in lower price dispersion across consumers. As preferences differ, search efforts vary and price dispersion may not decrease.

Figure A.1. Search Time, Price and Quantity by Preference for Good 1

Panel A: High Search Efficiency



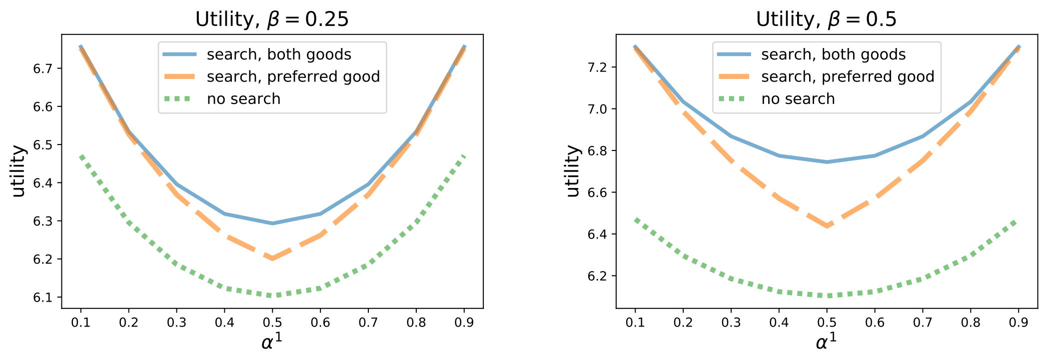
Panel B: Low Search Efficiency



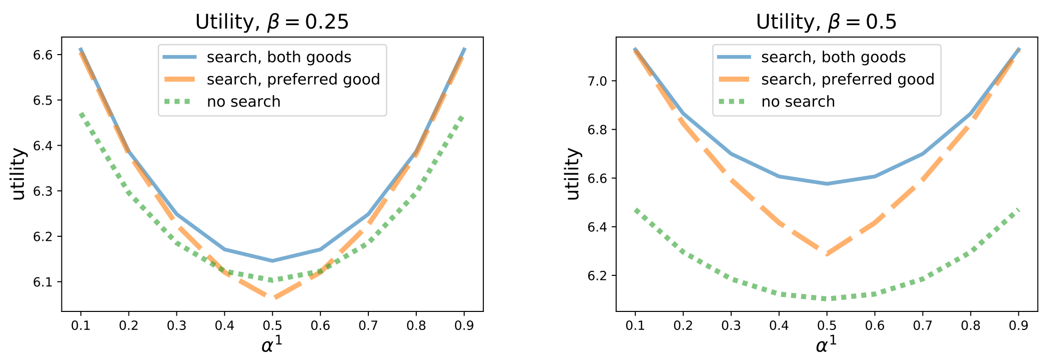
Notes: The figure depicts optimal shopping times, prices and quantities according to the model of Section 2. The model parameters are as follows: $T = 50$, $P^H = 1, \eta = 1$, $\mu = 0.5$, $T^0 = 0$, $W^0 = 50$, $W^1 = 5$. Search efficiency, β, is 0.5 in Panel A and 0.1 in Panel B. In the plots, search time for good c is reported as fraction of the total shopping time $T^c/(T^1 + T^2)$, and similarly for quantity, $Q^c/(Q^1 + Q^2)$. α^1 measures the relative preference for good 1, as $\alpha^1 + \alpha^2 = 1$.

Figure A.2. To Search or Not To Search. Utility under Different Scenarios

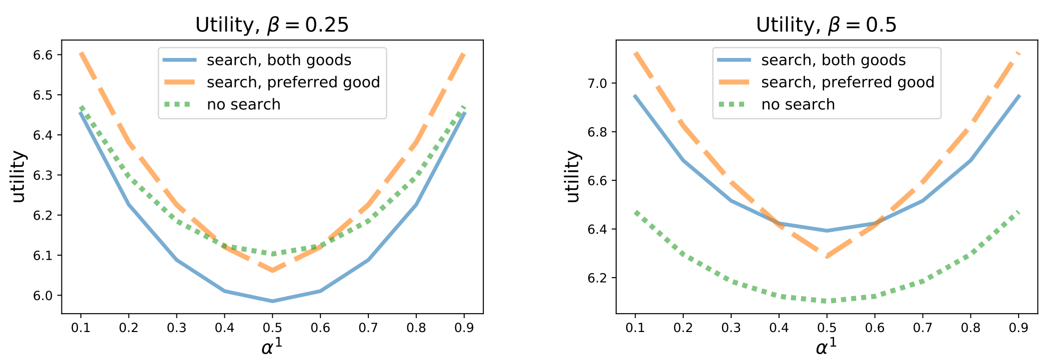
Panel A: No Fixed Search Cost



Panel B: Positive Search Fixed Cost

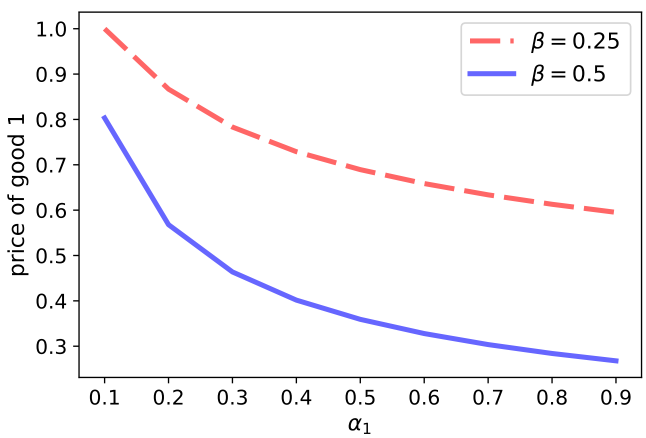


Panel C: Positive Search Fixed Cost, Higher for Two Goods



Notes: Each plot depicts utility under three scenarios: No search, search only for the most preferred good (highest α^u), and search for both goods. The model parameters are as follows: $T = 50$, $P_H = 1, \eta = 1$, $\mu = 0.5$, $W^0 = 50$, $W^1 = 5$. Searching efficiency, and relative preference for good 1 (β and α^1) vary as indicated in each subplot. In Panel A, the search fixed cost is zero, $T^0 = 0$. In panel B, $T^0 = 5$ when searching for one or two goods. In Panel C, $T^0 = 5$ when searching for one good, and $T^0 = 10$ when searching for two goods.

Figure A.3. Search Efficiency, Average Prices, and Price Dispersion



Notes: This figure illustrates that price dispersion may not decrease with improvements in search efficiency. Mean (SD) [CV] of prices with $\beta = 0.25 : 0.73$ (0.13) [0.18]. Mean (SD) [CV] of prices with $\beta = 0.50 : 0.42$ (0.16) [0.38].

Store Pricing When Consumers Search For Only Some Goods

Sellers rationally differentiate prices across stores and/or over time. Authors, going back to at least Salop and Stiglitz (1977), have constructed models where different prices for the same good across stores persist when some consumers are informed and others are not. Different prices can be rationalized from our consumer model as well. Intuitively, some consumers behave as if they are uninformed about prices because the value of work time (or leisure) is too high to search, while some consumers behave as if they are informed about prices because they rationally search for low prices for all goods they consume. In the literature, price setting when consumers vary in their (overall) search intensity has been shown to imply price differentiation, and it is intuitive that the pattern that we document can also rationalize price differentiation.

In this sub-section, we outline a store-pricing model, which can rationalize price dispersion. Economists have previously developed models for why stores may post different prices for identical goods. For example, Chevalier and Kashyap (2019) assume three types of consumers and two goods (1 and 2) that can be stored. Some consumers have an inelastic demand for good 1, other consumers have an inelastic demand for good 2, and the rest are bargain hunters. This last group will shop for low prices and store goods. Such a model can rationalize why stores have periodical sales.

Kaplan et al. (2019) document price dispersion across stores. Different stores tend to sell different goods at different prices, and store prices are quite persistent. Based on these facts, they develop a model, matching price persistence, where some agents are shoppers and some are inattentive in order to explain pricing patterns.

We build on these models and suggest a model of price dispersion across stores and goods where some consumers are bargain hunters (searchers or shoppers) only for the goods for which they have relatively strong demand. We will consider this model for the simplest case of two goods.

Consider two goods, indexed by the numbers 1 and 2. Assume stores can set a price P_H, which is the highest price that a consumer who does not search for that good will pay—for simplicity, we assume this price is constant. For the good a consumer wants in large quantities (his/her preferred good), he or she will search until the marginal value of further search is nil. Assume that consumers who search pay a low price P_L^s, which differs by store s. We assume that the price P_L^s is set competitively such that stores with a higher price provide more amenities. For example, it could be that it takes longer to get to stores with the lower prices due to location (which would literally fit into our framework).

Consumer may search for good 1, good 2, both goods, or not search at all. In this illustration, we assume half of consumers search for good 1 only and half search for good 2 only. When consumers go to the store, they purchase a smaller amount of their less preferred good, if any. A consumer who prefers good 1 searches until he or she finds the lowest price P_L^s that is consistent with optimal time spent searching, buying an amount M_L^s. S/he also buys an amount M_H ($M_H < M_L^s$) of the less preferred good 2 at price P_H. A consumer who prefers good 2 searches until he or she finds the optimal price for good 2 (symmetric to good 1), and buys a smaller amount of good 1 at the higher price. Further assume that there are a large number of stores so that other stores will not respond to a given store's change in pricing. A store may set a price P_L^s for good 1 and P_H for good 2. The store pays a constant cost c^s for goods. The store's profit, where the factor reflects that half the potential purchases go to another store, is:

$$\frac{1}{2}[(P_L^s - c^s)M_L^s + (P_H - c^s)M_H] \ .$$

Due to competition, P_L^s is set at a minimum that allows a normal profit. An alternative pricing strategy would be to charge P_L^s for both goods to attract both types of purchases—at any price higher than P_L^s, consumers will go elsewhere to find their more preferred good. In this case, the store's profit is:

$$\frac{1}{2}[(P_L^s - c^s)M_L^s + (P_L^s - c^s)M_H] + \frac{1}{2}[(P_L^s - c^s)M_H + (P_L^s - c^s)M_L^s] = (P_L^s - c^s)(M_L^s + M_H) \ .$$

A store cannot charge more than P_L^s without losing all the purchases of consumers who prefer good 1, and it cannot charge more than P_H without losing all sales. A store has no incentive to charge less than P_H unless it lowers the price to P_L^s.

For a store to differentiate prices the following condition must hold:

$$\frac{1}{2}[(P_L^s - c^s)M_L^s + (P_H - c^s)M_H] > (P_L^s - c^s)(M_L^s + M_H),$$

or

$$(P_H - P_L^s)M_H > (P_L^s - c^s)(M_L^s + M_H).$$

That is, the extra gain from charging a high price for the inelastic demand M_H outweighs the profit from selling the amount $M_L^s + M_H$ at a lower price.

Data

In our dataset, age is reported in categories, and the age distribution by category in January of 2017 is as follows: 22 percent are younger than 45 years old; 25 percent are aged 45 to 54; 22 percent are aged 55 to 64; and 31 percent are 65 or older. Household income is reported by category: 16 percent have income that is less than \$20,000; 22 percent earn \$20,000 to \$35,000; 25 percent earn \$35,000 to \$55,000; 18 percent earn \$55,000 to \$75,000; 11 percent earn \$75,000 to \$100,000; and 8 percent have income that is more than \$100,000. Education categories have the following distribution: 5 percent of panelists have not completed high school; 32 percent are high school graduates; 39 percent have some education beyond high school without a college degree, while the rest have graduated from college. Relative to the U.S. population, the IRI sample is somewhat older and poorer, and spending in the IRI categories represents roughly 20 percent of PSID food-at-home expenditure.

Table A.1. Summary Statistics for Panelist in January of 2007

	Count	Mean	SD	Min	Max
Years of Education	4,434	13.76	2.01	6	18
Age	4,740	55.34	12.73	21	70
Household Income	4,738	52,537	36,662	5,000	150,000
Old (65+)	4,740	0.31	0.46	0	1
Expenditure (monthly)	4,740	79.47	63.93	5	1,015

Notes: Authors' calculations using all IRI panelist data for January of 2007.

Table A.2. Summary Statistics for Regressions

	Count	Mean	SD	Min	Max
Bargain Hunting Index (BHI)	551,438	7.45	9.29	–12	34
BHI (demeaned)	551,438	–0.00	8.72	–27	32
BHI (demeaned), 65+	190,607	0.62	9.21	–27	32
BHI (demeaned), age<65	360,831	–0.33	8.44	–27	32
BHI (demeaned), exp. $<$ median exp.	275,596	0.50	9.78	–27	32
BHI (demeaned), exp. $\geq$ median exp.	275,842	–0.50	7.49	–27	31
Category-Specific BHI	3,728,872	0.00	14.33	–68	63
Category-Specific Quantity Index	3,728,872	0.99	0.74	0	4
Expenditure (monthly)	551,438	69.51	55.32	5	2,281
Old (65+)	551,438	0.35	0.48	0	1
# trips (monthly)	551,438	8.96	6.39	1	126
# stores visited (monthly)	551,438	2.97	2.01	1	34

Notes: Authors' calculations using all IRI panelist data from 2003 through 2012. The BHI computation is described in equation (7). The index measures how much a consumer saves (positive values), in percent, or overpays (negative values) relative to buying his or her consumption bundle at average prices. The BHI is broken up by age group and expenditure group. The category-specific BHI is described in equation (7) and focuses on savings in a specific category. The category-specific quantity index, which measures whether a consumer purchases more or less of that category than does the average consumer, is computed according to equation (5). The other variables are used in our regressions: (1) Expenditure is total dollars spent in a given month by a panelist in IRI transactions; (2) Old (65+) is a dummy variable for whether consumers are 65 or older; (3) # trips to store (monthly) is the total number of trips to stores by a panelist in a given month; (4) # stores visited (monthly) is the number of different stores that a consumer visits in a given month.

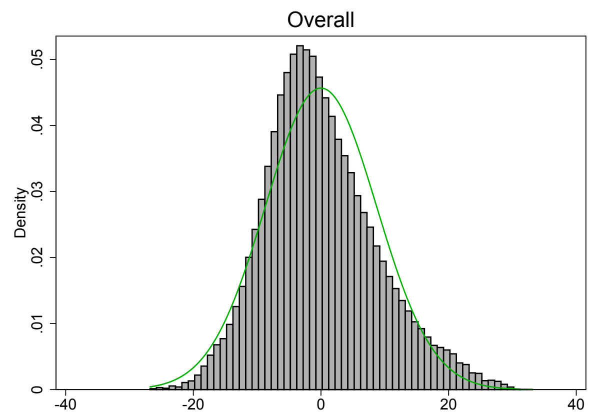
Additional Figures

In Figure A.4, we use a histogram to display the dispersion of the (demeaned) overall BHI. The BHI is slightly leptokurtic (kurtosis is 3.3) and skewed to the right (skewness is .43). The bottom two panels split the sample into 65-plus and younger panelists, and into panelists with below- and above-median expenditure in a given period. As our model predicts, the older individuals pay lower prices on average than do the younger panelists, and the poorer panelists (as proxied by expenditure) also pay relatively lower prices.

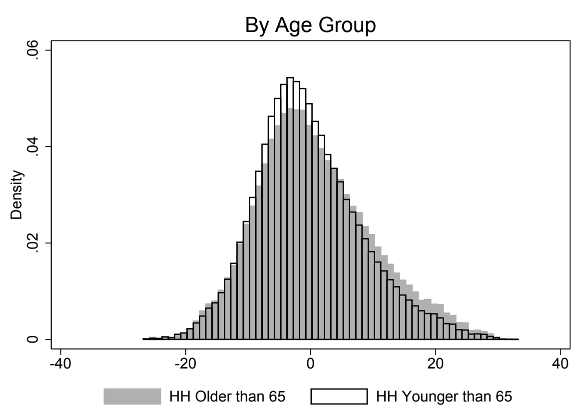
Figure A.5 depicts histograms for the overall BHI and the store BHI. The histograms indicate savings from both store selection (consumers' purchasing products in stores where they are relatively cheaper) and the timing of purchases within a given store.

Figure A.4. The bargain-hunting index

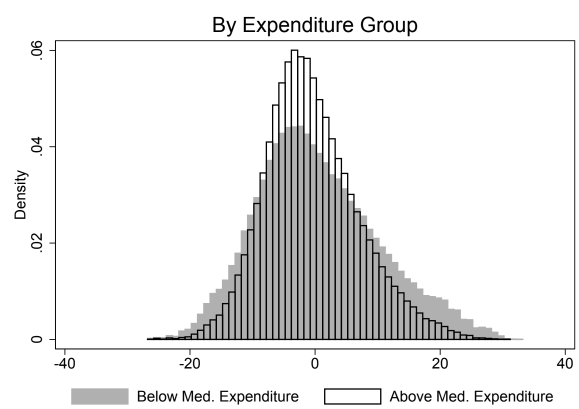
Panel A: Overall



Panel B: By Age Group



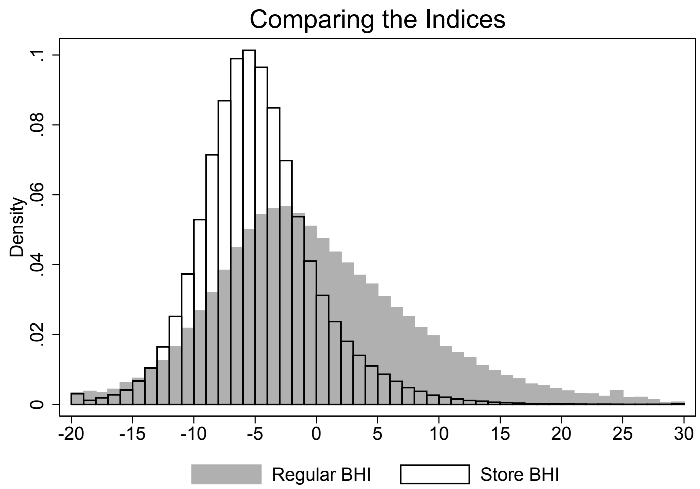
Panel C: By Expenditure Group



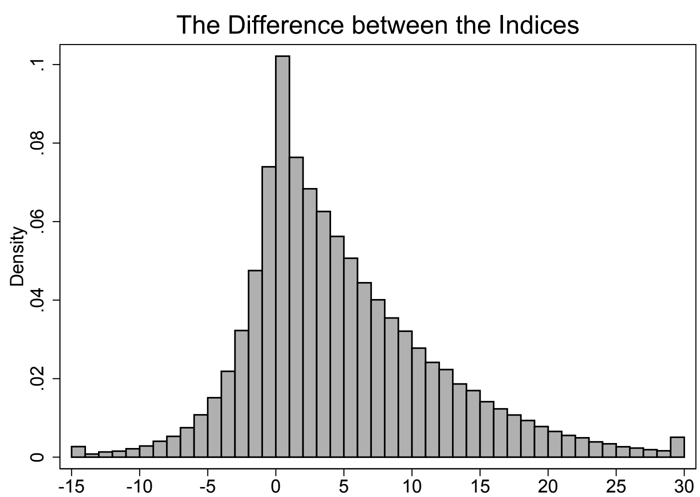
Notes: The BHI index shows how much a consumer saves, in percentages, relative to the counterfactual of buying his or her consumption bundle at average prices. The BHI index has been normalized to have a mean of 0 every month-year by market. *Source:* IRI, all panelist data from 2003 through 2012.

Figure A.5. The BHI vs. the Store BHI

Panel A: Comparing the Indices



Panel B: The Difference between the Indices



Notes: The regular BHI index is defined in equation (7) and represents how much a consumer saves relative to buying at average prices across stores. The store BHI is defined in equation (9) and measures how much a consumer would save if he or she paid average prices in the store relative to buying the consumption bundle at average prices across all stores. Panel B plots the distribution of the difference between the indices (individual by individual). *Source:* IRI, all panelist data from 2003 through 2007.

Further Robustness

To test whether our results are robust across categories, we estimate the regression separately for each category c, using the average category-specific quantity index as an instrument. The data in each regression form an individual $\times$ time panel, and all coefficients, including dummies, can take different values for the different categories.

$$\mathrm{BHI}^c_{i,t} = \mu^c + \gamma^c_{m,t} + \beta^c\,\mathrm{QI}^c_{i,t} + X_{i,t}\,\alpha^c + \epsilon_{i,c,t}$$

Table A.3 shows the regressions category-by-category.[27] We will not discuss each category in detail, but together the results reveal that our main qualitative result is remarkably robust—the coefficient to the quantity index is positive and highly significant in almost all categories. The exceptions are beer, for which the estimated coefficient is virtually 0, and cigarettes for which the coefficient is negative and insignificantly different from 0. These two categories are the ones with the lowest price dispersion and, therefore, the lowest return to bargain hunting. The size of the coefficients to the quantity indices vary by category, with the smallest coefficients found for categories with relatively less price variation at the UPC level. In particular, all categories with a coefficient less than unity are among those with the lowest price variation. The largest coefficient is for hot dogs, the category with the second highest price variation. In sum, while the variation in the size of the coefficients is not one-to-one with price dispersion, the variation in the coefficients reflects the potential gains from bargain hunting as captured by the price

[27] The quantity indices in these regressions have been standardized to have a mean 0 and a standard deviation of 1 by category for an easier comparison across the 30 regressions.

variation.

Table A.4 shows that the results are qualitatively similar to those obtained at the monthly frequency when aggregating purchases and averaging prices to the quarterly frequency, which supports the causal interpretation of the results.

Table A.3. The BHI and the QI by Category. Separate IV-Regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Quantity Index	0.01	0.78**	1.92***	–0.23*	1.87***	3.47***	5.33***	1.45**	3.00***	1.69***
	(0.04)	(0.35)	(0.13)	(0.13)	(0.26)	(0.23)	(0.65)	(0.59)	(0.36)	(0.30)
Log. Expenditure	–0.14***	–0.96***	–1.85***	0.16	–1.21***	–2.10***	–2.10***	–1.45***	–1.78***	–1.75***
	(0.03)	(0.23)	(0.09)	(0.13)	(0.14)	(0.13)	(0.19)	(0.33)	(0.15)	(0.17)
Old (65+)	–0.11**	0.35	0.64***	–0.39	1.34***	–0.68***	0.78**	1.30***	0.31	0.70***
	(0.05)	(0.35)	(0.14)	(0.27)	(0.21)	(0.18)	(0.31)	(0.46)	(0.23)	(0.21)
Observations	86504	17228	354994	25430	153068	301697	42551	11575	110072	164925
F-test excl. inst.	65883	3705	199769	24933	45308	115289	9021	1705	37443	48932

	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
Quantity Index	1.65***	1.24***	6.00***	3.23***	2.07***	6.82***	0.59***	5.33***	4.03***	4.45***
	(0.26)	(0.27)	(0.39)	(0.35)	(0.24)	(0.33)	(0.09)	(0.48)	(0.24)	(0.34)
Log. Expenditure	–1.72***	–0.52***	–2.77***	–3.34***	–0.56***	–1.81***	–0.38***	–1.37***	–2.01***	–1.20***
	(0.15)	(0.11)	(0.17)	(0.18)	(0.11)	(0.12)	(0.06)	(0.15)	(0.13)	(0.14)
Old (65+)	0.64***	0.03	0.28	0.57**	0.17	0.65***	0.04	0.24	–0.37*	0.85***
	(0.21)	(0.17)	(0.25)	(0.28)	(0.18)	(0.20)	(0.11)	(0.21)	(0.20)	(0.24)
Observations	159206	52823	112348	146606	138726	120653	423015	73911	115133	101725
F-test excl. inst.	30098	9631	18727	39901	50813	23369	297080	8467	52571	24106

	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)	(29)	(30)
Quantity Index	4.19***	1.65***	2.21***	3.07***	3.87***	1.27***	4.85***	3.41***	5.25***	1.03***
	(0.83)	(0.52)	(0.17)	(0.41)	(0.30)	(0.26)	(0.25)	(0.88)	(0.39)	(0.16)
Log. Expenditure	–1.87***	–1.66***	–1.08***	–1.31***	–1.38***	–0.83***	–2.61***	–0.66**	–2.01***	–0.67***
	(0.42)	(0.53)	(0.10)	(0.17)	(0.13)	(0.18)	(0.12)	(0.27)	(0.15)	(0.09)
Old (65+)	0.58	0.62	0.78***	0.09	1.77***	0.67***	–0.10	–0.08	0.55**	0.70***
	(0.68)	(0.92)	(0.15)	(0.29)	(0.22)	(0.25)	(0.17)	(0.43)	(0.26)	(0.17)
Observations	4752	2159	345689	41029	134273	20863	199147	21116	67796	219417
F-test excl. inst.	870	425	111775	6322	26163	7575	54252	3235	13165	79723
Month-Year × Market FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Regression: $\text{BHI}^c_{i,t} = \gamma^c_{m,t} + \beta^c \text{QI}^c_{i,t} + X_{i,t}\alpha^c + \epsilon_{i,c,t}$, estimated category by category. The quantity index, $QI^c_{i,t}$, is standardized by category (mean 0, sd 1) for easier interpretation. All regressions include market × month FE and are estimated by IV. Our instrument is the average category-specific quantity index, defined more precisely in the notes to Table 2. Standard errors clustered by panelist. *** (**) [*] significant at the 1 (5) [10] percent level.
Categories as follows: (1) beer, (2) blades, (3) carbonated beverages, (4) cigarettes, (5) coffee, (6) cold cereal, (7) deodorants, (8) diapers, (9) facial tissue, (10) frozen dinners, (11) frozen pizza, (12) cleaning supplies, (13) hot dogs, (14) laundry detergent, (15) margarine/butter, (16) mayonnaise, (17) milk, (18) mustard/ketchup, (19) paper towels, (20) peanut butter, (21) photography, (22) razors, (23) salted snacks, (24) shampoo, (25) spaghetti sauce, (26) sugar substitutes, (27) toilet tissue, (28) toothbrushes, (29) toothpaste, (30) yogurt.

Table A.4. Rational Inattention. Pooled Regressions. Quarterly Frequency

	(1) All Years BHI	(2) All Years BHI	(3) Pre-2008 BHI	(4) Pre-2008 Store BHI
Quantity Index	1.70***	1.64***	1.65***	0.26***
	(0.06)	(0.06)	(0.06)	(0.02)
Log. Expenditure	–1.04***	–1.31***	–1.43***	–0.43***
	(0.06)	(0.06)	(0.06)	(0.03)
Old (65+)	0.51***	0.15	–0.11	–0.08*
	(0.12)	(0.11)	(0.12)	(0.05)
# stores visited (quarterly)		0.33***	0.53***	0.17***
		(0.02)	(0.02)	(0.01)
# trips (quarterly)		0.03***	0.03***	0.01***
		(0.00)	(0.00)	(0.00)
Quarter-Year × Market FE	Yes	Yes	Yes	Yes
Category FE	Yes	Yes	Yes	Yes
Observations	1600439	1600439	889316	889316
Adj. R-squared	0.02	0.03	0.04	0.01
F-test excl. inst.	873232	870518	519741	519741

Notes: Expenditure is aggregated at the quarterly level, and store-average prices are calculated at the same frequency. Regression: $\text{BHI}^c_{i,t} = \nu_c + \gamma_{m,t} + \beta \text{QI}^c_{i,t} + X_{i,t}, \alpha + \epsilon_{i,c,t}$, where $\text{BHI}^c_{i,t}$ is the category-specific bargain-hunting index for individual i in quarter t, ν_c denotes category fixed effects. $\gamma_{m,t}$ is a market × month FE, X is a vector of regressors, and $QI^c_{i,t}$ is the quantity index described in equation (5). The quantity index, which measures whether a consumer purchases more or less of a category than the average consumer, is standardized (mean 0, sd 1) for easier interpretation. In column (4), $\text{BHI}^c_{i,t}$ is replaced by a category-specific store BHI, $\text{BHI}^{c,s}_{i,t}$. All regressions are estimated by IV, using the average category-specific quantity index as an instrument, adapted to the quarterly frequency and defined more precisely in the notes to Table 2. Standard errors clustered by individual. *** (**) [*] significant at the 1 (5) [10] percent level.