Heterogenous Consumer Shopping Behavior: Evidence from Retail Scanner Data

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PRELIMINARY AND INCOMPLETE

Abstract

This paper studies if and how consumers search for low prices (bargains). We find that consumers found lower prices after the Great Recession which we interpret as an outcome of increased search intensity. The is large heterogeneity among consumers and we categorize consumers, by year, into three types by the order of search intensity: bargain hunters, average consumers, and inattentive shoppers and find that consumer types are not very persistent. Further, we find that consumers rationally search for lower prices for product categories which they consumer a lot of while they search less for lower prices for products they consumer less of. We write a simple model of shopping time allocation for two goods in the spirit of Becker (1961) which rationalize that a consumer will search more intensively for lower prices on the good on which he or she spends more.

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1 Introduction

To what extent do heterogeneous consumers shop differently in a recession? A consumer can spend more time on shopping and lower expenditure in different ways: buying during sales, using coupons, switching to generic brand products, buying in bulk and visiting cheaper shopping outlets. Since the seminal work by Aguiar and Hurst (2005), it has been well known that consumers with certain demographic characteristics, such as higher age and being unemployed, pay lower prices than others.

This paper fills a gap in the literature on consumer saving from shopping by conducting a systematic study of bargain hunting using data from IRI Academic Data Set, which contains 11 years of weekly store data for 30 grocery categories and panel data of household purchase transactions in two pilot markets, Pittsfield, Massachusetts and Eau Claire, Wisconsin. We ask whether savings from higher shopping intensity are evenly distributed across consumers within a certain demographic group. We find two stylized facts: (1) within each demographic group there is much variation in the bargain hunting index and (2) consumers with different bargain hunting indexes respond differently to income shocks.

Our work is also one of the first papers studying the business cycle aspect of bargain hunting. The existing literature is mostly cross-sectional and do not explore the business cycle dimension of consumption using retail scanner data. A notable exception is Nevo and Wong (2014), to which our paper is closely related. They also find that households across demographic groups change their shopping behaviors during the Great Recession.

We start by constructing a bargain hunting index (BHI) which is a measure of savings relative to store-posted prices. For each household, we compute BHI by comparing the expenditure they pay for their consumption bundle, to the hypothetical expenditure of the same bundle if "average" market prices were paid instead. A household is defined as a bargain hunter in given hear if its BHI

lies in the bottom quartile, and a bargain hunter for a product category if in the bottom quartile of the distribution of BHI for the category. Similarly, a household is defined as inattentive if the BHI lies in the top quartile. Other households are defined as average.

We regress the household BHI on demographic variables and city unemployment rates over the period from 2001 to 2011. Consistent with the literature (Aguiar and Hurst (2007), Kaplan and Menzio (2014)), we find that households who are older, have non-employed members and lower incomes pay lower prices. As an example of the heterogeneity in bargain hunting, households whose BHI is in the top quartile have stronger response to an increase in the local unemployment rate than those in other quartiles.

Another contribution to the literature is deepening our understanding of time allocation in the home production model (Benhabib, Rogerson and Wright (1991) and Greenwood and Hercowitz (1991)). When there is a negative income shock, individuals substitute between time and market goods, and then smooth their consumption by spending more time on shopping and lowering the effective price they pay. We deepen the understanding of consumer behavior by showing that there is a concentration of savings from bargain hunting in certain product categories and in a few products within a category. 60 percent of savings for an average household come from the top five most favored items. This finding suggests consumers do not allocate their bargain hunting effort evenly and instead concentrate on their favorite items.

The rest of the paper is organized as follows. Section 2 reviews the literature while Section 3 describes the data. In Section 4, we display the shape of the bargain hunting index and study heterogeneity in bargain hunting across demographic groups. In Section 5, we present the determinants of bargain hunting and the effect of income shocks and, in Section 6, we show the concentration of savings from bargain hunting. Section 7 is the conclusion.

2 Literature Review

This paper is closely related to Nevo and Wong (2014). They find that changes in shopping patterns occur over the business cycle. Households across demographic groups purchase more sale items, use more coupons, buy more generic products and large sized items, and spend a larger share of expenditure on Big Box stores, all of which contributes to lower effective prices paid by households, during the Great Recession. Continuing this direction of research, we also find that the local unemployment rate is a determinant of bargain hunting. During the Great Recession, households whose heads are retired and thus less affected by negative shocks in the economy pay 3.2 percent more than households whose heads are non-retired, in response to an 1% increase in the local unemployment rate.

Our work relates to various strands of literature in consumer shopping behavior and self-insurance. First, our work relates to recent studies on opportunity cost of time over the business cycle. Aside from formal savings and public insurance, households can also smooth unanticipated income shocks by spending more time on shopping when the opportunity cost of time is low in a recession. Nevo and Wong (2014) find that households' opportunity cost of time declined by 25-30 percent over 2008-2010. Aguiar, Hurst and Karabarbounis (2013) show that around 30 percent of the lost labor hours are reallocated toward non-market work, including shopping, during the Great Recession. Our work quantifies the amount of saving, in terms of a lower household price index, this extra shopping time and effort translates into.

Second, our study of shopping activities adds to the literature of inattentive consumers. Reis (2006) studies the consumption decisions of agents who face costs of acquiring, absorbing and processing information. With such costs, consumers rationally update their consumption plans only occasionally which implies a slow adjustment of consumption to news. In his model, individ-

ual consumption is sensitive to ordinary and unexpected past news, but not to extraordinary or predictable events as it pays to reconsider consumption plans when the economic circumstances change substantially. Our work gives direct empirical evidence for the theory of rational inattentive consumers. Households who spend more on a product category are less likely to be inattentive consumers of that category. Within a category, the more a household spends on an item, the less likely they to be an inattentive consumer of that particular item.

Third, our paper complements to studies on consumer heterogeneity. Chevalier and Kashyap (2011) posit a model with two types of consumers, (1) loyals who stick to their preferred brands and do not time their purchases and (2) shoppers who pay the best price possible as they chase discounts, substitute across brands and/or stockpile products during sales. Our results provide further evidence of this model. Bargain hunters and inattentive consumers, as defined in our data, correspond to "shoppers" and "loyals" in their model. They indeed display different shopping behaviors and the difference between two groups of average price indexes change over the business cycle.

3 Data Description

3.1 IRI Academic Data Set

In this paper we use the IRI academic data set, which has very detailed information on grocery purchases over 2001-2011 in 31 categories from 50 markets (each roughly corresponding to a Metropolitan Statistical Area (MSA)). Transaction prices and quantities are collected both at the store level and the individual transaction level. The data set is described in details in Bronnerberg et al.(2008).

At the store level, weekly total sales and quantity data for each UPC (Universal Product Code)

are collected for stores in all 50 markets. A UPC is the barcode used for scanning at the point of sales. Information of the transaction including the price and quantity of each product bought by the consumer is transmitted to the retailer's database. There are two types of stores in the data: grocery stores and drug stores. Many stores are chains of the same retailer, but each store has a unique identifier and chain number, from which we can track the weekly revenue and quantity for every UPC sold in the store over time. Retailers (or chains of retailers) cannot be identified by name.

At the individual transaction level, the household panel records prices and quantities for all transactions made by households in two small metropolitan areas: Eau Claire, Wisconsin and Pittsfield, Massachusetts. Every entry in the household panel is a transaction of a product, narrowly defined by the UPC, made by a household at a particular time. We also know certain household characteristics: household heads' age, race, marital status, education, employment status, occupation, family size, household income and home ownership. All these variables are categorical variables.

The data set contains rich information on product attributes such as volume, pack size, brand name, producer, and flavor and scent for some products. Take a milk product as an example. For a product with the UPC "00-01-20742-00303", from the data set we know its brand name is "New Square," produced by the company "Ahava Food", and with a volume of 32 oz. We also know it is fat-free skim milk with Vitamin A&D additives, white color, packaged in a plastic jug and is pasteurized homogenized. Note that products that are essentially the same but only differ in size have different UPCs and thus are considered a different product. For instance, a 12-pack Pepsi Coke has a different UPC from a 6-pack Pepsi Coke, and price and quantity data for them have separate entries.

The household panel in the IRI Academic Data Set has advantages and disadvantages comparing

to two other well-known consumption data sets: Panel Study of Income Dynamics (PSID) and Consumer Expenditure Survey (CEX). The PSID and the CEX collect data on expenditure on food purchase, while the household panel in the IRI academic data set has prices and quantities, including the exact products they buy (at the UPC level), the exact stores, and the exact time (up to the exact week in 2001-2007 and up to the exact minute in 2008–2011). This advantage helps us better understand the composition in a consumer's consumption bundles and their shopping behavior at finer product categories. An obvious drawback is the household panel covers just two small MSAs, and the sample is not nationally representative.

Two other retail scanner data sets used in the literature are ACNielsen's Homescan Panel(Aguiar and Hurst (2007), Hausman and Leibtag (2007), Kaplan and Mezio (2013)) and the TNS Worldpanel for Great Britain (Griffith et al. 2009). Only individual purchase records, but not store level data, are available in these two data sets. One advantage of the ACNielsen's panel is that it contains direct information regarding discounts from coupons and sales, while in the IRI academic data set, temporary price reductions (promotions or sales) are flagged as a binary variable, which equals one if the temporary price reduction is 5% or greater. Because regular prices are not available when the product is on sale, discounts from sales can only be inferred by comparing the reduced price to previous regular prices. In the household panel such flag variables do not exist. We only observe the actual price a household pays but not the regular prices or whether a product is on sale or not.

In this paper, we focus on the the household panel data because our research interest is consumption smoothing by households. For male household heads, the age distribution is 10 percent below 45, 25 percent aged 45–54, 21.7 percent aged 55–64, 22 percent over 65, and 21 percent unclassified. In terms of household income, 12.5 percent have income under $20,000; 20.3 percent earn $20,000–$35,000, 27.4 percent earn $35,000–$55,000, 19.2 percent earn $55,000–$75,000, 12.7 percent have $75,000–$100,000, and 7.8 percent over $100,000. For education, 35.7 percent of heads

have high school or less education and 18.9 percent have graduated from college or higher. As a summary, the sample is older and less educated than a typical sample from the PSID.

3.2 Definition a Good

Kaplan and Menzio (2014) proposes four definitions of a good at different levels from narrowest to broadest: UPC, generic brand aggregation, brand aggregation, and brand and size aggregation. Throughout the paper, we define a good by its UPC. Goods within the same product categories but with different UPCs are considered different goods. For example, an one litre Coca Cola soda is a different good from a two litres Coca Cola soda. An one litre Coca Cola is a different good from an one litre Pepsi soda.

3.3 Definition of the Average Price

Aguiar and Hurst (2007) define the average price of product as the average price paid by households for a particular good j (at a UPC level) in a particular time t as

$$\overline{p_{j,t}} = \sum\nolimits_{i,t} \left(\frac{q_{i,j,t}}{\sum_{i,t} q_{i,j,t}} \right) p_{i,j,t}$$

where i denotes a household. The average price of a good is a quantity-weighted average of individual transactions of the good j in time t, which is a month in a year.

We define the average price of a good as the simple average of prices posted by all stores in a market m in a week k as

$$\overline{p_{j,m,k}} = \frac{1}{N} \sum_{s=1}^{N} p_{j,s,m,k}$$

where s is a store, and N is the total number of stores in a market. The store-posted price is defined as weekly sale revenue of good j over the quantity of the product sold in a store in a week:

$$p_{j,s,m,k} = \frac{Rev_{j,s,m,k}}{q_{j,s,m,k}}$$

where Rev is the weekly sale revenue from good j.

For our research objective, this definition has several advantages. This measure gives equal weight to each store and reflect the expected price for a consumer who walks into a randomly selected store. Second, our definition reduces the measurement errors of the average prices for goods with few transactions. Even there is only one transaction of the good in a store in a week, it is the still exact price charged by the store. Note that a store sales discount apply to all buyers, and discounts from manufacture coupons do not affect the revenue of a product, even though it does reduce the final bill for a household, since the retailer gets reimbursement from the manufacture who is the coupon issuer.

3.4 Definition of the Bargain Hunting Index

The bargain hunting index (BHI) is defined as:

$$BHI_{i,m,t} = \frac{Actual\ Exp_{i,m,t}}{Hypo\ Exp_{i,m,t}} - 1 = \frac{\sum_{j,k} P_{i,j,m,k} * Q_{i,j,m,k}}{\sum_{j,k} \overline{P_{j,m,k}} * Q_{i,j,m,k}} - 1$$

where i is a household, m is one of the two cities (Eau Claire, WI or Pittsfield, MA),t is a quarter or a year, j is a good, and k is a week. For each transaction of a good by a household in a week, we find the exact prices of the product (identified by its UPC) in all stores in the city the households resides in the same week. Hypothetical expenditure is measured using the average store-posted price ($\bar{P_{mk}}$) of the good in the same week in the same city, given the consumer's own consumption bundle. Expenditure is aggregated over a quarter or a year. A lower BHI means paying less relative to the store-posted prices given the household's consumption bundle, which reflects higher shopping intensity.

3.5 Three Types of Consumers

We categorize households into three types: bargain hunters, average consumers and inattentive shoppers. We first rank the BHI of all households in a city m in a time period t (a year or a quarter) from low to high. Households in the bottom quartile are labeled "bargain hunter", those in the top quartile "inattentive shoppers", and the rest "average consumers".

4 Dispersion of Bargain Hunting Index

We start by graphically display the dispersion of BHI for the year 2011 in Figure 1. A typical distribution of bargain hunting index is right-skewed and leptokurtic. More than 50% of consumers in each sub-sample pay less than the store-posted prices. This reflects the fact that a larger share of household heads in the sample are more than 55, who are prone to be bargain hunters (Aguiar and Hurst 2005, 2007).

In Figure 1, we split the sample into two, age of household heads over 60 and under 60, and plot their histograms of bargain hunting index separately. The shape of the BHI distribution in each age group is very similar. Two findings are interesting. First, there is a wide dispersion of BHI within each age group. Among the households whose heads aging more than 60, some of them shop less intensively and pay 30% more than others, holding their own consumption bundles. Second, the relative position of the two histograms explains the well known fact in the literature - older consumers pay less than younger one. The histogram for older households is close to a leftward parallel shifting of the histogram for younger households with higher kurtosis. In other words, an average older consumer pay less than an average younger consumer. However, an older inattentive shopper pay more than a younger bargain hunter.

5 Change of Bargain Hunting Index over the Business Cycle

The section examines the effect of income shocks on households' BHI. Ideally, we would like to know the response of households to negative shocks such as job loss. However, certain household characteristics such as employment status are surveyed only three times (twice in 2007, once in 2012), not in every year. Consequently, most of the variation in household characteristics is cross-sectional, with limited intertemporal variation. We use data from the 2007 survey for the 2001–2007 data and data from the 2012 survey for the 2008–2012 data. We supplement the household panel data with MSA-level unemployment rates for these two cities as a measure of city-wide shocks. We use monthly unemployment rates from the Bureau of Labor Statistics (BLS). Quarterly unemployment rates are the mean of three monthly rates in the quarter.

We regress the BHI index on indicators of time available for shopping; namely, employment status, the unemployment rate in the city (as a proxy for household head unemployment which is not observed) and year and household fixed effects. The results, reported in Table 1, are that wealthier households pay more (consistent with a higher value of time in formal employment), retirees and other non-employed pay less (although those coefficient are not significant and typical significance levels) and household pay less relative to the store average, , with very high statistical significance, when unemployment is high.

6 Bargain Hunting Index by Product Category

6.1 Definition

We now turn to a finer definition of BHI. We ask whether a consumer can be a bargain hunter for a product category and in the meanwhile an inattentive shopper for another category. To our

knowledge, there is no existing study of the relative shopping intensity across goods.

Similar to the definition of BHI for total expenditure, the definition of BHI for a product category is:

$$BHI_{i,c,m,t} = \frac{Actual\ Exp_{i,c,m,t}}{Hypo\ Exp_{i,c,m,t}} - 1 = \frac{\sum_{j,k} P_{i,j,m,k} * Q_{i,j,m,k}}{\sum_{j,k} \overline{P_{j,m,k}} * Q_{i,j,m,k}} - 1$$

where i is a household, c is a product category, j is a good in the product category c, m is one of the two cities (Eau Claire, WI or Pittsfield, MA),t is a year, k is a week.

Again, we categorize a household into three types of consumers by the order of their BHI for a product category from low to high. A household is a bargain hunter for a category if their BHI lies in the bottom quartile, an inattentive consumer if in the top quartile, and an average consumer for the rest.

We find there is a wide dispersion of BHI across product categories. A household is found to be bargain hunters of some categories and inattentive or average consumers for other categories.

Figure 2 illustrates the average number of product categories for which a household is a(n) bargain hunter/inattentive shopper over time. To obtain the average number, we first label the type of consumer for every household and all product categories in every year. Now each household has the number of categories for which they are a(n) bargain hunter/average consumer/inattentive consumer. We calculate the average number for each type across all households in a city in a year. Then we take the average across the two cities and plot Figure 2.

Over the business cycle, we see households respond to the overalleconomic condition by adjusting their overall shopping intensity. During the Great Recession, there is a clear departure in the pattern from that during the boom year from 2003 to 2007. On average, households became bargain hunters in more categories and inattentive shoppers in fewer categories.

6.2 A Model of Shopping Time Allocation over Products

Here we develop a simple model, in the spirit of Becker (1961), to study the allocation of shopping time over two goods.

The objective function:

$$max\ U = \alpha lnC_1 + (1-\alpha)lnC_2 - \mu(T_1 + T_2) \tag{1}$$

subject to two constraints:

$$T_1 + T_2 = T$$

$$P_1(T_1)C_1 + P_2(T_2)C_2 = Y$$

C_1 and C_2 are the purchased quantities of good 1 and good 2. μ is the opportunity cost of time. We assume the price of a good is a concave function of shopping time devoted to the good.

Set up the Lagrangian equation:

$$\alpha lnC_1 + (1-\alpha)lnC_2 - \mu(T_1 + T_2) + \lambda(Y - P_1C_1 - P_2C_2)$$

The first order conditions:

$$\alpha\frac{1}{C_1} = \lambda P_1 \tag{2}$$

$$(1-\alpha)\frac{1}{C_2} = \lambda P_2 \tag{3}$$

Divide (2) by (3),

$$\frac{\alpha}{1-\alpha}\frac{C_2}{C_1} = \frac{P_1}{P_2} \tag{4}$$

The first order conditions for T_1 and T_2:

$$-C_1\frac{\partial P_1}{\partial T_1} = -C_2\frac{\partial P_2}{\partial T_2} = \frac{\mu}{\lambda} \tag{5}$$

At the equilibrium, one extra hour of shopping time spent on good 1 or good 2 should bring the same amount of savings, which is equal to the opportunity cost of time. Rearrange terms, we have

$$\frac{C_2}{C_1} = \frac{\frac{\partial P_1}{\partial T_1}}{\frac{\partial P_2}{\partial P_1}} \frac{\alpha}{1-\alpha} \tag{6}$$

Combine (4) and (6), we have

$$\frac{\frac{\partial P_1}{\partial T_1}}{\frac{\partial P_2}{\partial P_1}} \frac{\alpha}{1-\alpha} = \frac{P_1(T_1)}{P_2(T_2)} \tag{7}$$

and then

$$\alpha P_2(T_2)\frac{\partial P_1}{\partial T_1} = (1-\alpha)P_1(T_1)\frac{\partial P_2}{\partial T_2} \tag{8}$$

Take the partial derivative with respect to α on both sides.

$$P_2\frac{\partial P_1}{\partial T_1} + \alpha(P_2\frac{\partial^2 P_1}{\partial T_1^2} - \frac{\partial P_1}{\partial T_1}\frac{\partial P_2}{\partial T_2})\frac{\partial T_1}{\partial \alpha} = -P_2\frac{\partial P_2}{\partial T_2} + (1-\alpha)(\frac{\partial P_1}{\partial T_1}\frac{\partial P_2}{\partial T_2} - p_1\frac{\partial^2 P_2}{\partial T_2^2}) \tag{9}$$

So the marginal effect of expenditure share of good 1 on the shopping time spent on good 1:

$$\frac{\partial T_1}{\partial \alpha} = \frac{-P_1\frac{\partial P_2}{\partial T_2} - P_2\frac{\partial P_1}{\partial T_1}}{\alpha P_2\frac{\partial^2 P_1}{\partial T_1^2} + (1-\alpha)P_1\frac{\partial^2 P_2}{\partial T_2^2} - \frac{\partial P_1}{\partial T_1}\frac{\partial P_2}{\partial T_2}} \tag{10}$$

The numerator on the right hand side is positive. If the denominator is positive, then the marginal effect of expenditure share on shopping time is positive. In the data, we do not observe the actual time allocation by households over goods. Therefore we use BHI for a product category as a proxy for the shopping time, as more shopping time translates into lower prices and thus lower BHI.

6.3 Evidence

In Table 2, we explore whether consumers obtain better prices for product categories in which they spend more. We find fairly weak results when consumer fixed effects are not included. This

is reflects that wealthier households are likely to have higher expenditure across all categories on average, while such household likely choose to search less for low prices. When we control for household fixed effect, removing interpersonal comparisons and isolating whether a given household search relatively more for low prices for goods consumer more, we find that this is so with very high statistical significance.

In Table 3, we return to interpersonal comparisons and the main focus is on the second column in which category*year fixed effects are included. Some categories of goods tend to have many sales and whoever consumes a lot of that good may fairly randomly appear to be a high-intensity searcher. Such a pattern is consistent with the first column, which does not control for category*year effects, and the more interesting results are in the second column which does control for category*year effects. This column revels significant differences between households; in particular, households which consumer relatively more of a category search more for low prices and old household search more. Retirement is also significant, with more search, even after controlling for age, and unemployment is significant with a very large t-value over 60.

7 Conclusion

References

Aguiar, Mark and Erik Hurst, "Consumption versus Expenditure," *Journal of Political Economy*, October 2005, *113* (5), 919–948.

_ **and** _ , "Life-Cycle Prices and Production," *American Economic Review*, December 2007, *97* (5), 1533–1559.

Figure 1: Histograms of Bargain Hunting Index for Households in Two Demographic Groups

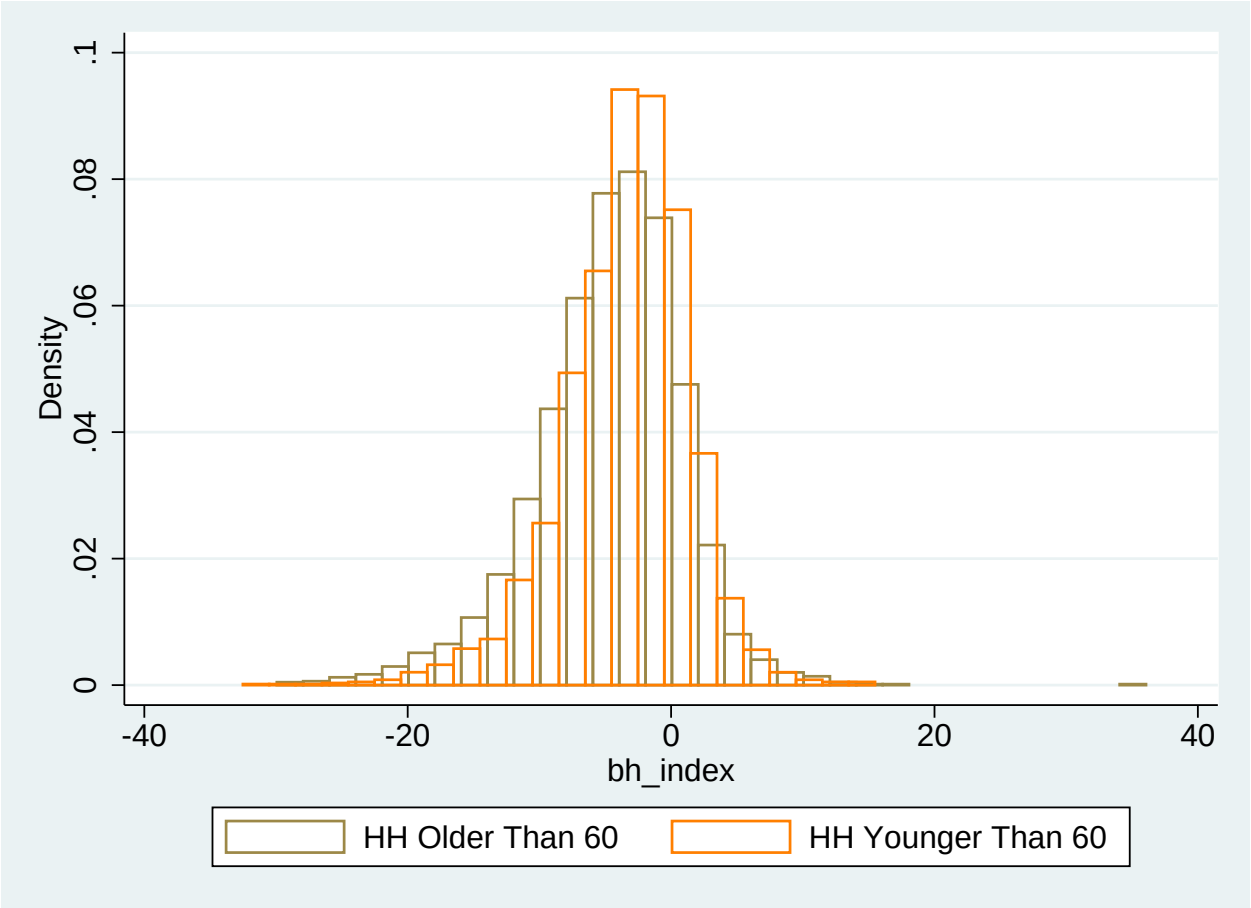

Figure 2: Average Number of Product Categories Where A Household Is A Bargain Hunter/Inattentive Consumer

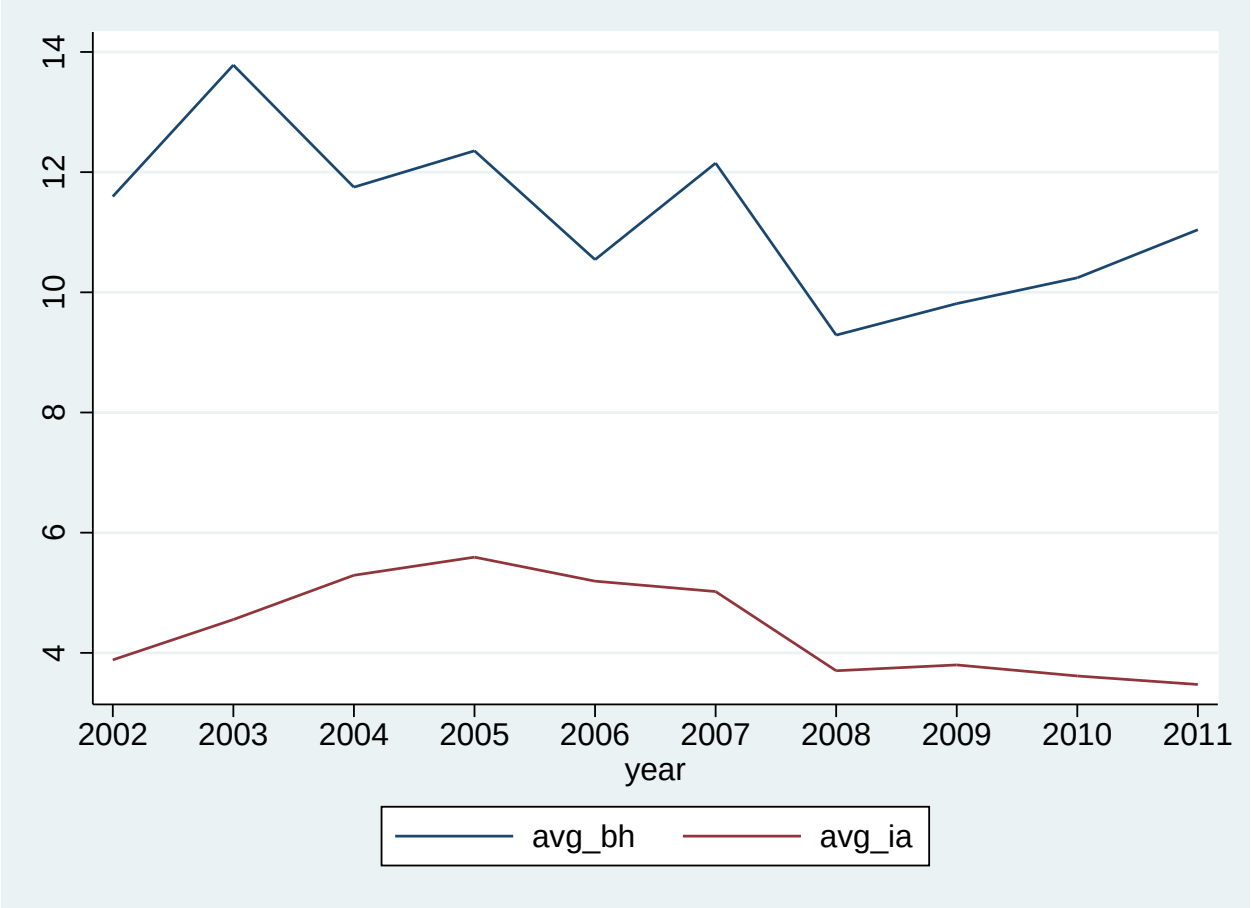

Table 1: Effects of Income Shocks on Bargain Hunting Index

Dependent Variable	Bargain Hunting Index	Bargain Hunting Index
Income	0.025	0.026
	(2.01)	(2.10)
Age	-0.011	-0.010
	(-1.78)	(-1.67)
Non-employed	-0.108	1.500
	(-1.10)	(3.74)
Retired	-0.092	-0.387
	(-1.21)	(-1.96)
Unemployment Rate	-0.276	-0.255
	(-9.89)	(-8.49)
Non-employed * UnRate		-0.355
		(-4.14)
Retired * UnRate		0.058
		(1.62)
Year Fixed Effect	YES	YES
Household Fixed Effect	YES	YES
Number of Observations	87098	87098

Notes: The results are from the panel regression

$$BHIndex_{i,m,t} = \alpha_i + \eta_t + X_{i,m,t}\beta + U_{m,t}\theta + X_{i,m,t}U_{m,t}\gamma + \varepsilon_{i,m,t}$$

in which i is a household, m is one of the two cities, Pittsfield MA or Eau Claire WI, t is a quarter. α_i is the household fixed effect and η_t is the time fixed effect The bargain hunting index is in percentage. Income is in ten thousands. "Retired" and "Non-employed" are dummy variables, "1" indicating "yes" and "0" indicating "no". Enclosed in the parenthesis are the t-statistics

Table 2: Effect of Expenditure on a Product Category and Likelihood of Being a Bargain Hunter for the Category

Dependent Variable	Bargain Hunter	Bargain Hunter
Log Expenditure	0.0924	0.1863
	(7.80)	(13.44)
UnRate * Expenditure	0.0191	-0.0013
	(8.97)	(-0.51)
Retired * Expenditure	-0.0096	-0.0091
	(-1.50)	(-1.40)
Non-employed * Expenditure	-0.0073	-0.0150
	(-0.93)	(-1.90)
Income	0.0006	-0.0018
	(0.86)	(2.32)
Age	0.0049	0.0038
	(19.97)	(14.89)
Non-employed	-0.0217	0.0547
	(-0.67)	(1.67)
Retired	0.0093	0.0446
	(0.37)	(1.74)
UnRate	-0.0103	-0.9232
	(-1.30)	(-58.79)
Category*Year Fixed Effect	No	YES
Number of Observations	719563	715214

Notes: The results are from the logit regression

$$BargainHunter_{i,m,c,t} = \alpha_c * \eta_t + log(exp)_{i,m,c,t}\beta + log(exp)_{i,m,c,t}U_{m,t}\gamma + log(exp)_{i,m,c,t}X_{i,m,t}\delta + X_{i,m,t}\phi \ + U_{m,t}\theta + \varepsilon_{i,m,c,t}$$

in which i is a household, m is one of the two cities, Pittsfield MA or Eau Claire WI, c is a product category, t is a year, and X is a vector of demographic variables. α_c is the category fixed effect and η_t is the time fixed effect. "Bargain Hunter" is a binary variable taking on value "1" if the household is a bargain hunter for that category in the year, and value "0" if not a bargain hunter. Income is in ten thousands. "Retired" and "Non-employed" are dummy variables, "1" indicating "yes" and "0" indicating "no". Enclosed in the parenthesis are the z-statistics.

Table 3: Effect of Expenditure on a Product Category and Likelihood of Being an Inattentive Consumer for the Category

Dependent Variable	Inattentive Consumer	Inattentive Consumer
Log Expenditure	-0.0031	-0.1327
	(-0.27)	(-9.55)
UnRate * Expenditure	-0.0242	-0.0027
	(-11.34)	(-1.08)
Retired * Expenditure	0.0082	0.0106
	(1.28)	(1.63)
Non-employed * Expenditure	0.0027	0.0146
	(0.35)	(1.84)
Income	-0.000	-0.0014
	(-0.12)	(-1.87)
Age	-0.0047	-0.0038
	(-19.11)	(-14.74)
Non-employed	0.0327	-0.0549
	(1.01)	(-1.66)
Retired	-0.0023	-0.0527
	(-0.09)	(-2.04)
UnRate	0.0407	0.9571
	(5.12)	(60.31)
Category*Year Fixed Effect	No	YES
Number of Observations	719563	715214

Notes: The results are from the logit regression

$$InattentiveConsumer_{i,m,c,t} = \alpha_c * \eta_t + log(exp)_{i,m,c,t}\beta + log(exp)_{i,m,c,t}U_{m,t}\gamma + log(exp)_{i,m,c,t}X_{i,m,t}\delta + X_{i,m,t}\phi + U_{m,t}\theta + \varepsilon_{i,m,c,t}$$

in which i is a household, m is one of the two cities, Pittsfield MA or Eau Claire WI, c is a product category, t is a year, and X is a vector of demographic variables. α_c is the category fixed effect and η_t is the time fixed effect. "Inattentive Consumer" is a binary variable taking on value "1" if the household is an inattentive consumer for that category in the year, and value "0" if not an inattentive consumer. Income is in ten thousands. "Retired" and "Non-employed" are dummy variables, "1" indicating "yes" and "0" indicating "no". Enclosed in the parenthesis are the z-statistics.

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