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Risk Aversion and Preference for Store Price Format

Koichi Yonezawa and Timothy J. Richards

When choosing among retail store formats, consumers face two alternatives: everyday-low-price (EDLP) stores that offer lower mean prices, with less variation over time, or promotion-based (HILO) stores that offer higher mean prices but more variation over time. In this study, we investigate a relationship between consumers' risk preferences and their store-choice decisions. We use data from a two-stage, incentive-compatible experiment to measure subjects' risk preferences and to examine how their attitudes toward risk influence their preferences for store price format. We find that retailers' pricing strategies allow consumers with different risk attitudes to choose a particular store price format.

Key words: choice-based conjoint, experimental economics, store choice, uncertainty

Introduction

Retail stores are largely differentiated on the basis of a variety of nonprice attributes, and market share depends, at least in part, on heterogeneous attribute preferences. Store location, service quality, and product variety are three examples of important nonprice attributes (Arnold, Oum, and Tigert, 1983; Bell and Lattin, 1998; Bawa and Ghosh, 1999; Briesch, Chintagunta, and Fox, 2009). Another important store attribute is price format, which can be either everyday low price (EDLP) or promotion-based (HILO) (Lal and Rao, 1997). Whereas EDLP stores set prices that are relatively constant over time, HILO stores set prices that are higher than EDLP stores on average but use frequent sales featuring deeply-discounted prices on a smaller set of products.[1] Because store price format is characterized by price variation, how consumers with different risk preferences perceive and respond to the source of risk may be critical to understanding their price-format choice behavior. Despite its salience to consumers, however, a relationship between risk preference and consumers' store-choice decisions has received little attention in the literature. In this paper, we analyze the role of consumers' risk attitudes in their choice of store price format.

Shopping-basket size and shopping frequency influence preferences for store price format. Bell and Lattin (1998) and Ho, Tang, and Bell (1998) show that large-basket shoppers (i.e., those who buy more and shop less frequently) prefer EDLP stores because they do not have the flexibility to take advantage of occasional price deals on each product in their basket. On the other hand, small-

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[1] In reality, there are no pure examples of either, as pricing strategies tend to be located on a continuum between pure EDLP and pure HILO depending on observed degrees of price variability. Walmart and Food Lion are the closest examples to pure EDLP stores, while Kroger and Safeway are the closest to pure HILO (Shankar and Bolton, 2004; Ellickson and Misra, 2008).

basket shoppers (i.e., those who buy less and shop more frequently) prefer HILO stores because they can take advantage of price variations for each product. Small-basket shoppers can lower their basket price by buying each product on sale, despite the higher average store price. Neither of these studies, however, incorporates risk parameters, and each implicitly assumes that consumers are risk neutral. That is, they are silent about how consumers' risk attitudes under basket-price uncertainty influence their choice of store price format.

A typical shopping basket is composed of many products across many product categories (Hui, Fader, and Bradlow, 2009; Symphony IRI Group, 2012). If a consumer were interested in paying as little as possible for her groceries, she would have to visit multiple stores to get the best deal for each item. However, in general, consumers tend to prefer one-stop shopping in order to economize on fixed shopping costs—witness the rise of super-centers and convenience stores attached to gas stations. Wildenbeest (2011) and De Los Santos, Hortaçsu, and Wildenbeest (2012) find that consumers incur substantial costs in searching for even mundane items, and these costs increase with the amount of shopping that takes place. If consumers choose fewer stores relative to the number of items and are heterogeneous in risk preference, then the variability of prices within each store may be important to where they choose to shop.[2] Risk-averse consumers may prefer EDLP stores offering stable prices over time, while risk-loving consumers may tend to choose HILO stores with considerable price variation. Therefore, we hypothesize that consumers' perception of basket-price uncertainty is one of the considerations made when choosing where to shop.

We investigate the impact of consumers' risk attitudes on their store choice decisions using data from a two-stage experimental design. In the first stage, we elicit consumers' risk attitudes using an incentive-compatible lottery-choice experiment Holt and Laury (2002). The primary advantage of using the Holt-Laury experiment is that it is more likely to capture actual individual behavior under uncertainty because real money is at stake.[3] Conditional on consumers' revealed attitudes toward risk, we then implement an incentive-compatible choice-based conjoint study that provides data on subjects' store price format preferences. The Holt-Laury experiment is context-free, so it is widely used in experimental economics to measure risk preferences (Lusk and Coble, 2005; Anderson and Mellor, 2008; Nguyen and Leung, 2009; Dohmen and Falk, 2011; Anderson, Freeborn, and Hulbert, 2012). Muthukrishnan, Wathieu, and Xu (2009) use a similar approach to test for a relationship between ambiguity aversion in a lottery-choice experiment and a preference for established brands. Although the context of our experiment differs from theirs, they demonstrate the validity of a two-stage approach to estimate the effect of risk attitudes on choice.

Our results provide evidence to support the hypothesis that consumers' risk attitudes can predict their store choice decisions. Specifically, more risk-averse consumers are likely to choose EDLP stores rather than HILO stores. They perceive that shopping at HILO stores is risky due to the higher price variability for the goods that comprise their typical shopping basket and, therefore, have an incentive to choose EDLP stores. On the other hand, more risk-loving consumers prefer

[2] Store fliers may help to reduce price uncertainty but do not provide a perfect solution because they do not cover the price of every item included in a shopping basket. In fact, consumers do not know every price in their basket (Dickson and Sawyer, 1990) and make 76% of their purchase decisions in store rather than at home (Point of Purchase Advertising International, 2012). So, price variability may still matter to consumers.

[3] There are several alternatives to the Holt and Laury (2002) method of eliciting risk preferences, differing in the trade-off between simplicity and richness of elicited risk preferences. Eckel and Grossman (2002, 2008) design a simple way to elicit risk preferences in which subjects are asked to make a single choice among five lotteries with constant probabilities but changing payoffs, while Gneezy and Potters (1997) and Charness and Gneezy (2012) propose a risk-elicit method in which subjects are asked to allocate their endowment between safe and risky investments. However, these approaches do not allow us to differentiate between degrees of risk-loving behavior, and we require consumer heterogeneity in both the risk-averse and risk-loving domains. Lejuez et al. (2002) and Crosetto and Filippin (2013) develop a pictorial method of eliciting risk preferences without explicitly using the probability distribution of the realization of risky outcomes. In our empirical model, though, we require quantitative information on subjects' risk preferences, so their approach is not suitable. Finally, Dohmen et al. (2011) use self-reported questions to elicit risk attitudes that are relatively easy to understand. Similar to the previous approach, this method does not enable us to calibrate expected utility functions, nor are subjects incentivized to respond accurately. In sum, while other methods are superior in some aspects, the Holt and Laury (2002) method is the most suitable for the problem at hand.

HILO stores because they have a positive probability of finding a product with a lower price. We find that consumer heterogeneity in risk preference plays an important role even after controlling for basket size and purchase frequency, suggesting that the heterogeneity in risk preference is the mechanism underlying the findings of Bell and Lattin (1998) and Ho, Tang, and Bell (1998).

Our study contributes to the food marketing and retailing literature in three ways. First, we are the first to combine experimental evidence on risk aversion and store choice in a consistent way. To the best of our knowledge, experimental risk preferences have not been used in store-choice experiments. Second, this is the first store-choice study to incorporate consumers' risk attitudes. Because consumers are exposed to price uncertainty and prices are important drivers of any choice decision, our study provides a fundamental explanation of how consumers choose a particular store price format. Finally, we provide an empirical evidence of store differentiation in terms of heterogeneity in risk preference.

Experimental Design

Overview

The purpose of this paper is to reveal the relationship between consumers' risk preferences and store choice decisions. Household-panel data is one option, but it has significant drawbacks. First, it is difficult to define a shopping basket over time, as consumers do not purchase the same items on every purchase occasion. Second, because there are no pure examples of EDLP or HILO stores, identifying and classifying stores into different pricing formats is difficult with household panel scanner data. In fact, Ellickson and Misra (2008) point out that most stores do not announce their pricing strategies and, moreover, individual stores within the same chain often adopt different pricing strategies depending on their location and competition.[4] Third, it is impossible to obtain a precise measure of the distance between store locations or between stores and individual households. Fourth, there are many variables that are important to store choice but are inherently unobservable, such as assortment depth, availability, and product quality. Further, risk preferences are unobservable in household-panel data. Our experimental approach overcomes each of these problems. Experimental data allow us to measure consumers' risk attitudes and design a very specific set of pricing strategies using the mean and variance of a basket price to control for store location, assortment depth, and product quality and to precisely estimate the effect of consumers' risk attitudes on store preferences.

The experiment consists of two stages. We identify subjects' risk attitudes in the first stage and preference for store price format in the second.[5] Each stage is implemented using the Qualtrics online research panel (http://www.qualtrics.com). To participate in the experiment, subjects had to be at least eighteen years of age, live in the United States, purchase grocery items for their household at a supermarket at least once a month, and usually drive to their chosen supermarket. A total of 275 subjects participated in the experiment. The experiment is incentive compatible in that subjects are paid according to their performance during each stage. Compensation was recorded during the experiment in monetary units called "experimental units (EU)," and one EU was converted into 0.25 dollars for payment at the end of the experiment. Subjects spent 18.7 minutes to complete the experiment and earned \$10.70 on average.

[4] Ellickson and Misra's (2008) classification into different store price formats depends not on investigation of each transaction but on interviews with store managers. That is, it is difficult to identify store price format using the household-panel data commonly available to researchers.

[5] Following Dohmen and Falk (2011); Barham et al. (2015); and Bradbury, Hens, and Zeisberger (2015), we assume that the order of the first- and second-stage experiment does not affect our main results.

Table 1. Incentive-Compatible Lottery-Choice Experiment

Choice Task	Option A	Option B
1	10% chance of 20.00 EUs, 90% chance of 16.00 EUs	10% chance of 38.00 EUs, 90% chance of 2.00 EUs
2	20% chance of 20.00 EUs, 80% chance of 16.00 EUs	20% chance of 38.00 EUs, 80% chance of 2.00 EUs
3	30% chance of 20.00 EUs, 70% chance of 16.00 EUs	30% chance of 38.00 EUs, 70% chance of 2.00 EUs
4	40% chance of 20.00 EUs, 60% chance of 16.00 EUs	40% chance of 38.00 EUs, 60% chance of 2.00 EUs
5	50% chance of 20.00 EUs, 50% chance of 16.00 EUs	50% chance of 38.00 EUs, 50% chance of 2.00 EUs
6	60% chance of 20.00 EUs, 40% chance of 16.00 EUs	60% chance of 38.00 EUs, 40% chance of 2.00 EUs
7	70% chance of 20.00 EUs, 30% chance of 16.00 EUs	70% chance of 38.00 EUs, 30% chance of 2.00 EUs
8	80% chance of 20.00 EUs, 20% chance of 16.00 EUs	80% chance of 38.00 EUs, 20% chance of 2.00 EUs
9	90% chance of 20.00 EUs, 10% chance of 16.00 EUs	90% chance of 38.00 EUs, 10% chance of 2.00 EUs
10	100% chance of 20.00 EUs, 0% chance of 16.00 EUs	100% chance of 38.00 EUs, 0% chance of 2.00 EUs

Notes: One EU is 0.25 dollars.

First-Stage Experiment

In the first stage, we conduct an incentive-compatible lottery experiment (Holt and Laury, 2002) in order to identify subjects' risk preferences. Subjects were presented with ten choice tasks, each consisting of two lotteries (called option A and option B), and asked to choose between the options in each task. Table 1 shows the specific choice tasks the subjects faced. In any choice task, option A is referred to as the "safe" choice and option B as the "risky" choice because the payoffs from option A are less variable than option B. As subjects proceed through the choice tasks, the expected value of both options increase, but the expected value of option B becomes greater than that of option A. In our lottery-choice experiment (as in others), subjects typically begin by choosing option A, switch to option B at some point, and continue to choose option B until the end of the task list. Risk-neutral subjects are expected to choose option A in the first four choice tasks and option B in the last six choice tasks because the expected payoff from option A exceeds that from option B in the first four choice tasks. Risk-loving subjects are expected to start by choosing option B prior to the fourth choice task, and risk-averse subjects are expected to continue to choose option A even after the fifth choice task, switching to option B somewhere between the sixth and tenth choice task. One lottery is randomly chosen for payment, and subjects are paid the amount indicated by their selection. It is through this mechanism that the Holt-Laury experiment is incentive compatible.

With certain assumptions about the functional form of utility, lottery choices are used to identify either the coefficient of absolute risk aversion or the coefficient of relative risk aversion. We assume utility takes a constant absolute risk aversion (CARA) form:

$$U(Y) = -\exp(-\rho_i Y), \tag{1}$$

where ρ_i is the coefficient of absolute risk aversion for subject i and Y is the payoff in the lottery. For example, consider a subject who chooses option A in the first three tasks and then chooses option B in subsequent tasks. The lower bound of ρ_i for this subject is determined such that she or he is indifferent between option A and option B in the third choice task. That is, ρ_i must satisfy the following equation:

$$-0.3\exp(-20\rho_i) - 0.7\exp(-16\rho_i) = -0.3\exp(-38\rho_i) - 0.7\exp(-2\rho_i) \Leftrightarrow \rho_i = -0.030. \tag{2}$$

For the same subject, the upper bound of ρ_i is obtained by the subsequent choice task:

$$-0.4\exp(-20\rho_i) - 0.6\exp(-16\rho_i) = -0.4\exp(-38\rho_i) - 0.6\exp(-2\rho_i) \Leftrightarrow \rho_i = -0.008. \tag{3}$$

Because this process only identifies a range for the constant absolute risk aversion coefficient, we use the midpoint of the upper and lower bounds of ρ_i and use this as the coefficient of risk aversion

Table 2. Coefficient of Absolute Risk Aversion

Choice Task in Which Subject Switches to Option B	Lower Bound	Upper Bound	Midpoint
First choice task	−0.095	−0.095	−0.095
Second choice task	−0.095	−0.056	−0.075
Third choice task	−0.056	−0.030	−0.043
Fourth choice task	−0.030	−0.008	−0.019
Fifth choice task	−0.008	0.013	0.002
Sixth choice task	0.013	0.033	0.023
Seventh choice task	0.033	0.056	0.044
Eighth choice task	0.056	0.084	0.070
Ninth choice task	0.084	0.126	0.105
Tenth choice task	0.126	0.126	0.126

in the subsequent analysis (Lusk and Coble, 2005; Anderson and Mellor, 2008; Nguyen and Leung, 2009; Dohmen and Falk, 2011; Anderson, Freeborn, and Hulbert, 2012). In the above example, ρ_i is set to -0.019; ρ_i for other lottery choices can be similarly obtained as reported at table 2. A value of $\rho_i < 0$ indicates a risk-loving subject, while $\rho_i = 0$ indicates risk neutrality and $\rho_i > 0$ risk aversion.

Second-Stage Experiment

In the second stage, we administer an incentive-compatible choice-based conjoint (Louviere and Woodworth, 1983; Louviere, 1988; Louviere, Hensher, and Swait, 2000) experiment designed to elicit data on subjects' store-choice behavior. The "stores" are defined as generic supermarkets that differ in terms of the variability of shopping-basket prices, the number of brands available for each consumer packaged good (CPG), and driving time, which represents distance from the shopper. Basket-price variation is the key attribute, as it defines the pricing format for each store. In addition to prices, selection and convenience are important store choice criteria (Arnold, Oum, and Tigert, 1983; Bell and Lattin, 1998; Bawa and Ghosh, 1999; Briesch, Chintagunta, and Fox, 2009). In our experiment, we use the number of brands as a measure of selection and driving time as a measure of shopping convenience. Arnold, Oum, and Tigert (1983) find that the quality of fresh produce is also an important determinant of store choice. We control for this effect by instructing subjects that they are only shopping for CPGs. When shopping for CPGs, quality does not vary from store to store. Shopping-basket size is an important chooser attribute in determining store choice (Bell and Lattin, 1998; Ho, Tang, and Bell, 1998), so we hold shopping-basket size constant on each choice occasion.[6]

Basket-price variation is represented by presenting subjects with a set of "usual" and "sale" prices for products in a typical shopping basket. Presented with the two prices (usual and sale), subjects do not know the exact price charged for each product in the basket before shopping and, therefore, are forced to make their store-choice decision under price uncertainty. The degree of uncertainty assumes three levels, indicating either an EDLP store, HILO store, or something in between, which we refer to as a Hybrid store. In this way, basket-price variation reflects the revealed pricing pattern of each store price format in a general way. That is, subjects are not told that a particular store is EDLP, HILO, or Hybrid, but they observe the variation in prices we reveal to them (Ellickson and Misra, 2008).[7] Following Bell and Lattin (1998), we define the shopping basket as consisting of twelve CPGs (bacon, butter, margarine, ice cream, soda crackers, liquid detergent,

[6] Our focus is consumers' store choice decisions rather than product choice decisions. So, holding the basket composition constant is important because consumers are interested in the prices of baskets instead of individual items when they choose a store (Bell and Lattin, 1998; Wildenbeest, 2011).

[7] The second-stage price variation and the first-stage price variation play a distinct role in the econometric model discussed in the next section. The risk parameter calibrated in the first-stage experiment allows us to econometrically control for heterogeneity in risk response, so the second-stage price variation can purely capture choice variation that is unique to changes in basket prices.

Table 3. Attributes and Attribute Levels (Twelve CPGs in the Shopping Basket)

Attribute	Attribute Level
Basket-price variation	The usual price is 23.00 EUs but, there is a chance it could be 21.00 EUs if items are on sale.
	The usual price is 24.00 EUs but, there is a chance it could be 20.00 EUs if items are on sale.
	The usual price is 25.00 EUs but, there is a chance it could be 19.00 EUs if items are on sale.
The number of brands available for each CPG	1 brand
	3 brands
	6 brands
Driving time to the supermarket	5 minutes
	10 minutes
	20 minutes

Notes: The twelve CPGs includes bacon, butter, margarine, ice cream, soda crackers, liquid detergent, ground coffee, hot dogs, soft drinks, granulated sugar, facial tissues, and paper towels. The selection of the items and basket-price variation are based on Bell and Lattin (1998).

ground coffee, hot dogs, soft drinks, granulated sugar, facial tissues, and paper towels) and generate price variability using the mean and variance of the basket price calculated in their study. They use household panel scanner data, estimate the mean basket size for grocery shoppers, and calculate the mean and variance of that shopping basket. The basket size, usual price, and sales price in our experiment depend on their result. Specifically, we use their mean price as our usual price and their mean price minus two standard deviations as our sales price, assuming the basket price follows a normal distribution.

The number of brands available for each CPG has three levels: One brand, three brands, and six brands. This assumption is based on the observation that, on average, consumers consider approximately three alternatives and choose one when purchasing CPGs (Hauser and Wernerfelt, 1990; Mehta, Rajiv, and Srinivasan, 2003). One brand represents no selection at all, three brands an average selection, and six brands an extensive selection. Finally, driving time has three levels: 5 minutes, 10 minutes, and 20 minutes. We choose these levels based on Fox, Montgomery, and Lodish (2004), who report an average shopping-trip time of around 10 minutes. All attributes and levels are summarized in table 3.

We use SAS experimental design macros (Kuhfeld, 2005) to create a full-factorial choice design with three three-level attributes. We first set the number of alternatives to three and create possible combinations of the attributes and the attribute levels for one alternative at a time. Then, we search for an efficient design for a main-effects model (i.e., a design in which the variances of the parameter estimates are minimized under the assumption that the parameter vector of the design matrix is equal to zero). Our design, therefore, consists of three alternatives plus a "no shopping" option and nine choice sets.[8] In this design, all parameters for a main-effects model are estimable and the variances are similar and close to the minimum, which is the inverse of the number of choice sets.[9]

We use a Becker-DeGroot-Marschak (1964) procedure to ensure that it is in a subject's best interest to reveal his or her true preference on each choice alternative. Following the BDM mechanism, we assign a specific value (shopping utility) to each shopping option that reflects the price of the twelve products the subject purchases (variability of shopping-basket price), the cost of travel (driving time), and the value of having access to a larger selection (the number of brands available for each CPG). Our assigned value thus reflects a reasonable estimate of the total value of each option to the subject. Subjects start with a budget of 26 EUs to spend on each choice set. They can either choose a shopping option or choose not to shop at all. Subjects know that the assigned value depends on all the attributes that comprise each alternative but do not know the actual assigned

[8] The "no shopping" option captures a subject's decision to purchase the items at nontraditional outlets—such as convenience stores, discounters, or club stores—or wait for the next purchase trip if they do not like any of the shopping options presented in the given choice task. 4.89% of the responses in our study represented the "no shopping" option; future research should consider dropping this for a study of food shopping where it is debatable that shoppers would choose not to shop at all.

[9] The SAS code and output are available upon request.

Table 4. Demographic Variables

Variable	Symbol	N	Mean	Std Dev
Annual income	Inc_i	218	59219.720	40104.063
Household size	Hsz_i	218	2.514	1.307
Age	Age_i	218	45.826	15.577
Education	Edu_i	218	0.431	0.495
Employment	Emp_i	218	0.431	0.495
Shopping frequency (times per month)	$Sfrq_i$	218	7.931	6.044

Notes: Education takes one if subject is a college graduate and zero otherwise. Employment takes one if subject is a full time worker and zero otherwise.

value until the end of the experiment. We then choose one choice set at random. For the option chosen out of that choice set, we choose a price at random from a uniform distribution between 0 EU and the total budget. If the value of the shopping option is above the random price, subjects receive the value of their choice but pay an amount equal to the random price. If the value of their choice is below the random price, subjects keep their entire budget and pay nothing. If subjects select the "no shopping" option in the chosen choice set, they receive the value of the bundle (0 EU), as they do not shop, and keep their entire budget. For example, if a subject starts with a budget of 26 EUs, chooses an option worth 25 EUs, and a random number is 11 EUs, he or she pays 11 EUs out of the budget, receive 25 EUs, and his or her net gain is 40 EUs (26EUs − 11EUs + 25EUs). If this subject chooses an option with a value of 10 EUs and the random number is 11 EUs, he or she does not receive or pay anything, keeps 26 EUs, and his or her net gain is 26 EUs. This mechanism is well understood to be incentive compatible under a wide variety of auction scenarios.[10]

The instructions carefully explain how the BDM mechanism works using a numerical example and why it is in subjects' best interest to make the choice that best reflects the importance they place on each attribute (see the appendix for experiment instructions). Before the experiment, we conducted a trial run with the same attributes but different attribute levels so that all subjects were familiar with the process and understand how choosing their true valuations was indeed in their best interests. We are confident that they fully understood the experimental procedures and that they understood the BDM mechanism.

In our experiment, the size of each shopping basket is fixed at twelve items. However, Bell and Lattin (1998) and Ho, Tang, and Bell (1998) find that consumers' basket sizes plays a crucial role in their choice of store. We account for the importance of basket size by conducting the same experiment again with a relatively small basket size. Specifically, we define the smaller shopping basket to consist of six items (bacon, butter, margarine, ice cream, soda crackers, and liquid detergent) and reduce both basket prices and the total budget by half. The resulting attribute levels for this "small basket" experiment are summarized in the online supplement.

After the experiment has been conducted, we gather demographic and behavioral information from each subject, including income, household size, age, education, employment status, and shopping frequency. Each of these covariates is used in the econometric model described in the next section. As shown in table 4, the average subject in our sample is forty-six years old and belongs to a household earning $59,220 per year, consisting of 2.5 people. Fully 52% of the subjects are female, and 43% hold a bachelor's degree and are full-time workers. On average, subjects go grocery shopping approximately 7.9 times per month, which is more than once per week.

[10] Karni and Safra (1987) point out that the BDM mechanism is not incentive compatible when the good being evaluated is a lottery. Horowitz (2006) further shows that BDM is not incentive compatible even when the value of the good is certain. This is because subjects are still uncertain about whether the bit is accepted and how much they are asked to pay, so their willingness to pay typically depends on the distribution of an unknown price. We acknowledge that in our experiment, subjects make decisions on the basis of their guess about the value of each shopping option. However, such a situation is common in most experiments. In conjoint experiments, subjects are often asked to evaluate a new combination of attributes, and do not know about how that new combination fits their preferred attribute set. So, we assume that the arguments do not have a substantial impact on our findings.

Econometric Model

Estimates from the first-stage lottery-choice experiment provide the coefficient of absolute risk aversion for each subject, while in the second-stage experiment, subjects were asked to reveal their preferred store defined by a bundle of attributes such as store price format, the number of brands available for each CPG at the store, and driving time to the store. In this section, we present an econometric model that allows us to investigate the relationship between subjects' risk preferences and their choices of store price format. Following Louviere and Woodworth (1983), Louviere (1988) and Louviere, Hensher, and Swait (2000), we use the random utility framework to analyze the data from the experiment. Specifically, the utility level of consumer i from choosing store $j \in \{0,1,2,3\}$ is given by

$$
\begin{aligned}
U_{ij} &= \begin{pmatrix} \phi_{1i} + \psi_1 \rho_i + \omega_{11} Inc_i + \omega_{12} Hsz_i \\ +\omega_{13} Age_i + \omega_{14} Edu_i + \omega_{15} Emp_i + \omega_{16} Sfrq_i \end{pmatrix} \times W_{j,EDLP} \\
&\quad + \begin{pmatrix} \phi_{2i} + \psi_2 \rho_i + \omega_{21} Inc_i + \omega_{22} Hsz_i \\ +\omega_{23} Age_i + \omega_{24} Edu_i + \omega_{25} Emp_i + \omega_{26} Sfrq_i \end{pmatrix} \times W_{j,Hybrid} \\
&\quad + \begin{pmatrix} \phi_{3i} + \psi_3 \rho_i + \omega_{31} Inc_i + \omega_{32} Hsz_i \\ +\omega_{33} Age_i + \omega_{34} Edu_i + \omega_{35} Emp_i + \omega_{36} Sfrq_i \end{pmatrix} \times W_{j,HILO} \\
&\quad + \gamma_1 Nb_j + \gamma_2 Time_j + \varepsilon_{ij}, \ j \neq 0, \qquad (4) \\
\phi_{1i} &= \overline{\phi_1} + \Theta_{1i}, \ \Theta_{1i} \sim N(0, \sigma_1^2), \\
\phi_{2i} &= \overline{\phi_2} + \Theta_{2i}, \ \Theta_{2i} \sim N(0, \sigma_2^2), \\
\phi_{3i} &= \overline{\phi_3} + \Theta_{3i}, \ \Theta_{3i} \sim N(0, \sigma_3^2), \\
U_{i0} &= \varepsilon_{i0},
\end{aligned}
$$

where ρ_i is the coefficient of absolute risk aversion for consumer i, Inc_i is household income, Hsz_i is household size, Age_i is consumer i's age, Edu_i is consumer i's educational attainment, Emp_i is consumer i's employment status, and $Sfrq_i$ is consumer i's usual shopping frequency, W_{js}, $s \in \{EDLP, Hybrid, HILO\}$ is an indicator variable that takes a value of one if store j adopts store price format s and zero otherwise, Nb_j is the number of brands available for each CPG at store j, $Time_j$ is driving time to store j, and ε_{ij} is an error term that reflects factors that are unobservable to the econometrician.

Because each store offers a store price format that generates a specific variation pattern of basket price, we hypothesize that subjects' risk attitudes influence their choices of store price format. Accordingly, the marginal utility of the price-format variable, W_{js} includes the coefficient of absolute risk aversion, ρ_i. This specification allows us to test the relationship between consumers' risk attitudes and preferences for a particular store price format. More risk-averse consumers, who are characterized by a higher coefficient of absolute risk aversion, may perceive that shopping at HILO stores is risky due to higher price variability and, therefore, have an incentive to choose EDLP stores. On the other hand, more risk-loving consumers, who are characterized by a lower coefficient of absolute risk aversion, may prefer HILO stores because they have a positive probability of finding a product with lower price. Thus, our hypothesis is that $\psi_3 < \psi_2 < \psi_1$.[11] Bell and Lattin (1998) find demographic attributes affect consumers' preference for store price format, so we also include household income, size, age, education level, employment status, and shopping frequency in

[11] Ai and Norton (2003) and Greene (2010) caution against misinterpreting the effect of interaction terms on choice probability in a logit model. However, we avoid this problem by interpreting our results in the underlying linear utility rather than the choice probability (Meas et al., 2015). So, we rely on equation (4) to interpret the effects in the subsequent sections.

the marginal utility of the price-format variables to control for differences among consumers while testing the core hypothesis. Finally, equation (4) incorporates unobservable sources of heterogeneity.

For estimation purposes, we assume that ε_{ij} are distributed i.i.d. extreme value, so the probability that alternative j is chosen is given by[12]

$$P_j = \iiint \frac{\exp(V_j)}{1 + \sum_{j=1}^{3} \exp(V_j)} dF(\Theta_{1i}) \times dF(\Theta_{2i}) \times dF(\Theta_{3i}), \tag{5}$$

where V_j is the deterministic component of the utility, $F(\cdot)$ is the cumulative standard normal distribution, and Θ_{si} is an i.i.d. normal error term designed to account for any unobserved heterogeneity in the marginal utility. We use the simulated maximum likelihood to approximate the integrals in equation (5) and maximize the logarithm of the resulting simulated likelihood function with respect to the parameters (Train, 2009). This method provides consistent parameter estimates under rather weak regularity conditions. To aid in the computational speed and efficiency of estimation, we use 100 Halton draws for realizations of Θ_{1i}, Θ_{2i}, and Θ_{3i} (Bhat, 2003).

Results and Discussion

We estimate a number of alternative specifications for equation (4) in order to examine the robustness of our model. Therefore, we begin by describing our experimental data, report specification tests that compare the goodness of fit across models, and then present and interpret the results obtained by estimating the preferred store-choice model. We then draw a number of conclusions regarding the practical importance of our findings.

A total of 275 subjects completed all parts of the experiment. However, in order to ensure that all subjects fully understood the rules of the lottery experiment, we embedded a control question. If subjects responded to this question in a way that suggested they were not making rational decisions, we excluded them from further analysis. Of the total sample, fifty-seven subjects chose option A in the tenth choice task of the lottery experiment. Because this means that the subject prefers a certain 20 EUs to a certain 38 EUs, we interpreted this as an indication that the subject did not understand the rules of the lottery. That such subjects exist is perhaps not surprising, because we draw our sample from the general public, who may not be familiar with this type of experiment. Because it is impossible to calculate the coefficient of absolute risk aversion from data that include responses such as this, we exclude these subjects and use the responses from the remaining 218 subjects for the subsequent analysis. The exclusion of these responses is not likely to have any adverse effects, because those who make irrational lottery choices appear randomly in our sample. In other words, we retain the random nature of our sample by randomly excluding part of the observations. This procedure is well accepted in the literature (Harrison, List, and Towe, 2007; Anderson and Mellor, 2008).

Among the remaining responses, 138 subjects start with option A, switch to option B, and continue to select option B thereafter, while 80 subjects switch back to option A even after having chosen option B. This type of behavior is also reported in other lottery-choice experiments (Holt and Laury, 2002; Lusk and Coble, 2005; Harrison, List, and Towe, 2007; Anderson and Mellor, 2008). In

[12] The coefficient of absolute risk aversion from the first-stage experiment can be used in equation (5) because it well approximates risk aversion toward price uncertainty in the contest of our experiment. The difference between them largely depends on the budget share and the own uncompensated price elasticity of demand for a single shopping basket (Turnovsky, Shalit, and Schmitz, 1980). First, the average budget share of a typical shopping basket is around 0.05% of disposable personal incomes and negligibly small (Food Marketing Institute, 2012; U.S. Department of Agriculture, Economic Research Service, 2014). Second, because food is a necessity, the own uncompensated price elasticity of demand for all food products is −0.297 (Muhammad et al., 2011), and the elasticity for a single shopping basket is expected to be even smaller due to store differentiation (Arnold, Oum, and Tigert, 1983; Bawa and Ghosh, 1999; Briesch, Chintagunta, and Fox, 2009). Therefore, it may be reasonable to assume that the two risk aversions are similar.

Table 5. Coefficient of Absolute Risk Aversion

Range of Coefficient of Absolute Risk Aversion	Obs.
$\rho_i \leq -0.095$	13
$-0.095 < \rho_i \leq -0.056$	0
$-0.056 < \rho_i \leq -0.030$	11
$-0.030 < \rho_i \leq -0.008$	19
$-0.008 < \rho_i \leq 0.013$	36
$0.013 < \rho_i \leq 0.033$	59
$0.033 < \rho_i \leq 0.056$	30
$0.056 < \rho_i \leq 0.084$	20
$0.084 < \rho_i \leq 0.126$	12
$0.126 \leq \rho_i$	18
Total	218

Table 6. Coefficient of Absolute Risk Aversion and Choice Share

Range of Coefficient of Absolute Risk Aversion	Obs.	EDLP (%)	Hybrid (%)	HILO (%)	Non-Shopping (%)	Total (%)
$\rho_i \leq -0.056$	117	23.077	26.496	50.427	0.000	100
$-0.056 < \rho_i \leq -0.008$	270	27.778	30.741	36.296	5.185	100
$-0.008 < \rho_i \leq 0.033$	855	27.018	31.696	36.608	4.678	100
$0.033 < \rho_i \leq 0.084$	450	29.111	29.778	34.889	6.222	100
$0.084 \leq \rho_i$	270	24.815	33.333	36.667	5.185	100
Total	1,962	27.064	31.040	37.003	4.893	100

Notes: Obs. = number of subjects × number of choice occasions.

these cases, we employ the same method of calculating the coefficient of absolute risk aversion used by these authors. Namely, for subjects who made multiple switches, we use the midpoint between the lower bound and the upper bound of the coefficient of absolute risk aversion, where the lower bound is determined by the first switch from option A to option B and the upper bound is determined by the last time a subject chose option B. For example, suppose a subject chose option A for the first three choice tasks, switched to option B in the fourth task, switched back to option A in the fifth task, chose option B in the eighth task, and then continued to choose option B for all remaining tasks. In this case, the lower bound is -0.030 and the upper bound is 0.084, so the midpoint used for the estimation is 0.027.

We find considerable heterogeneity in subjects' attitudes toward risk. Table 5 reports the distribution of subjects' coefficient of absolute risk aversion, while table 6 provides some descriptive data on the relationship between risk aversion and store choice. Specifically, table 6 compares the choice share of each store price format and the "no shopping" option, for a range of coefficient of absolute risk aversion values. The summary statistic in the table reveals some preliminary support for our hypothesis, as there appears to be a positive relationship between the coefficient of absolute risk aversion and the EDLP and Hybrid shares: more risk-averse subjects appear to choose EDLP or Hybrid stores more often. Moreover, the summary statistic shows a negative relationship between the coefficient of absolute risk aversion and the share of the HILO store.[13] However, the trend could be due to any one of a number of factors—such as assortment depth, store location, and subjects' demographic attributes—so more conclusive evidence will need to found from the econometric estimates.

Our choice-based conjoint experiment is designed so that store choice depends on the variability of shopping-basket price, the number of brands available for each CPG, and driving time to

[13] We observe the similar trends for the small basket case. This result is available in the online supplement.

Table 7. Estimation Result of the Proposed Model

Variable	Parameter	Symbol	Estimate	Std Error
coeff. of absolute risk aversion × EDLP	Mean coeff.	ψ_1	-4.109^{*}	2.190
coeff. of absolute risk aversion × Hybrid	Mean coeff.	ψ_2	-3.978^{*}	2.183
coeff. of absolute risk aversion × HILO	Mean coeff.	ψ_3	-6.665^{**}	2.210
EDLP	Mean coeff.	$\overline{\phi_1}$	2.729^{**}	0.551
	Std. dev. coeff.	σ_1	0.075	0.524
Hybrid	Mean coeff.	$\overline{\phi_2}$	3.008^{**}	0.549
	Std. dev. coeff.	σ_2	0.024	0.336
HILO	Mean coeff.	$\overline{\phi_3}$	2.332^{**}	0.564
	Std. dev. coeff.	σ_3	0.852^{**}	0.302
The number of brands	Mean coeff.	γ_1	0.243^{**}	0.017
Driving time	Mean coeff.	γ_2	-0.098^{**}	0.006
Income × EDLP	Mean coeff.	ω_{11}	-0.685^{**}	0.289
Income × Hybrid	Mean coeff.	ω_{21}	−0.466	0.285
Income × HILO	Mean coeff.	ω_{31}	−0.461	0.287
Household size × EDLP	Mean coeff.	ω_{12}	0.586	0.922
Household size × Hybrid	Mean coeff.	ω_{22}	0.135	0.920
Household size × HILO	Mean coeff.	ω_{32}	0.781	0.928
Age × EDLP	Mean coeff.	ω_{13}	-1.535^{*}	0.818
Age × Hybrid	Mean coeff.	ω_{23}	-1.687^{**}	0.815
Age × HILO	Mean coeff.	ω_{33}	0.234	0.828
Education × EDLP	Mean coeff.	ω_{14}	0.735^{**}	0.256
Education × Hybrid	Mean coeff.	ω_{24}	0.499^{**}	0.254
Education × HILO	Mean coeff.	ω_{34}	0.152	0.258
Employment × EDLP	Mean coeff.	ω_{15}	-0.973^{**}	0.259
Employment × Hybrid	Mean coeff.	ω_{25}	-0.873^{**}	0.258
Employment × HILO	Mean coeff.	ω_{35}	-0.923^{**}	0.260
Shopping frequency × EDLP	Mean coeff.	ω_{16}	0.335	0.223
Shopping frequency × Hybrid	Mean coeff.	ω_{26}	0.299	0.223
Shopping frequency × HILO	Mean coeff.	ω_{36}	0.444^{**}	0.225
Simulated log likelihood at convergence			−1,943	
AIC			3,943	
BIC			4,105	

Notes: A single asterisk (*) indicates significance at the 10% level. A double asterisk (**) indicates significance at the 5% level.

the store. As shown in the previous section, subjects' demographic attributes and risk attitudes, which are collected in the first-stage experiment, are included in the marginal utility of choosing a particular store price format. In order to evaluate the validity of the model specification, we conduct specification tests using the Akaike information criterion (AIC), Bayesian information criterion (BIC), and likelihood ratio (LR) test statistics. The AIC and BIC for our proposed model are $3,943$ and $4,105$; for an alternative model that does not include demographic attributes or risk attitudes, the AIC and BIC are $3,975$ and $4,020$, respectively. The results show that the proposed model achieves the lower value for AIC but not for BIC. Despite the negative result from the BIC criterion, the LR test supports the proposed model. For the LR test, we define the proposed model as the alternative specification and the model without demographic attributes and risk attitudes as the null specification. The LR statistic is 74.430, the degree of freedom is 21, and the critical value for 95% is 32.671, which rejects the null in favor of the alternative according to the LR test. In addition, the proposed model provides insights not available in the other model. Thus, we present and interpret the estimation results from the model that includes both demographic attributes and risk attitudes as the preferred specification.[14]

Estimates from the preferred specification again support our primary hypotheses (see table 7). In order to examine the nature of the relationship between risk preference and store choice, we interact each subject's coefficient of absolute risk aversion with a set of store-format indicator variables. In each case, these coefficients are all significant, suggesting that consumers' risk attitudes are important in explaining the marginal utility from choosing each store price format.[15]

Our main interest lies in examining the relative values of ψ_1, ψ_2, and ψ_3 in order to test whether there is any systematic relationship between consumers' risk attitudes and preferences for store price format. The values of these coefficients in table 7 imply that the more risk-averse the subject, the more he or she prefers EDLP to HILO stores. However, it is not clear whether this relationship is statistically significant. The 90% confidence interval for ψ_1 is $[-7.712, -0.506]$ and for ψ_3 is $[-10.300, -3.030]$. Because there is some overlap in the region between them, it is possible that $\psi_1 < \psi_3$ rather than $\psi_3 < \psi_1$ depending on the sample. To address this issue, we have to formally test the relative values of each parameter. We first test the relationship between ψ_1 and ψ_3. Following Kane and Rouse (1995), we consider the following specification of the utility:

$$
\begin{aligned}
U_{ij} &= \begin{pmatrix} \phi_{1i} + \psi_1\rho_i + \omega_{11}Inc_i + \omega_{12}Hsz_i \\ +\omega_{13}Age_i + \omega_{14}Edu_i + \omega_{15}Emp_i + \omega_{16}Sfrq_i \end{pmatrix} \times W_{j,EDLP} \\
&\quad + \begin{pmatrix} \phi_{2i} + \psi_2\rho_i + \omega_{21}Inc_i + \omega_{22}Hsz_i \\ +\omega_{23}Age_i + \omega_{24}Edu_i + \omega_{25}Emp_i + \omega_{26}Sfrq_i \end{pmatrix} \times W_{j,Hybrid} \\
&\quad + \begin{pmatrix} \phi_{3i} + \omega_{31}Inc_i + \omega_{32}Hsz_i \\ +\omega_{33}Age_i + \omega_{34}Edu_i + \omega_{35}Emp_i + \omega_{36}Sfrq_i \end{pmatrix} \times W_{j,HILO} \\
&\quad + \psi_3 \times \left(\rho_i \times W_{j,EDLP} + \rho_i \times W_{j,HILO}\right) \\
&\quad + \gamma_1 Nb_j + \gamma_2 Time_j + \varepsilon_{ij},\ j \neq 0, \\
\phi_{1i} &= \overline{\phi_1} + \Theta_{1i},\ \Theta_{1i} \sim N(0, \sigma_1^2), \\
\phi_{2i} &= \overline{\phi_2} + \Theta_{2i},\ \Theta_{2i} \sim N(0, \sigma_2^2), \\
\phi_{3i} &= \overline{\phi_3} + \Theta_{3i},\ \Theta_{3i} \sim N(0, \sigma_3^2), \\
U_{i0} &= \varepsilon_{i0}.
\end{aligned} \tag{6}
$$

The term $\psi_3 \times \rho_i \times W_{j,EDLP}$ is added to the utility specification in equation (4) to establish equation (6). The coefficient on $\rho_i \times W_{j,EDLP}$ is key to testing the statistical difference between the coefficients for $\rho_i \times W_{j,EDLP}$ and $\rho_i \times W_{j,HILO}$. If we reject the hypothesis, $H_0 : \psi_1 = 0$ in equation (6), then the coefficient for $\rho_i \times W_{j,EDLP}$ is $\psi_1 + \psi_3$, which is different from the coefficient for $\rho_i \times W_{j,HILO}$. If we fail to reject the hypothesis, on the other hand, it is possible that ψ_1 is zero and the coefficients for $\rho_i \times W_{j,EDLP}$ and $\rho_i \times W_{j,HILO}$ are the same and equal to ψ_3.

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[14] To investigate the influence of the assumption about utility form, we also estimate the proposed model using different risk measures, such as coefficient of constant relative risk aversion, the number of safe choices, and choice task corresponding to the first risky choice. We obtain similar results regardless of which risk measure we use. Nevertheless, the proposed model achieves the highest log likelihood value and smallest standard errors for the interaction terms between subjects' risk measures and each store price format. These estimation results are available upon request.

[15] Notice that all of these coefficients are negative. This is because subjects can receive a certain budget amount by choosing the "no shopping" option in each choice set. In the econometric model, the utility from choosing a "no shopping" option is normalized, so all estimates are measured relative to this option. Because the "no shopping" option is regarded as the safest choice available in each choice set in terms of price variation, it is natural that the coefficients of the interactions between subjects' coefficient of absolute risk aversion and each store price format are all negative.

Table 8. Testing of the Magnitude Relationships

Variable	Parameter	Symbol	Estimate	Std Error
Testing of the magnitude relationship between ψ_1 and ψ_3:				
coeff. of absolute risk aversion × EDLP	Mean coeff.	ψ_1	2.556*	1.345
coeff. of absolute risk aversion × Hybrid	Mean coeff.	ψ_2	−3.977*	2.183
coeff. of absolute risk aversion × EDLP + coeff. of absolute risk aversion × HILO	Mean coeff.	ψ_3	−6.664**	2.210
Testing of the magnitude relationship between ψ_2 and ψ_3:				
coeff. of absolute risk aversion × EDLP	Mean coeff.	ψ_1	−4.108*	2.190
coeff. of absolute risk aversion × Hybrid	Mean coeff.	ψ_2	2.687*	1.373
coeff. of absolute risk aversion × Hybrid + coeff. of absolute risk aversion × HILO	Mean coeff.	ψ_3	−6.664**	2.210
Testing of the magnitude relationship between ψ_1 and ψ_2:				
coeff. of absolute risk aversion × EDLP	Mean coeff.	ψ_1	−0.132	1.380
coeff. of absolute risk aversion × EDLP + coeff. of absolute risk aversion × Hybrid	Mean coeff.	ψ_2	−3.978*	2.183
coeff. of absolute risk aversion × HILO	Mean coeff.	ψ_3	−6.665**	2.210

Notes: A single asterisk (*) indicates significance at the 10% level. A double asterisk (**) indicates significance at the 5% level. The full results are available in the online supplement.

In this case, we cannot conclude that there is a statistically significant difference between the coefficients for $\rho_i \times W_{j,EDLP}$ and $\rho_i \times W_{j,HILO}$. The same test is necessary for the relationship between ψ_2 and ψ_3 and the relationship between ψ_1 and ψ_2.

Table 8 reports ψ_1, ψ_2, and ψ_3 from the specification that tests the magnitude the relationship between ψ_1 and ψ_3 (specification in equation 6) as well as the relationship between ψ_2 and ψ_3 and the relationship between ψ_1 and ψ_2.[16] For the test between ψ_1 and ψ_3, we find that the coefficient on $\rho_i \times W_{j,EDLP}$ is positive and significant, which means that the coefficient on $\rho_i \times W_{j,EDLP}$ is greater than the coefficient on $\rho_i \times W_{j,HILO}$ and that this difference is statistically significant. Based on this test, our results show that consumers' risk attitudes have a different impact on the marginal utility from choosing EDLP and HILO stores in the context of the utility model in equation (4). Namely, more risk-averse consumers gain more from choosing EDLP than HILO because they perceive shopping at a HILO store to be risky due to greater price variation. Next, we conduct a test for investigating the magnitude of the relationship between ψ_2 and ψ_3. For this test, the coefficient on $\rho_i \times W_{j,Hybrid}$ is positive and significant, implying that the coefficient for $\rho_i \times W_{j,Hybrid}$ is greater than $\rho_i \times W_{j,HILO}$. This relationship is also statistically significant. Finally, we compare ψ_1 with ψ_2 in the same way. The results in table 8 show that the coefficient for $\rho_i \times W_{j,EDLP}$ is not significant, suggesting that there is no statistical difference between the coefficients for $\rho_i \times W_{j,EDLP}$ and $\rho_i \times W_{j,Hybrid}$ in equation (4). In total, these tests reveal that more risk-averse consumers tend to prefer EDLP to HILO stores and Hybrid to HILO stores.

Among the other estimates reported in table 7 are a number of results that may also be of interest. First, each store price format—EDLP, Hybrid, and HILO—has a positive and significant impact on utility. The magnitude of this format effect is slightly larger for Hybrid than for the others, suggesting that consumers may prefer moderate price variation. Further, the standard deviation of the coefficient for the HILO store is significant, indicating that there is considerable variation in preferences for the HILO format. Second, the number of brands available for each CPG has a positive and statistically significant impact on utility. Consumers prefer stores with deeper assortments, which is consistent with Oppewal and Koelemeijer (2005); Borle et al. (2005); and Briesch, Chintagunta, and Fox (2009). As expected, the distance to the store, as measured by driving time, has a negative and statistically significant effect on utility. This finding both makes sense, as consumers tend to shop at stores that are nearer to them, and is consistent with the literature (Arnold, Oum, and Tigert, 1983; Bell and Lattin, 1998; Bawa and Ghosh, 1999).

[16] Full results for each case are available in the online supplement.

Table 9. Estimation Result of the Proposed Model with Small Shopping Basket

Variable	Parameter	Symbol	Estimate	Std Error
coeff. of absolute risk aversion × EDLP	Mean coeff.	ψ_1	−2.132	1.919
coeff. of absolute risk aversion × Hybrid	Mean coeff.	ψ_2	−1.044	1.918
coeff. of absolute risk aversion × HILO	Mean coeff.	ψ_3	−3.910**	1.885
EDLP	Mean coeff.	$\overline{\phi_1}$	2.096**	0.475
	Std. dev. coeff.	σ_1	−0.037	0.447
Hybrid	Mean coeff.	$\overline{\phi_2}$	1.795**	0.477
	Std. dev. coeff.	σ_2	−0.007	0.363
HILO	Mean coeff.	$\overline{\phi_3}$	2.035**	0.471
	Std. dev. coeff.	σ_3	0.246	0.708
The number of brands	Mean coeff.	γ_1	0.235**	0.015
Driving time	Mean coeff.	γ_2	−0.094**	0.006
Income × EDLP	Mean coeff.	ω_{11}	−0.169	0.267
Income × Hybrid	Mean coeff.	ω_{21}	−0.218	0.268
Income × HILO	Mean coeff.	ω_{31}	−0.278	0.263
Household size × EDLP	Mean coeff.	ω_{12}	0.240	0.830
Household size × Hybrid	Mean coeff.	ω_{22}	1.168	0.827
Household size × HILO	Mean coeff.	ω_{32}	0.594	0.812
Age × EDLP	Mean coeff.	ω_{13}	−1.292*	0.693
Age × Hybrid	Mean coeff.	ω_{23}	−1.026	0.696
Age × HILO	Mean coeff.	ω_{33}	−0.344	0.682
Education × EDLP	Mean coeff.	ω_{14}	0.148	0.222
Education × Hybrid	Mean coeff.	ω_{24}	0.121	0.222
Education × HILO	Mean coeff.	ω_{34}	−0.085	0.218
Employment × EDLP	Mean coeff.	ω_{15}	−0.538**	0.226
Employment × Hybrid	Mean coeff.	ω_{25}	−0.360	0.226
Employment × HILO	Mean coeff.	ω_{35}	−0.236	0.222
Shopping frequency × EDLP	Mean coeff.	ω_{16}	0.262	0.195
Shopping frequency × Hybrid	Mean coeff.	ω_{26}	0.222	0.195
Shopping frequency × HILO	Mean coeff.	ω_{36}	0.268	0.192
Simulated log likelihood at convergence			−2,016	
AIC			4,091	
BIC			4,253	

Notes: A single asterisk (*) indicates significance at the 10% level. A double asterisk (**) indicates significance at the 5% level.

Demographic heterogeneity appears to be important in explaining store choice. Specifically, income has a statistically significant negative effect on marginal utility from choosing an EDLP store, while its effect on other store price formats is not significant. This result is intuitive; low-income households prefer certain low prices and tend to shop more often at EDLP stores (Bell and Lattin, 1998; Ellickson and Misra, 2008). We find that age has a statistically significant impact on the marginal utility from choosing EDLP and Hybrid stores but not from choosing HILO, indicating that younger people have a stronger preference for EDLP and Hybrid stores. We also find that education has a positive effect on the marginal utility from choosing EDLP and Hybrid stores. It may be the case that higher-educated consumers tend to be more conscious about price fluctuations, do not prefer variation in the prices they face, and choose to shop at EDLP and Hybrid stores as a result. For all formats, employment status has negative and significant impact. Because employment status is defined so that 1 = full-time employment, this may be simply because busy full-time workers are reluctant to shop at all. The result is consistent with consumers' economizing on shopping time (Arnold, Oum, and Tigert, 1983; Bell and Lattin, 1998; Bawa and Ghosh, 1999). Finally, shopping frequency plays an important role in explaining the marginal benefit from shopping at a HILO store.

The positive and significant effect of shopping frequency on subjects' preferences for HILO stores suggests that frequent shoppers prefer the ability to find a good deal. As shown in Bell and Lattin (1998), frequent shoppers are able to take advantage of price variation because they tend to have greater knowledge about shelf prices in general through their deeper shopping experience.

Finally, we investigate how the results of our proposed model change when we reduce the size of the shopping basket (table 9). One notable difference between the results reported in tables 7 and 9 is that the coefficients of the interactions between subjects' coefficient of absolute risk aversion and the EDLP and Hybrid indicators become insignificant in table 9.[17] This result implies that consumers' risk attitudes become less important when their basket size is smaller. When the total amount at risk is reduced, consumers logically become less sensitive about price variation, so this result is intuitive.

Conclusions and Implications

In this paper, we investigate the relationship between consumers' risk preferences and their choice of store price format. Retailers choose a store price format that is characterized by either more variable prices (HILO), less variable, lower-mean prices (EDLP), or somewhere in between (Hybrid). As prices vary over time and each format is defined by the mean and the variance of prices, consumers perceive different formats as offering either a low-risk or high-risk proposition. In any uncertain choice context, attitudes toward risk are important for observed behavior, so we expect the same to be true for consumers' store choice decisions. To test our conjecture, we conduct a two-stage, incentive-compatible experiment in which we elicit subjects' risk attitudes through a lottery-choice experiment in the first stage and then use a choice-based conjoint experiment in the second stage to determine how heterogeneity in risk preference influences consumers' choice of store price format.

We show that consumers' perceptions of risk have a significant impact on their choice of store. Our estimates reveal a systematic relationship between consumers' risk attitudes and preferences for particular store price formats. More risk-averse consumers are more likely to choose an EDLP store that is characterized by less price variability and lower average price. Moreover, we find that this effect is less important when basket size is small.

Although our findings are only directly applicable to the laboratory setting, as with any experiment, they imply that store price format is not merely a strategic choice of prices but also a screening device that effectively separates consumers with different risk attitudes. Because risk attitudes differ and consumers with different risk attitudes prefer different store price formats, any type of store price format has the potential to succeed, and each market needs a variety of stores to cater to the revealed risk preferences of its clientele.

Our findings suggest a number of avenues for future research. While our model offers new insight about consumers' store-choice decisions, it does not consider consumers' store-search behavior. In our experiment, the variance of basket price is held constant across subjects. However, it is possible that the variance is endogenous and, in fact, changes depending on subjects' search behavior, exposure to supermarket flyers, or previous shopping experience. It would be worthwhile to incorporate consumers' potential information gain from search into our experiment and analytical model. Next, this research could also be extended to incorporate strategic pricing decisions by retailers. It may be the case that retailers optimally react to consumers' store price format choices in consideration of rival retailers' strategies. Equilibrium analysis of the interactions between utility-maximizing consumers with different risk attitudes and profit-maximizing retailers may provide insight into retailers' strategies. We leave them for future research.

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[17] We find a similar tendency even when we use different risk measures, such as the coefficient of constant relative risk aversion, the number of safe choices, and choice task corresponding to the first risky choice. This implies that our finding is not due to our assumption regarding the nature of the utility function. These estimation results are available upon request.

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Appendix: Experiment Instructions

Overview

You are to choose where to go shopping for your favorite grocery items from several different types of food and household essentials. In this experiment, you will pick a number of items from several different categories and have an amount of money to spend (each of the number of items, number of categories, and budget are determined during the game). We refer to this basket of goods as your "bundle." There will be 9 questions. Each choice represents a supermarket that has the following 3 attributes: (1) total bill, (2) the number of brands available in each category, and (3) the driving time to the supermarket. Assume you do not know the exact price charged for each product before going to a store. That is, you do not know which products will be on sale, so your total bill is not known prior to checking out. Therefore, the "total bill" attribute reflects both the usual price and sale price, but you only know that sometimes you pay the sale price and sometimes the regular price. In each question, please indicate the decision you would make based on your own preferences. Alternatively, you may choose not to shop at either supermarket listed in that question. Please carefully examine each option before you make a decision and click on the decision that you would make based on your own preferences. Assume that the options in each question are the only ones available to you. Do not compare choices across questions.

Compensation

You will start with a budget to spend on your chosen bundle. The budget will vary depending on the shopping game, but will be sufficient to purchase whatever bundle you prefer. Please choose between one of the three bundles or to not shop at all. We will then assign a value to each bundle that reflects not just the price of the items you purchase, but the cost of travel, and the value of having access to a larger selection. If you select not to shop, the value of the bundle is 0 EU as you do not go shopping. We will then draw a number at random between 0 EU and your total budget for that question. If the value of the bundle you have selected is above this random draw, then you will get the value of the bundle, but pay an amount equal to the random draw. If the value of the bundle is below the random draw, then you keep your entire budget and pay nothing. For example, if your budget is 30 EUs, the value of the bundle is 20 EUs, and the random number is 10 EUs, then you will pay 10 EUs out of your budget, but receive 20 EUs back. Think of this as getting 20 EUs in groceries for a price of 10 EUs. You will then receive 40 EUs (30 EUs − 10 EUs + 20 EUs) at the end of the game. If your budget is 30 EUs, the value of the bundle is 10 EUs and the random number is 20 EUs, then you keep 30 EUs in payment at the end of the game. In this way, it is in your interest to make the choice that best reflects the importance you place on grocery prices, the ability to select from among many brands, and the cost of traveling to the store. After you finish making all choices, we will randomly pick one choice that determines your payoff. Call this the "payoff choice." All choices have an equal probability of being chosen for payment, so please carefully choose the bundle that most reflects your preference in all the choice occasions.

Shopping Basket Size and Total Budget

Assume the followings in the next nine questions that appear within this web page.

- Items: 12 items – You will go shopping for your favorite 12 grocery items.
- Budget: 26.00 EUs – You have 26.00 EUs to spend.
- Categories: 12 categories – You are allowed to buy one item from each of the following 12 categories, bacon, butter, margarine, ice cream, soda crackers, liquid detergent, ground coffee, hot dogs, soft drinks, granulated sugar, tissue, and paper towels.
- You know your favorite item(s) in all of these 12 categories even if you usually do not buy anything from one or some of them.

Supplement

Table S1. Attributes and Attribute Levels (Six CPGs in the Shopping Basket)

Attribute	Attribute Level
Basket-price variation	The usual price is 11.50 EUs but, there is a chance it could be 10.50 EUs if items are on sale.
	The usual price is 12.00 EUs, but there is a chance it could be 10.00 EUs if items are on sale.
	The usual price is 12.50 EUs, but there is a chance it could be 9.50 EUs if items are on sale.
The number of brands available	1 brand
for each CPG	3 brands
	6 brands
Driving time to the supermarket	5 minutes
	10 minutes
	20 minutes

Notes: The 6-CPG includes bacon, butter, margarine, ice cream, soda crackers, and liquid detergent. The selection of the items and basket-price variation are based on Bell and Lattin (1998).

Table S2. Coefficient of Absolute Risk Aversion and Choice Share (Small Shopping Basket)

Range of Coefficient of Absolute Risk Aversion	Obs.	EDLP (%)	Hybrid (%)	HILO (%)	Non-Shopping (%)	Total (%)
$\rho_i \leq -0.056$	117	23.932	28.205	47.863	0.000	100
$-0.056 < \rho_i \leq -0.008$	270	24.815	31.111	36.296	7.778	100
$-0.008 < \rho_i \leq 0.033$	855	28.889	29.591	34.854	6.667	100
$0.033 < \rho_i \leq 0.084$	450	28.444	27.556	36.889	7.111	100
$0.084 \leq \rho_i$	270	24.815	36.296	32.222	6.667	100
Total	1,962	27.370	30.173	35.933	6.524	100

Notes: Obs. = number of subjects × number of choice occasions.

Table S3. Testing of the Magnitude Relationship between ψ_1 and ψ_3

Variable	Parameter	Symbol	Estimate	Std Error
Coeff. of absolute risk aversion × EDLP	Mean coeff.	ψ_1	2.556*	1.345
Coeff. of absolute risk aversion × Hybrid	Mean coeff.	ψ_2	−3.977*	2.183
Coeff. of absolute risk aversion × EDLP + Coeff. of absolute risk aversion × HILO	Mean coeff.	ψ_3	−6.664**	2.210
EDLP	Mean coeff.	$\overline{\phi_1}$	2.729**	0.551
	Std. dev. coeff.	σ_1	0.075	0.524
Hybrid	Mean coeff.	$\overline{\phi_2}$	3.008**	0.549
	Std. dev. coeff.	σ_2	0.024	0.336
HILO	Mean coeff.	$\overline{\phi_3}$	2.332**	0.564
	Std. dev. coeff.	σ_3	0.852**	0.302
The number of brands	Mean coeff.	γ_1	0.243**	0.017
Driving time	Mean coeff.	γ_2	−0.098**	0.006
Income × EDLP	Mean coeff.	ω_{11}	−0.685**	0.289
Income × Hybrid	Mean coeff.	ω_{21}	−0.466	0.285
Income × HILO	Mean coeff.	ω_{31}	−0.461	0.287
Household size × EDLP	Mean coeff.	ω_{12}	0.585	0.922
Household size × Hybrid	Mean coeff.	ω_{22}	0.135	0.920
Household size × HILO	Mean coeff.	ω_{32}	0.780	0.928
Age × EDLP	Mean coeff.	ω_{13}	−1.535*	0.818
Age × Hybrid	Mean coeff.	ω_{23}	−1.687**	0.815
Age × HILO	Mean coeff.	ω_{33}	0.234	0.828
Education × EDLP	Mean coeff.	ω_{14}	0.735**	0.256
Education × Hybrid	Mean coeff.	ω_{24}	0.499**	0.254
Education × HILO	Mean coeff.	ω_{34}	0.152	0.258
Employment × EDLP	Mean coeff.	ω_{15}	−0.973**	0.259
Employment × Hybrid	Mean coeff.	ω_{25}	−0.873**	0.258
Employment × HILO	Mean coeff.	ω_{35}	−0.923**	0.260
Shopping frequency × EDLP	Mean coeff.	ω_{16}	0.335	0.223
Shopping frequency × Hybrid	Mean coeff.	ω_{26}	0.299	0.223
Shopping frequency × HILO	Mean coeff.	ω_{36}	0.444**	0.225
Simulated log likelihood at convergence			−1,943	
AIC			3,943	
BIC			4,105	

Notes: A single asterisk (*) indicates significance at the 10% level. A double asterisk (**) indicates significance at the 5% level.

Table S4. Testing of the Magnitude Relationship between ψ_2 and ψ_3

Variable	Parameter	Symbol	Estimate	Std Error
Coeff. of absolute risk aversion × EDLP	Mean coeff.	ψ_1	-4.108^{*}	2.190
Coeff. of absolute risk aversion × Hybrid	Mean coeff.	ψ_2	2.687^{*}	1.373
Coeff. of absolute risk aversion × Hybrid + Coeff. of absolute risk aversion × HILO	Mean coeff.	ψ_3	-6.664^{**}	2.210
EDLP	Mean coeff.	$\overline{\phi_1}$	2.729^{**}	0.551
	Std. dev. coeff.	σ_1	0.075	0.524
Hybrid	Mean coeff.	$\overline{\phi_2}$	3.008^{**}	0.549
	Std. dev. coeff.	σ_2	0.024	0.336
HILO	Mean coeff.	$\overline{\phi_3}$	2.332^{**}	0.564
	Std. dev. coeff.	σ_3	0.852^{**}	0.302
The number of brands	Mean coeff.	γ_1	0.243^{**}	0.017
Driving time	Mean coeff.	γ_2	-0.098^{**}	0.006
Income × EDLP	Mean coeff.	ω_{11}	-0.685^{**}	0.289
Income × Hybrid	Mean coeff.	ω_{21}	−0.466	0.285
Income × HILO	Mean coeff.	ω_{31}	−0.461	0.287
Household size × EDLP	Mean coeff.	ω_{12}	0.586	0.922
Household size × Hybrid	Mean coeff.	ω_{22}	0.135	0.920
Household size × HILO	Mean coeff.	ω_{32}	0.781	0.928
Age × EDLP	Mean coeff.	ω_{13}	-1.535^{*}	0.818
Age × Hybrid	Mean coeff.	ω_{23}	-1.686^{**}	0.815
Age × HILO	Mean coeff.	ω_{33}	0.234	0.828
Education × EDLP	Mean coeff.	ω_{14}	0.735^{**}	0.256
Education × Hybrid	Mean coeff.	ω_{24}	0.499^{**}	0.254
Education × HILO	Mean coeff.	ω_{34}	0.152	0.258
Employment × EDLP	Mean coeff.	ω_{15}	-0.973^{**}	0.259
Employment × Hybrid	Mean coeff.	ω_{25}	-0.873^{**}	0.258
Employment × HILO	Mean coeff.	ω_{35}	-0.923^{**}	0.260
Shopping frequency × EDLP	Mean coeff.	ω_{16}	0.335	0.223
Shopping frequency × Hybrid	Mean coeff.	ω_{26}	0.299	0.223
Shopping frequency × HILO	Mean coeff.	ω_{36}	0.444^{**}	0.225
Simulated log likelihood at convergence			−1,943	
AIC			3,943	
BIC			4,105	

Notes: A single asterisk (*) indicates significance at the 10% level. A double asterisk (**) indicates significance at the 5% level.

Table S5. Testing of the Magnitude Relationship between ψ_1 and ψ_2

Variable	Parameter	Symbol	Estimate	Std Error
Coeff. of absolute risk aversion × EDLP	Mean coeff.	ψ_1	−0.132	1.380
Coeff. of absolute risk aversion × EDLP + Coeff. of absolute risk aversion × Hybrid	Mean coeff.	ψ_2	−3.978*	2.183
Coeff. of absolute risk aversion × HILO	Mean coeff.	ψ_3	−6.665**	2.210
EDLP	Mean coeff.	$\overline{\phi_1}$	2.729**	0.551
	Std. dev. coeff.	σ_1	0.074	0.524
Hybrid	Mean coeff.	$\overline{\phi_2}$	3.008**	0.549
	Std. dev. coeff.	σ_2	0.024	0.336
HILO	Mean coeff.	$\overline{\phi_3}$	2.332**	0.564
	Std. dev. coeff.	σ_3	0.852**	0.302
The number of brands	Mean coeff.	γ_1	0.243**	0.017
Driving time	Mean coeff.	γ_2	−0.098**	0.006
Income × EDLP	Mean coeff.	ω_{11}	−0.685**	0.289
Income × Hybrid	Mean coeff.	ω_{21}	−0.466	0.285
Income × HILO	Mean coeff.	ω_{31}	−0.461	0.287
Household size × EDLP	Mean coeff.	ω_{12}	0.586	0.922
Household size × Hybrid	Mean coeff.	ω_{22}	0.135	0.920
Household size × HILO	Mean coeff.	ω_{32}	0.781	0.928
Age × EDLP	Mean coeff.	ω_{13}	−1.535*	0.818
Age × Hybrid	Mean coeff.	ω_{23}	−1.687**	0.815
Age × HILO	Mean coeff.	ω_{33}	0.234	0.828
Education × EDLP	Mean coeff.	ω_{14}	0.735**	0.256
Education × Hybrid	Mean coeff.	ω_{24}	0.499**	0.254
Education × HILO	Mean coeff.	ω_{34}	0.152	0.258
Employment × EDLP	Mean coeff.	ω_{15}	−0.973**	0.259
Employment × Hybrid	Mean coeff.	ω_{25}	−0.874**	0.258
Employment × HILO	Mean coeff.	ω_{35}	−0.923**	0.260
Shopping frequency × EDLP	Mean coeff.	ω_{16}	0.335	0.223
Shopping frequency × Hybrid	Mean coeff.	ω_{26}	0.299	0.223
Shopping frequency × HILO	Mean coeff.	ω_{36}	0.444**	0.225
Simulated log likelihood at convergence			−1,943	
AIC			3,943	
BIC			4,105	

Notes: A single asterisk (*) indicates significance at the 10% level. A double asterisk (**) indicates significance at the 5% level.