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RESEARCH ARTICLE

Demand for Plant-Based Meat Alternatives and the Role of Habit Formation and Variety Seeking

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Abstract
Novel plant-based meat alternatives (PBMAs) have the potential to disrupt traditional meat industries, but only if consumers substitute PBMAs for meat over time. This study uses weekly household scanner data from 2018 to 2020, to estimate demand for PBMAs in the ground meat market. We use a basket-based demand approach by estimating a multivariate logit model (MVL) to determine cross-product relationships between PBMAs, ground turkey, ground chicken, and ground beef, while simultaneously exploring the role of prior consumption habits and demographics on demand. The only demographic characteristic affecting PBMA demand is the household education level of having a college degree when controlling for other factors. We found no significant seasonal difference in purchasing patterns, after controlling for cross-product effects, prior purchases, and demographics. Demand for PBMAs is driven by habit formation rather than variety seeking, as higher past purchases of PBMAs lead to a higher likelihood of current PBMA purchases. Consumers with higher past ground beef purchases are less likely to choose PBMAs, suggesting growth of this new product is coming from consumers on the margin rather than from heavy beef buyers substituting away from their traditional purchases. PBMAs and ground beef are utility complements with all meat products, suggesting that traditional meat and PBMA companies, along with retailers, should explore synergies in product marketing and offerings.

Keywords: Beef; chicken; demand; habit; plant-based meat alternatives; Turkey; variety

JEL Codes: Q00; Q10; Q13; D12

1. Introduction

Encouraging substitution to plant-based diets, including novel plant-based meat alternatives (PBMAs) designed to mimic the taste and texture of meat, has been suggested as a way to reduce land-use, water use, and greenhouse gas emissions, while lowering the risk of chronic diseases and mortality rates, and improving animal welfare (Clark et al., 2019; Clark and Tilman, 2017; Eshel et al., 2014; Fehér et al., 2020; Godfray et al., 2018; Heller et al., 2018; Springmann et al., 2016; Zheng et al., 2019). Multiple fast food chains, such as KFC and Burger King, have prominently featured PBMAs on their menu (Burger King, 2021; Valinsky, 2022), and the PBMA market has received substantial attention in media (Reynolds, 2022; Turow-Paul and Egan, 2022). Whether the PBMAs deliver on their promises ultimately depends on consumer acceptance and the extent to which consumers are willing to substitute away from meat towards PBMAs. We bring revealed preference, longitudinal, household scanner data to bear on the question in a way that allows us to track a given household's purchases over time, which permits a study of the extent to which habit formation or variety seeking help explain adoption and substitution patterns. Moreover, it allows us to study estimates of the cross-product relationships between PBMAs and ground meats.

We build on prior literature that leverage hypothetical choice experiments, retail scanner data, and household scanner data to understand consumer demand for PBMA, each with their own set of limitations. Stated preference data from hypothetical choice experiments (Bryant et al., 2019; Carlsson et al., ; Onwezen et al., 2021; Slade, 2018; Tonsor et al., 2022; Van Loo et al., 2020) constrain consumers' options to predetermined hypothetical choices at a single point in time and assume all products are substitutes, limiting insights into dynamic purchasing behavior. Retail scanner data (Capps and Wang, 2024; Brown et al., 1994; Fousekis and Revell, 2000) capture market-level demand patterns but do not account for household dynamics (Zhao et al., 2022), making it difficult to study factors like habit formation or variety-seeking behavior. Household scanner data provide a way to track purchases at the household level over time, yet prior studies using these data have not accounted for cross-product relationships (Cuffey et al., 2022; Neuhofer and Lusk, 2022).

Demand for PBMAs has been explored in the literature using hypothetical and non-hypothetical methods revealing key insights into this novel product. One prior nonhypothetical demand analysis using retail scanner data aggregated to the national level (Zhao et al., 2022), found that PBMAs and beef were demand complements, while finding PBMAs to be price substitutes for chicken, turkey, and fish. Other elasticity estimates from hypothetical choice experiments suggest that PBMAs are weak price substitutes for beef (Tonsor et al., 2022). Household scanner data studies employing both econometric (Cuffey et al., 2022) and descriptive methods (Neuhofer and Lusk, 2022) suggest that a majority of PBMA buying households made purchases of PBMAs on multiple occasions though their meat expenditures did not decline.

This study addresses key limitations in different consumer demand methodologies while building on prior research by using revealed preference, longitudinal, household scanner data, allowing us to analyze dynamic purchasing behaviors and cross-product relationships. First, we determine the cross-product relationships for ground meats and PBMAs using a basket-based choice model, which permits a flexible representation of substitution or complementary patterns in the utility relationship between goods. We use the metrics of cross-utility parameters to compare products. Our cross-utility parameters can be interpreted as utility complements or utility substitutes, which imply that household utility either increases or decreases when purchasing two products simultaneously. This is different from cross-price elasticities which are demand changes in a product with respect to price changes in another product, as our utility estimates are not a function of price. Our second objective is to understand how prior consumption patterns affect demand for meat and PBMAs. If consumers' PBMA demand exhibits variety-seeking behavior, or ground beef demand is characterized by a high degree of habit formation, growth in the market for PBMAs is likely to face headwinds. This deviates from prior studies that analyzed semblances of habit formation, whether households made a subsequent purchase (Neuhofer and Lusk, 2022) or how their dollar expenditures changed on PBMAs and other goods after a purchase (Cuffey et al., 2022), but these were not estimated in a model allowing for flexible choice substitution.

Despite initial strong growth and gains in market shares, recent reports and media coverage suggest novel PBMA sales are declining (Ignaszewski, 2023; Little, 2022; Olen, 2022; Reiley, 2022; Reorink, 2022; Reynolds, 2022). It has also been speculated that the novelty of PBMAs has worn off, with media sources suggesting much of the early growth was a result of variety-seeking behavior (Reiley, 2022; Reynolds, 2022). If PBMAs are primarily novelty-driven, long-term market penetration may be limited. Moreover, despite the expectation that PBMAs will displace meat consumption, studies show that consumers who buy PBMAs also continue purchasing meat (Cuffey et al., 2022; Neuhofer and Lusk, 2022; Zhao et al., 2022). In fact, this complementarity in consumption is somewhat reflected in the interest by large food processors in the U.S. such as Tyson and Smithfield to add PBMA offerings to their portfolio (Best, 2024; Feedstuffs, 2019).

This study contributes to the literature by providing new insights into demand for PBMAs using revealed preferences from household scanner data. The demand relationship between PBMAs and ground meats is critical in understanding the impact of PBMA sales on the livestock industry, with demand shifts toward PBMAs having larger negative impacts on cattle herds and rancher profitability when there is greater substitutability between PBMAs and ground beef (Lusk et al., 2022). Estimates using an equilibrium displacement model suggest that a 10% decline in PBMA price would increase PBMA consumption by 23%, but would have small impacts in the number of domestic cattle slaughtered, leading to a 0.15% reduction (Lusk et al., 2022). These changes culminate to a 1.14% reduction in emissions from U.S. beef production, reinforcing the need to further investigate substitution effects.

We find that a household head (HH) having a college degree significantly increases PBMA demand. Demand for PBMAs is driven by habit formation rather than variety seeking, as higher past purchases of PBMAs lead to a higher likelihood of current PBMA purchases. Consumers with higher prior ground beef purchases are less likely to choose PBMAs. We also find that PBMAs and ground beef are utility complements with all meat products.

The rest of this paper is organized as follows; section 2 denotes the econometric framework of the multivariate logit model (MVL), which includes the utility function, the prior purchase variables, cross-product parameters, and price effect estimation; section 3 denotes a data overview of the IRI household scanner data set used in this study; section 4 is the results from the econometric estimation; and section 5 are the discussions and conclusions of the study.

2. Empirical design

It is often the case that multiple items are purchased simultaneously. As such, the conventional single discrete choice modeling framework, such as the multinomial logit (MNL), is likely inappropriate. This is particularly true if some products are demand complements, as the MNL forces all products to be demand substitutes. Following recent literature (Caputo and Lusk, 2022; Richards and Bonnet, 2018), a MVL is used to analyze the data. Rather than modeling a single choice out of a set, the MVL considers the bundle or combination of choices made in a given period, allowing for flexible substitution patterns between products. The MVL is similar to the MNL but instead of assuming a consumer is limited to only one choice of J possible products, it is instead assumed the consumer chooses one product or multiple products in the same shopping trip out of 2^J possible bundles. In our case, there are four possible ground products (beef, chicken, turkey, and PBMA) plus "none," implying there are $2^4 = 16$ possible baskets that could be constructed.

There are two primary strengths of using a MVL basket-based approach. First, as previously indicated, it is not uncommon for a household to make two or more unique product selections during a shopping trip. A traditional choice model assumes that each choice is unique and independent of other choices, which is not necessarily the case in a grocery store setting. A second strength of the basket-based approach is that it permits a wider array of complements/substitutes relationships.[1] A habit in our context is denoted as a repeated purchase that gives utility to the

[1]We opted for the basket-based choice model over a continuous demand system approach, like the Almost Ideal Demand System (AIDS) (Deaton and Muellbauer, 1980). The large number of "zeros" poses a problem for AIDS and related models, leading to undefined expenditure shares (Tiffin and Arnoult, 2010). Authors sometimes use various econometrics methods to address the selection bias presented by zero purchases (Heien and Wessells, 1990; Yen and Lin, 2006), but the approaches rest on functional form assumptions and first-stage instruments for identification. Another common issue with demand system approaches is that the addition of demand shifters, such as demographics, can lead to estimates that violate invariance as they depend on the units of measurement (Alston et al., 2001). A final concern with continuous demand system approaches is that they are conditional demand systems, which assume that consumers follow two-stage budgeting and allocate a given amount of expenditures to "meat." However, PMBAs have the potential to expand the market size and draw in new customers and spending to the category, which leads us to prefer the MVL.

household, while variety seeking would indicate disutility that would contribute to a different purchase in a subsequent time period. We estimate the effects of the frequency of prior purchases on subsequent purchases. A positive own-product prior purchase coefficient indicates that households are more likely to purchase the product on subsequent shopping trips and are engaging in routine choice or habit formation and a negative coefficient would imply disutility with the purchase, and an increased probability of a different selection in future time periods (Adamowicz, 1994; Adamowicz and Swait, 2013; Guilfoos et al., 2023; Neuhofer and Lusk, 2022).

The MVL operates within the random utility framework (Mcfadden, 1974). The random utility derived from the b^{th} basket is assumed to follow $U_{ibt} = V_{ibt} + \varepsilon_{ibt}$ where:

$$V_{ibt} = \sum_{j=1}^{J} \alpha_{ijt} x_{jt} + 0.5 \sum_{j=1}^{J} \sum_{k \neq j}^{J} \gamma_{jk} x_{ijt} x_{ikt} \tag{1}$$

x_{ijt} is a dummy variable taking the value of 1 if basket b contains the jth item in time t and zero otherwise. The parameter α_{ijt}represents the utility of selecting food item j. The base utility can be specified as a function of product and household specific variables such as, price, demographic characteristics, quarterly fixed effects, and prior purchases as detailed below.

The parameters denoted by γ_{jk} represent the cross-product relationships between the different products in the basket, which show the effects an additional product purchased has on the utility of the basket. A value of $\gamma_{jk} > 0$ indicates that the products are utility complements, which implies that the utility for product j increases when product k is also in the basket. When $\gamma_{jk} < 0$, the utility of product j falls when product k is in the basket, indicating that products j and k are substitutes in utility[2].

The MVL model can be estimated as a series of logit models with some cross-equation restrictions (Caputo and Lusk, 2022; Russell and Petersen, 2000). The two cross-equation restrictions revolve around the γ_{jk} parameters; 1) $\gamma_{jj} = 0$ implying that no additional utility is gained from the selection of two of the same product, and 2) a symmetry restriction of $\gamma_{jk} = \gamma_{kj}$ implying that the cross-product relationship is symmetric for products j and k in their respective logit models.

2.1 Specification of baseline utility

Demographic variables were added to the model to control for preference heterogeneity across households. In addition, quarterly time fixed effects were added to account for demand shifts that potentially occurred due to seasonality or other unique demand shocks (e.g., from the spike in grocery spending around COVID-19 shutdowns). We specify the initial base utility as:

$$\alpha_{ijt} = \alpha_{0jt} + \beta p_{ijt} + X_i \delta_j + \theta_{jt} T_t, \tag{2}$$

where the base utility α_{ijt} is a function of an alternative specific constant α_{0jt}, the price of product j in time t paid by household i, p_{ijt}, a vector of household demographics X_i, and a vector of quarterly fixed effects T_t. The parameters are given by β, δ_j, and θ_{jt}.

Table 1 defines the individual household characteristics variables used in the model. Among households that have both a male and female head of household, we used the female demographics as the demographic variables of interest for age and education. The female HH characteristics are used because prior research suggests the females are the primary grocery shoppers (Schaeffer, 2019). Some demographics are recorded for the HH, and others for the entire household (EH). These demographics are presented as categories with ranges and we have condensed them further to limit the number of covariates to aid in model convergence and appropriate sample sizing as scanner data sets tend to lean toward older families (Muth et al., 2016).

[2]For more information on assumptions in the MVL model, we follow the procedures in Caputo and Lusk (2022).

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Table 1. Demographics

Characteristic	Levels	For household head (HH) or entire household (EH)	Number of households	% in Category
Age	Young (<35)	HH	410	5.14%
	Middle Age (35 – 64)		4956	62.14%
	Old (65+)		2609	32.71%
Household size	1	EH	1004	12.59%
	2		3950	49.53%
	3		1311	16.44%
	4		1052	13.19%
	5+		658	8.25%
Marital Status	Married	EH	6156	77.19%
	Single Female		1478	18.53%
	Single Male		341	4.28%
Education level	College	HH	3196	40.08%
Employment	Employed	EH	5778	72.45%
Household Income	Low (<$45,000)	EH	2205	27.65%
	Middle ($45,000 – $99,999)		3822	47.92%
	High (>$100,000)		1948	24.43%
Household Race	Minority Race	HH	1430	17.93%
Presence of Children	Children present	EH	1741	21.83%

This table shows the household demographics, the different levels for the demographics, whether they are for the household head or entire household, and the share of households in each category.

The demographic breakdowns for the HH specific characteristics are age (Young <35, Middle Age 35 – 64, and Old 65+), education level (College degree or not), race (minority race or not). The breakdowns for the EH are household size (1 – 5+), marital status (married, single female, and single male), employed (employed or not), income (<$45,000, $45,000 – $99,999), and $100,000) and the presence of children under 18 (children present or not). In our selected set of households, we observe predominantly middle age households (35 – 64) (62.14%), followed by older households (65+) (32.71%). The age categories from youn g and middle age combine a few age categories for a HH as young combines both 18 – 24 and 25 – 34, and middle age combines 3 nine-year age group categories. The largest household size is two people at 49.53% but we also observe households with 1, 3, 4, and 5+ members. For marital status the largest category is "married" accounting for 77.19% of our households. We also have sizable single female and single male households. Single male and female households combine the marital status of single, divorced, and widowed. While socially there are differences between the marital statuses, we combine categories to limit the number of covariates as well as to the fact that all of these marital statuses capture the preferences of a single person in a household as the primary shopper. For education level, 40.08% of households have a head with a college degree. We use college degree status as the cutoff due to prior studies denoting that possession of a bachelor's degree is a primary driver for PBMA demand and not as divided by further categories (Neuhofer and Lusk, 2022; Van Loo et al., 2020).

Most of the households have a member of the household who is currently employed (72.45%) with the remainder consisting of those not employed which would include retired. A minority of households have a HH of a minority race (17.93%) which includes African-American, Asian-American, and other. Lastly, we control for whether the household has children under 18 present which consists of 21.83% of households.

2.2 Habit formation and prior purchases

Economists have long been interested in the effects of the prior consumption on future demand, recognizing that demand is dynamic (Pollak, 1970). Given the panel nature of our dataset, we can explore the extent to which prior purchases influence current decisions (Adamowicz, 1994; Adamowicz and Swait, 2013). Multiple studies have examined habit formation or variety seeking in demand. In many cases demand is correlated with prior purchases, as seen in models that examine household living expenses (Alessie and Kapteyn, 1991; Kapteyn et al., 1997), meat (Holt and Goodwin, 1997), addictive goods like alcohol and tobacco (Pierani and Tiezzi, 2009), tourism (Adamowicz, 1994; Boto-garcía, 2022; Guilfoos et al., 2023), and travel (Xu et al., 2017). Additionally, there is a substantial literature on variety-seeking behavior (Kahn, 1995; McAlister and Pessemier, 1982; Verplanken, 2018), which has been identified in markets such as food purchases in tourism (Mak et al., 2012), food (Adamowicz and Swait, 2013), and wine (Caracciolo et al., 2022).

Our MVL approach can account for both habit forming and variety seeking by allowing the baseline utility of each product to be specified as a function of past purchases of the same product. In addition, we control for the prior purchases of other products to further understand the cross-product effects and relationships between the ground meats. Many previous studies estimate demand in the current period to be a function of a single-period lag of prior purchases (Adamowicz and Swait, 2013; Boto-garcía, 2022). However, given that most of our consumers do not make repeated purchases from one week to the next, we opt to model effects of previous purchases through the total number of prior purchase occasions of products (Adamowicz, 1994; Xu et al., 2017). Examining the weighted number of prior purchase occasions is a useful way to determine habit formation or variety seeking even when multiple time periods have passed. Additionally, cumulative purchase occasions allow for us to examine the likelihood of subsequent purchases as frequency increases.[3] We specify the baseline utility with prior purchase variables as:

$$\alpha_{ijt} = \alpha_{0jt} + \beta p_{ijt} + X_i\delta_j + \theta_{jt}T_t + \sum_{j=1}^{J}\varphi_j N_{ijt} \tag{3}$$

where N_{ijt} is the cumulative number of times product j was purchased by household i prior to period t divided by the number of weeks prior to the purchase, so for example, if the first PBMA was purchased in week 1 and week 2 and no subsequent weeks, the variable in week 5 would take the value 2/5. Dividing by the previous number of weeks results in a variable bound between zero and one, which aided in model convergence.[4] Habit forming behavior occurs when $\varphi_j > 0$, implying more past purchases of j increases the current utility of j (Adamowicz, 1994). A value of $\varphi_j < 0$, indicates variety-seeking behavior as more past purchases of product j reduce the utility of j at present (Adamowicz, 1994). For other products k, a value of $\varphi_{ikt} > 0$ indicates that more prior purchases of product k increase the likelihood and utility of selecting product j, and a

[3]In addition, we considered a specification in which demand was specified as a function of prior purchases only in the prior three weeks. The results of this model are shown in Appendix Table 3. Model fit statistics, such as AIC, indicate the model with the cumulative number of purchases over all previous weeks in the sample provide a better it to the data.

[4]We also considered a specification that ignored the cross-product effects of prior purchases (e.g., past purchases of beef were only permitted to affect beef demand). This model is shown in Appendix Table 2. A Likelihood Ratio Test rejects this model (Chi-Square value of 4,433, degrees of freedom of 12, and p-value of 0.00) in favor of the model presented in the main text with the prior cross-product effects, indicating a better fit.

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value of $\varphi_j < 0$ indicates that more prior purchases of product k decrease the likelihood and utility of selecting product j.

2.3 Prices and endogeneity

As with all analyses of household scanner datasets, price series must be constructed before demand estimation can proceed. For missing price values we followed methods used in prior studies that impute mean or median prices for products that were either random weight or for products that were not selected in the given week in the choice model (Brooks and Lusk, 2010; Jonas and Roosen, 2008; Roosen et al., 2022; Sweitzer et al., 2017).[5] For chosen items that are not random weight, unit prices are calculated: expenditure is divided by the total weight (in lbs.). Many meat products, however, are sold random weight, meaning expenditure but not weight is known. For random weight products, we assigned per-pound prices by averaging the prices of nonrandom weight items of the same type (beef, chicken, turkey, or PBMA) in the same week the purchase was made. In the case of PBMAs, all averages are from actual price values, as there are no random weight PBMAs in the dataset.

Similarly, for products that were not purchased in a basket, we impute prices by calculating the average weekly per-pound price of all items purchased that week of the same type. In the calculation of prices, there were some extreme outliers, likely indicating mistakes in data recording (e.g., prices greater than \$50/lb.). We trimmed the price distribution by replacing outliers in the 1% tails of the distribution with the mean observed per-pound price of all other items of the same type purchased in the same week. While these procedures have the potential to introduce measurement error, they also have the advantage of reducing concerns about endogeneity issues associated with strategic pricing or unobserved qualities affecting prices.

We adopt the control function approach of Petrin and Train (2010) to aid in estimating price effects. Demographic factors are included in the first-stage control function under the premise that these can capture some of the quality variation across households (Brooks and Lusk, 2010 and Cox and Wohlgenant, 1986). As described above, random weight items and prices of products that were not selected have no price variation within a given time period as these observations use the mean price as the imputed value, and as such we include a dummy indicating whether the selected product has a unique per-pound price that is not the imputed mean price for the week. This nonimputed dummy variable and subsequent interaction terms are included for unobserved quality differences (Brooks and Lusk, 2010; Cox and Wohlgenant, 1986). In addition to the demographic regressors for quality control in the control function, we include some wholesale meat prices as instruments to control for potential supply side shocks on the farm, as wholesale prices would react to potential changes in the supply chain (Goodwin, 2006; Heien, 1980). We used the average beef cutout price for ground beef, average chicken price across all cuts, the average for whole turkey hens, and soybean meal for PBMAs; all data are originally reported by USDA and were obtained from the Livestock Marketing Information Center. All of the wholesale prices are collected at the national level as recorded from the USDA. These wholesale prices were chosen because typically ground meats are formed from the trimmings of other meat cuts, and thus weighted averages are likely better reflections of input prices (USDA, 2016, 2023). In the case of soybean meal, it is a common input in animal feed and soy is a common input in PBMAs. In the first-stage regression, each of the wholesale prices were lagged two weeks to account for differences in timing of cost incurred by retailers and ultimate retail prices charged to consumers. Additionally, we included the time period fixed effects[6].

[5]Share of price imputations per ground meat and PBMA product is available in Appendix Table 6. The effect of the imputation of prices leads to measurement error which will make the true relationship between price and choice appear weaker than it actually is.

[6]Prices may vary based on the geographic location of the purchases; however, our household panel data does not include any geographic variables on the purchases so no geographic instruments were used.

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Following the framework of Petrin and Train (2010), the residuals from the first-stage regression equation are included in the base utility terms in the second stage estimation of equation 3. A significant coefficient on the residuals in the second stage regression indicates the presence of endogeneity (Petrin and Train, 2010). We can specify the first-stage regressions as[7]:

$$p_{ijt} = \zeta_{ij} W_{t-2} + \widetilde{\theta_{jt}} T_t + X_i \widetilde{\delta_j} + I_{ijt}\lambda + I_{ijt} X_i \varrho + \tilde{\varepsilon}_{ijt} \tag{4}$$

Where we regress the endogenous price value for household i for product j in time period t (p_{ijt}) on the vector of wholesale prices of primal chuck boxed beef, frozen hens, chicken breasts, and soybean meal two time periods prior to time period t (W_{t-2}); a vector of quarterly fixed effects ($\tilde{T}||jt$), a vector of household demographics ($X||i$), an indicator variable to denote that the price was a unique nonimputed price (I_{ijt}), and an interaction between the demographic controls and the nonimputed price indicator to account for variations in product quality (Brooks and Lusk, 2010; Cox and Wohlgenant, 1986). The residual value that is input into the second stage regression is denoted as $\tilde{\varepsilon}_{ijt}$, which leads to our final base utility estimation[8] as:

$$\alpha_{ijt} = \alpha_{0jt} + \beta p_{ijt} + \tilde{\varepsilon}_{ijt} + X_i \delta_j + \theta_{jt} T_{jt} + \sum_{j=1}^{J} \varphi_j N_{ijt} \tag{5}$$

3. Data overview

We use weekly IRI household panel data on ground meat (beef, chicken, turkey) and PBMA purchases from November 2018 to November 2020. To limit the sample of households to more frequent shoppers, our selection criterion was limited to households that purchased one of the four products at least once every quarter (13 weeks). Households that did not purchase at least one ground meat or PBMA during each quarter were removed from the dataset. The final dataset consists of the purchase patterns of 7,975 households in each of the 104 weeks studied[9]. The purchase data is recorded at a Universal Product Code (UPC) level. Each UPC code is attached to a specific product description, which includes a multitude of product characteristics such as brand, processing method, refrigerated vs. frozen, and packaging type. Additionally, demographic and socio-economic information is available for each household, such as income, household size, age, education, and race[10].

To construct the consumers' choice sets we focus attention on ground meat purchases including ground beef, ground turkey, ground chicken[11], and PBMAs. While other PBMA products exist, the recently introduced "novel" PBMAs resemble ground meats (Beyond Meat, 2021; Impossible Foods, 2021). Additionally, evidence suggests that demand for meat products, like ground meat is separable from general meat aggregates like "beef" or "chicken" (Eales and Unnevehr, 1988). The IRI household panel dataset does not have a strict code for PBMAs. To identify a PBMA we use key words in product descriptions that reference that the option is a

[7]Results from the first-stage regressions are found in Appendix Table 5.

[8]Following Petrin and Train (2010) we use a bootstrapping method to estimate the standard errors of our second stage regression. We used 1000 bootstrapped block samples of our data to estimate the standard errors. Appendix Table 4 shows the standard errors with no bootstrapping procedures.

[9]Our sample was formed from 43,694 households in the original meat purchase dataset.

[10]Due to the acquisition process of this data which was given for free from IRI to academic researchers the data is limited in certain aspects compared to datasets used in resources such as, Muth et al., 2016. Our dataset does not include specific trip or geographic information.

[11]One common product used in meat demand studies is pork. In our scanner dataset, none of the ground pork UPCs passed the threshold of being purchased on 50 or more occasions. Additionally, sausage options were not included due to different common uses than ground beef, chicken, turkey, and PBMAs. The inclusion of sausage would also require additional disaggregation between beef, Turkey, chicken, and pork, which would lead to difficulties in model convergence with a larger choice set.

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substitute or vegetarian product, some of these key words included "vegetarian," "plant-based substitute," and "vegetable," when associated with words like "patty" and "burger"[12]. In addition, we also identified popular brands that are known to be PBMAs. Our method of identifying PBMAs differs some from Zhao et al. (2022) and Cuffey et al. (2022). Zhao et al. (2022) focuses on the "fresh meat" category of Nielsen retail scanner data which leads to the primary sample consisting of products from brands such as "Impossible Foods" and "Beyond Meat." Cuffey et al. (2022) includes meat alternatives that are "Dry Goods" (nonfrozen) and frozen based on departments and product modules in the Nielsen household scanner data. Our data includes a variety of PBMAs that extend beyond the brands observed in the fresh meat retail scanner data, as our dataset also includes traditional vegetarian burgers, where retail scanner data is typically limited to the "novel" PBMAs. Our differences from Cuffey et al. (2022) are based on data availability and search methods. We identified PBMAs from product descriptions in our data set manually while they searched through specific product categories. Products such as tofu or seitan were excluded. Our UPC selection process was limited to products that were purchased on at least 50 occasions over the two-year span. We used this criterion because many of these product types were ambiguous and were unidentifiable as to species of animal product. Ultimately, the dataset used in this analysis consists of information on 244,421 transactions, 489 UPCs, and 7,975 households. Within these transactions and UPCs, major brands and manufacturers of PBMAs, ground beef, ground chicken, and ground turkey were included. Our dataset includes fresh and frozen products for all categories, as well as random weight, branded, and private label products.

3.1 Data aggregation

The UPC level data were aggregated to the product-week level: ground turkey, ground beef, ground chicken, or ground/patty PBMAs. We decided to aggregate the data to the product-week level because a week was the standard unit of time in our scanner data. We aggregated the product categories to 4 to aid in model convergence. A larger choice set creates difficulties in model convergence due to the higher number of cross-product combinations (Caputo and Lusk, 2022). In most weeks, the typical household did not purchase a product, and for these weeks, the household effectively chooses a "no purchase" option. The aggregation leads to the creation of a balanced panel dataset of 7,975 households over 104 weeks for a total of 829,400 observations.

Table 2 shows the percentage of times a product was chosen and the average prices of each item. Ground beef had the highest selection share at 18.59% of all choices; ground beef was in 69.69% of baskets conditional on a product being selected. The product with the second-largest market share is ground turkey at 6.63% of all baskets and 24.85% conditional on choosing a product at an average price $3.39 a pound, which was also the most affordable option on average. PBMAs were the third most selected product and were in 1.92% of baskets overall or in 7.18% of baskets conditional on a product being selected. The average price of PBMAs was $6.55/lb., higher than the average ground beef price of $3.84/lb. The least popular product was ground chicken, which was selected in 1.08% of baskets overall and in 4.06% of baskets in which a product was selected.

Table 3 shows summary statistics for purchasing frequency of ground meat products by households who also purchased PBMA and those who did not. Twenty-four percent of the sample purchased PBMA at some point during the 104 weeks study period with mean purchase of 8.25 occasions. Those who did not purchase PBMA had higher mean purchases of ground beef (21.31 times) than those who did purchase PBMA (12.68 times). Those who did not purchase PBMA had lower mean ground turkey purchases (5.97 times) than those who did (9.65 times).

[12]Due to our data contract, we are unable to disclose any keywords used from the product descriptions or any brand names of products.

Table 2. Products in basket

Product	% of Times Chosen	Average Price ($/lb.)	% of Times Chosen Conditional on Buying a Product
Ground Turkey	6.63%	$3.39	24.85%
PBMA	1.92%	$6.55	7.18%
Ground Chicken	1.08%	$3.76	4.06%
Ground Beef	18.59%	$3.84	69.69%
No Buy	73.32%	——	——

This table shows the frequency of selection of the option overall, the average price the product was purchased at, and the share of selections without accounting for the "no buy" option.

Table 3. Mean and standard deviation frequency of ground meat purchase for households who bought and did not buy PBMA

Product Type	Household Purchased PBMA	Household Did not Purchase PBMA
Ground Turkey	9.65*	5.97*
	(12.73)	(10.96)
Ground Beef	12.68*	21.31*
	(13.12)	(13.80)
Ground Chicken	1.64*	0.96*
	(5.53)	(3.95)
Share of households (%)	*24%*	*76%*
Average Purchases	*8.25*	

Means were statistically different (at least at the 0.05 level) between those who purchase and do not purchase PBMA as denoted by *.

Table 4 shows all the potential baskets and how often each was selected. The most commonly selected basket was "none" – selected 73.32% of the time. The next most popular basket was ground beef alone, which accounted for 17.42% of baskets, followed by ground turkey alone (5.47%), and PBMA alone (1.59%). The two most common baskets that contained multiple products were ground beef and ground turkey (0.82%) and the basket that contained ground beef and a PBMA (0.16%). The most common three-product basket consisted of ground turkey, ground beef, and ground chicken (0.03%).

4. Results

Estimates of equation (3) are shown in Table 5[13,14]. All the cross-product utility effects are positive, suggesting that all products are utility complements. For example, when ground beef is purchased alongside PBMAs, utility increases 0.152. Because these are estimates from a logit model, it indicates that the odds of purchasing beef are $\exp(0.152) = 1.16$ if a PBMA is also in the basket;

[13]The positive and significant effect associated with the first-stage residuals suggests the presence of endogeneity, which is accounted for by the control function approach, results from the first-stage residuals are in Appendix Table 5.

[14]In the appendix (Appendix Table 1, Appendix Table 2) we show alternative specifications; Appendix Table 1 shows a model ignoring habit/variety and Appendix Table 2 shows a model that includes only the own-product prior purchases. AIC model fit criteria indicate these models are inferior to the model reported in the main text.

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Table 4. Baskets and choice probabilities

Basket	Ground Beef	Ground Turkey	PBMA	Ground Chicken	None	Number of Observations	Percent of Times Chosen	Percent of Times Chosen Conditional on Buying a Product
1	Yes	—	—	—	—	144,466	17.42%	65.29%
2	—	Yes	—	—	—	45,340	5.47%	20.49%
3	—	—	Yes	—	—	13,165	1.59%	5.95%
4	—	—	—	Yes	—	5,931	0.72%	2.68%
5	Yes	Yes	—	—	—	6,777	0.82%	3.06%
6	Yes	—	Yes	—	—	1,289	0.16%	0.58%
7	Yes	—	—	Yes	—	1,262	0.15%	0.57%
8	—	Yes	Yes	—	—	1,112	0.13%	0.50%
9	—	Yes	—	Yes	—	1,329	0.16%	0.60%
10	—	—	Yes	Yes	—	140	0.02%	0.06%
11	Yes	Yes	Yes	—	—	121	0.01%	0.05%
12	Yes	Yes	—	Yes	—	256	0.03%	0.12%
13	Yes	—	Yes	Yes	—	14	0.00%	0.01%
14	—	Yes	Yes	Yes	—	52	0.01%	0.02%
15	Yes	Yes	Yes	Yes	—	3	0.00%	0.00%
16	—	—	—	—	Yes	608,143	73.32%	

This table show the number of times a choice set (basket) was chosen, as well as the percentage of selections.

Table 5. MVL estimates with demographics, time fixed effects, cross-product relationships, and cumulative prior purchases of products

Variable	Turkey	Beef	Chicken	PBMA	None
Cross-Product Relationships					
Ground Turkey	—	0.352* (0.021)	0.752* (0.068)	0.331* (0.040)	—
Ground Beef	0.352* (0.021)	—	0.469* (0.041)	0.152* (0.038)	—
Ground Chicken	0.752* (0.068)	0.469* (0.041)	—	0.033 (0.105)	—
PBMA	0.331* (0.040)	0.152* (0.038)	0.033 (0.105)	—	—
Base Utilities					
Constant	−0.881 (5.104)	0.651 (5.984)	−2.163 (5.690)	0.839 (10.160)	1.184* (0.033)
Price	−0.72 (1.485)	−0.72 (1.485)	−0.72 (1.485)	−0.72 (1.485)	—
Residuals	0.679 (1.501)	0.727 (1.489)	0.58 (1.529)	0.704 (1.510)	—
Q1	−0.102 (0.130)	−0.149 (0.368)	−0.417* (0.156)	−1.043 (0.949)	0.022* (0.010)
Q2	−0.035 (0.135)	−0.182 (0.425)	−0.228 (0.207)	−0.816 (1.006)	−0.019 (0.010)
Q3	−0.078 (0.150)	−0.178 (0.469)	−0.201 (0.131)	−0.49 (0.790)	−0.032* (0.010)
Q4	−0.018 (0.125)	−0.181 (0.439)	−0.107 (0.127)	−0.321 (0.352)	−0.034* (0.010)
Q5	0.001 (0.024)	−0.18 (0.339)	−0.146 (0.152)	−0.25 (0.342)	0.006 (0.010)
Q6	0.166 (0.122)	0.064 (0.162)	0.061 (0.049)	−0.123 (0.178)	−0.124* (0.010)
Q7	0.111* (0.053)	0.044 (0.025)	−0.019 (0.098)	0.042 (0.078)	−0.061* (0.010)
Single Female	0.126* (0.037)	−0.042* (0.013)	0.167 (0.094)	0.097 (0.037)	0.016 (0.020)
Single Male	0.048 (0.074)	−0.051* (0.026)	−0.073 (0.203)	0.028 (0.175)	−0.085* (0.042)
Household Size	0.033 (0.027)	0.037* (0.007)	−0.007 (0.041)	0.042 (0.040)	−0.055* (0.010)
College	0.087* (0.033)	−0.063* (0.010)	0.106 (0.064)	0.138* (0.062)	0.041* (0.015)
Employed	0.061 (0.033)	0.003 (0.012)	0.103 (0.091)	0.078 (0.077)	−0.057* (0.019)
High Income	0.05 (0.065)	0.02 (0.014)	0.16* (0.067)	0.132 (0.071)	−0.016 (0.018)
Children	−0.009 (0.041)	−0.051* (0.017)	0.067 (0.096)	−0.057 (0.101)	0.052* (0.025)

(*Continued*)

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Table 5. (*Continued*)

Variable	Turkey	Beef	Chicken	PBMA	None
Low Income	−0.09 (0.052)	−0.01 (0.014)	−0.142 (0.093)	0.002 (0.085)	0.01 (0.018)
Young	0.113* (0.056)	−0.032 (0.023)	0.152 (0.115)	0.018 (0.116)	−0.051 (0.033)
Old	−0.035 (0.035)	0.013 (0.013)	−0.195* (0.083)	−0.069 (0.093)	0.018 (0.019)
Non-White	0.081 (0.05)	−0.107* (0.016)	−0.032 (0.076)	0.021 (0.078)	0.063 (0.018)
Prior Purchase Effects					
Cumulative Prior Ground Turkey Purchases	6.906* (0.089)	−2.513* (0.126)	0.21 (0.250)	−0.672* (0.187)	—
Cumulative Prior Ground Beef Purchases	−3.029* (0.137)	4.051* (0.039)	−2.251* (0.264)	−4.82* (0.344)	—
Cumulative Prior Ground Chicken Purchases	0.193 (0.232)	−1.442* (0.209)	12.125* (0.382)	0.272 (0.440)	—
Cumulative Prior PBMA Purchases	−1.72* (0.208)	−3.604* (0.286)	−1.25 (0.870)	9.555* (0.272)	—
Log-Likelihood				2,194,953	
AIC				2,195,197	

A * denotes significance at the 5% level. Base utility estimates are relative to 2020 Q4, married, not college educated, not employed, middle income, without children, middle age, and White. SE are estimated with 1000 bootstrapped draws.

that is, adding ground beef to the basket is associated with a (1.16 – 1)*100 = 16% increase in PBMA also being placed in the basket[15].

Greater prior purchase amounts of a product lead to higher utility of the same product, indicating habit formation for ground beef, turkey, chicken, and PBMAs. We confirm habit formation based on the significant positive coefficients seen for the prior own-product purchases. If variety seeking was the primary driver of demand we would anticipate a significant negative coefficient, indicating a likely substitution to other products. The own-product habit effect of cumulative past purchases for PBMAs is estimated at 9.55. Recalling that we scaled past purchases by the prior week t the purchase occurred on, we will use an example of a single purchase as of week 50. A one-time increase in past purchases is equivalent to an increase in N_{ijt} of 1/50 = 0.02, if the value is estimated in week 50. Thus, one prior purchase of PBMA results in the odds of current PBMA purchase of exp(9.555*0.02) = 1.21. That is, the odds of choosing PBMA today increases by 21% in week 50 if PBMAs had been purchased once in the prior weeks. By contrast, a purchase of a PBMA in the past reduces the odds of selecting ground beef by 100*(exp(−3.604*0.02)−1)) = −6.95% in week 50.

If we continue with our example of a single prior purchase in week 50, we can estimate the effects of prior ground beef selections. If say 1 purchase of ground beef had been made in the prior weeks the odds of a purchase of ground beef in week 50 would be 8.44% (100*(exp(4.051*0.02)−1) = 8.44%),

[15]It is interesting to note that without including habit/variety effects (see model in Appendix Table 1), or only including the own-product effects, ground beef and PBMAs are estimated as utility substitutes (Appendix Table 1). That is, interpretation of whether beef and PBMAs are utility complements or substitutes hinges on the extent to which prior purchase behaviors are included in the model. Model fit criteria and likelihood ratio tests suggest the model with prior purchases better fits the data, and as such, the conclusion of utility substitutes between beef and PBMA is likely a result of omitted variable bias and not accounting for habit formation.

whereas the odds of selecting PBMA in the present *falls* by 9.19% (100*(exp(−4.82*0.02)−1 = −9.19%). Thus, while previous research has correctly observed the same households who buy PBMAs also buy ground beef (at least over some extended period of time), the results here show that "heavy buyers" of ground beef are less likely to choose a PBMA. More prior purchases of ground beef decreased the utility of purchasing ground turkey and PBMAs. Interestingly, we observed that more prior purchases of ground turkey decreased the utility of subsequent purchases of PMBA and ground beef. More prior purchases of ground chicken decrease the utility of ground beef purchases.

The time effects were largely insignificant except for the those associated with the "no choice" option. Households were less likely to buy ground chicken in the last quarter of 2018 than in 2020, and households were more likely to purchase ground turkey in the second quarter of 2020 than the third. Generally, this implies that when controlling for cross-product effects, demographics, and prior purchases that there is little seasonal difference in purchases. Single female households receive more utility from ground turkey than married households, while receiving less utility than married households for ground beef. Households with more members have higher demand for ground beef. College educated households received more utility from ground turkey and PBMAs than noncollege educated households, while receiving less for ground beef. A household with a college educated head rather than noncollege educated increases the odds of PBMA selection by 100*(exp(0.138)−1) = 14.80%. High income households received more utility from ground chicken than middle income households. Younger households received more utility from ground turkey than middle aged households, while older households received less utility for ground chicken than middle aged households. Non-White households less utility from ground beef than white households

5. Discussion and conclusions

Controlling for prior purchases provides insights into the relationships between products. Our results show evidence that habit formation is a primary driver of PBMA demand, as indicated by the significant and positive coefficients of the own-product prior purchase effects showing that households are more likely to purchase one on a subsequent occasion and are better off. These results imply that in a dynamic setting, households that are purchasing PBMAs make them a routine decision in their weekly shopping trips. Variety seeking would have indicated that households would have been more likely to shift their focus to a different product after the initial purchase.

Prior purchases of ground turkey, ground chicken, and PBMAs decrease the utility of subsequent ground beef purchases. We also find that more prior purchases of PBMAs decrease the utility of ground turkey selections and vice versa. These results build on prior studies that showed that consumers who purchased a meat alternative were more likely to purchase them on another occasion (Cuffey et al., 2022; Neuhofer and Lusk, 2022). These results imply that as households increase their PBMA consumption, subsequent ground beef purchases become less likely, even though PBMA purchasing households are less likely to buy ground beef to start with. Ultimately, higher volumes of PBMA purchases may in time contribute to substitution from ground beef (Cuffey et al., 2022; Neuhofer and Lusk, 2022).

The signs of our cross-product utility estimates show that ground beef and PMBAs are utility complements. These results imply that households are better off when buying both ground beef and a PBMA in a basket. The complementarity of products could suggest that households purchase both PBMAs and ground meats to satisfy heterogenous dietary preferences in the household. These results confirm the complementarity of PBMAs and ground meats suggested in prior revealed preference studies in a different measure than price elasticity (Cuffey et al., 2022; Neuhofer and Lusk, 2022; Zhao et al., 2022).

We determine that demand for PBMAs did not vary significantly with time when controlling for prior purchases and cross-product effects. College educated households were more likely to select PBMAs or ground turkey while being less likely to buy ground beef. We did not observe any other significant demographic effects with respect to PBMA demand.

Our study is not without limitations. The market for PBMAs is relatively new – compared to traditional ground beef offerings – and in the midst of change. Our dataset ranges from November 2018 to 2020, thus not allowing us to capture more recent fluctuations in this market (Reorink, 2022; Watson, 2021) but allowing us to understand PBMAs during their nascent stage, and laying the foundations for future analysis into their evolution. Another limitation is that a majority of the products are "random weight" and we are unable to deduce true per-pound price for these products and have to rely on average prices of observed brands. Some consequences of the high number of random weight entries are the lack of heterogeneity in prices, as well as increased difficulty of accounting for quality attributes of the products. Another issue with the dataset is that we have no way to account for regional variation apart for knowing that the purchases of the products occurred in the United States. An ideal dataset would account for regional differences in prices and our first-stage regressions would support that. Additionally, these limitations expand to our use of wholesale prices for instruments to account for supply side shocks. Wholesale prices are only available at the national level, and data on regional transactions that occur between retailers and meat processors are not available. These limitations contribute to imprecision in the estimates from the first-stage regressions.

Additionally, some differences in our results may be due to PBMA classification. We limited the PBMAs in the dataset to products resembling ground meats and burgers, while other studies were more expansive in their selection of products (Cuffey et al., 2022; Zhao et al., 2022). While both studies used more PBMAs in their analysis, our product selection considers more direct substitutes for their corresponding product of ground meat. Additionally, the focus on ground meats is due to the rise in the newer novel PBMAs that imitate ground meats.

Despite these limitations we are still able to provide consistent results with prior hypothetical and revealed preference studies, finding the utility complementarity between PBMAs and meats, while adding to the discussion surrounding the effects of prior purchases (Cuffey et al., 2022; Neuhofer and Lusk, 2022; Tonsor et al., 2022; Van Loo et al., 2020). We also confirm the results that find PBMA consumers to be educated at least to a college degree level (Bryant et al., 2019; Cuffey et al., 2022; Neuhofer and Lusk, 2022; Slade, 2018; Tonsor et al., 2022b; Van Loo et al., 2020).

Broadly, these findings provide insights into greater implications for beef markets. Our results show that while habit formation is a primary driver for PMBAs, the utility complementary between PBMAs and ground beef, as well as the higher share of beef selections indicates that PBMAs are not displacing beef at a high rate as the low share reflects less popularity. Greater implications of this effect would echo Lusk et al. (2022) which suggest that reductions in PBMA prices would do little to offset the beef industry and its subsequent climate impacts. Thus, the industry may need to look beyond to other protein alternatives to beef, rather than PBMAs alone, to reduce the impacts to the climate and meet protein demands for growing populations.

Our findings regarding the utility complementarity of PBMA and other ground meats are congruent with food processors' interest in PBMA offers and support the notion that meat companies and retailers might continue to explore strategies such as developing hybrid products combining PBMAs with ground meat or co-marketing campaigns that emphasize their complementarity to meet evolving consumer preferences. Our study would suggest that such collaborations have the potential to appeal to diverse dietary needs and heterogeneity in preferences within the household, without materially compromising market share of traditional offerings.

Poultry products could have a greater impact on beef markets. A fairly high share of baskets contained ground turkey and while there was utility complementarity between ground beef and ground turkey, higher purchase frequency of ground turkey decreased ground beef consumption similar to PBMAs. The basket with the highest share of multiple products purchases were combinations of ground beef and turkey. Despite the utility complementarity, the higher share of turkey purchase is evidence that it is a much more popular product. Studies suggest that in general poultry production systems are less impactful on the environment than other livestock systems (Leinonen and Kyriazakis, 2016), thus a decrease in beef demand from increased turkey and other poultry consumption could offset environmental impacts.

Several questions still remain about the current state and future opportunities for the PBMA market in consumer demand. One untouched research area is food away from home as several restaurant chains, such as Kentucky Fried Chicken, Burger King, and Del Taco have introduced PBMA options on their menu. To our knowledge, no revealed preference studies have been conducted to examine demand for PBMA in the food away from home market. Additionally, more research is needed in the realm of alternatives to traditional meat such as cultivated meat and fermented proteins (Ron and Smith, 2022). More insight is needed into markets for alternatives to other animal products and meats, particularly, sausage, chicken, and milk. Lastly, future research should examine how these dynamics have evolved in response to market disruptions and shifting consumer preferences, particularly as PBMAs transition from a nascent product to a more established market presence.

Data availability statement. Due to our data contract with IRI, we are unable to share the data used in this study.

Author contribution. Conceptualization: Z.T.N and J.L.L.; Methodology: Z.T.N.; Formal Analysis: Z.T.N., M.A.O; Data Curation: Z.T.N and J.L.L.; Writing – Original Draft.; Z.T.N.; Writing – Review and Editing. J.L.L, M.A.O.; Supervision: J.L.L.

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Appendix

Table A1. MVL with No Habit or Variety Seeking Effects

Variable	Turkey	Beef	Chicken	PBMA	None
			Cross Product Relationships		
Ground Turkey	—	−0.399* (0.009)	1.065* (0.020)	0.103* (0.021)	—
Ground Beef	−0.399* (0.009)	—	−0.005 (0.020)	−0.804* (0.020)	—
Ground Chicken	1.065* (0.020)	−0.005 (0.020)	—	0.077 (0.050)	—
PBMA	0.103* (0.021)	−0.804* (0.020)	0.077 (0.050)	—	—
			Base Utilities		
Constant	−0.288* (0.140)	1.735* (0.163)	−1.657* (0.164)	1.537* (0.278)	1.184* (0.013)
Price	−0.811* (0.040)	−0.811* (0.040)	−0.811* (0.040)	−0.811* (0.040)	—
Residuals	0.798* (0.043)	0.863* (0.043)	0.876* (0.080)	0.818* (0.044)	—
Q1	−0.036 (0.018)	−0.219* (0.015)	−0.194* (0.043)	−0.814* (0.042)	0.021* (0.010)
Q2	0.006 (0.018)	−0.222* (0.016)	−0.144* (0.043)	−0.798* (0.042)	−0.019 (0.010)
Q3	−0.042* (0.018)	−0.215* (0.017)	−0.137* (0.043)	−0.519* (0.038)	−0.032* (0.010)
Q4	−0.006 (0.018)	−0.212* (0.016)	−0.076 (0.042)	−0.313* (0.033)	−0.034* (0.010)
Q5	0.017 (0.018)	−0.205* (0.015)	−0.120* (0.043)	−0.264* (0.032)	0.006 (0.010)
Q6	0.178* (0.018)	0.044* (0.012)	0.083* (0.041)	−0.119* (0.031)	−0.124* (0.010)
Q7	0.112* (0.018)	0.045* (0.011)	0.017 (0.042)	0.016 (0.030)	−0.061* (0.010)
Single Female	0.174* (0.013)	−0.121* (0.009)	0.126* (0.031)	0.214* (0.023)	0.016* (0.007)
Single Male	0.214* (0.024)	−0.108* (0.015)	0.069 (0.057)	0.992* (0.033)	−0.085* (0.013)
Household Size	0.020* (0.006)	0.105* (0.004)	−0.137* (0.015)	−0.054* (0.011)	−0.055* (0.003)
College	0.285* (0.010)	−0.218* (0.006)	0.150* (0.023)	0.323* (0.018)	0.041* (0.005)
Employed	0.192* (0.013)	−0.033* (0.008)	0.457* (0.034)	0.262* (0.024)	−0.058* (0.007)
High Income	0.113* (0.011)	−0.013 (0.007)	0.057* (0.026)	0.032 (0.020)	−0.016* (0.006)
Low Income	0.165* (0.015)	−0.177* (0.010)	0.208* (0.036)	0.013 (0.028)	0.051* (0.009)

(*Continued*)

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Table A1. (*Continued*)

Variable	Turkey	Beef	Chicken	PBMA	None
Children	−0.121* (0.012)	0.024* (0.007)	−0.131* (0.029)	−0.085* (0.021)	0.011 (0.006)
Young	0.312* (0.018)	−0.107* (0.014)	0.114* (0.042)	0.278* (0.032)	−0.051* (0.011)
Old	−0.100* (0.012)	0.037* (0.007)	−0.276* (0.031)	−0.202* (0.022)	0.018* (0.007)
Non-white	0.315* (0.011)	−0.302* (0.008)	0.334* (0.025)	0.146* (0.02)	0.063* (0.007)
Log-Likelihood				−2,397,023	
AIC				2,397,235	

A* denotes significance at the 5% level. The values are relative to 2020 Q4, married, not college educated, not employed, middle income, without children, middle age, and white. This model does not contain any of the habit formation or variety seeking effects, this model was not chosen due to higher AIC value.

Table A2. MVL Estimates with Demographics, Time Fixed-Effects, Cross-Product Relationships, and Cumulative Own-Product Prior Purchases with No Cross Product Habit Effects

Variable	Turkey	Beef	Chicken	PBMA	None
Cross-Product Relationships					
Ground Turkey	—	0.019 (0.010)	0.885* (0.023)	0.369* (0.023)	—
Ground Beef	0.019 (0.010)	—	0.237* (0.021)	−0.309* (0.021)	—
Ground Chicken	0.885* (0.023)	0.237* (0.021)	—	0.070 (0.058)	—
PBMA	0.369* (0.023)	−0.309* (0.021)	−0.723* (0.037)	—	—
Base Utilities					
Constant	−1.323* (0.130)	0.468* (0.150)	−2.495* (0.156)	0.219 (0.258)	1.184* (0.013)
Price	−0.723* (0.037)	−0.723* (0.037)	−0.723* (0.037)	−0.723* (0.037)	—
Residuals	0.690* (0.039)	0.729* (0.040)	0.574* (0.059)	0.713* (0.039)	—
Q1	−0.014 (0.020)	−0.112* (0.015)	−0.316* (0.049)	−0.911* (0.045)	0.022* (0.010)
Q2	−0.006 (0.020)	−0.171* (0.016)	−0.173* (0.047)	−0.793* (0.044)	−0.019 (0.010)
Q3	−0.060* (0.020)	−0.171* (0.017)	−0.155* (0.047)	−0.484* (0.04)	−0.031* (0.010)
Q4	−0.008 (0.020)	−0.174* (0.016)	−0.068 (0.046)	−0.324* (0.036)	−0.034* (0.010)
Q5	0.010 (0.020)	−0.173* (0.015)	−0.110* (0.047)	−0.251* (0.036)	0.006 (0.010)
Q6	0.178* (0.020)	0.069* (0.012)	0.097* (0.045)	−0.118* (0.035)	−0.124* (0.010)

(*Continued*)

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Table A2. (*Continued*)

Variable	Turkey	Beef	Chicken	PBMA	None
Q7	0.113* (0.019)	0.046* (0.012)	0.008 (0.046)	0.030 (0.034)	−0.060* (0.010)
Single Female	0.157* (0.014)	−0.056* (0.009)	0.185* (0.034)	0.152* (0.026)	0.016* (0.007)
Single Male	0.064* (0.027)	−0.086* (0.016)	−0.083 (0.070)	0.115* (0.043)	−0.086* (0.013)
Household Size	0.004 (0.007)	0.032* (0.004)	−0.027 (0.016)	−0.015 (0.012)	−0.055* (0.003)
College	0.139* (0.011)	−0.091* (0.007)	0.159* (0.025)	0.216* (0.020)	0.041* (0.005)
Employed	0.051* (0.015)	−0.020* (0.008)	0.096* (0.037)	0.094* (0.027)	−0.057* (0.007)
High Income	0.055* (0.012)	0.014 (0.008)	0.163* (0.028)	0.159* (0.023)	−0.016* (0.006)
Children	0.038* (0.016)	−0.060* (0.01)	0.101* (0.038)	0.026 (0.031)	0.052* (0.009)
Low Income	−0.087* (0.013)	0.004 (0.007)	−0.157* (0.032)	0.012 (0.024)	0.010 (0.006)
Young	0.118* (0.020)	−0.073* (0.014)	0.130* (0.048)	0.113* (0.037)	−0.051* (0.011)
Old	−0.023 (0.014)	0.028* (0.008)	−0.210* (0.034)	−0.063* (0.025)	0.018* (0.007)
Non-White	0.170* (0.012)	−0.134* (0.008)	0.031 (0.029)	0.147* (0.023)	0.063* (0.007)
Prior Purchase Effects					
Prior Own-Product Purchases	7.551* (0.030)	4.486* (0.019)	12.463* (0.089)	10.834* (0.058)	—
Log-Likelihood				-2,209,553	
AIC				2,209,773	

A* denotes significance at the 5% level. The values are relative to 2020 Q4, married, not college educated, not employed, middle income, without children, middle age, and white. This model only has the own-product effects for the habit formation effects. It was not chosen due to higher AIC value.

Table A3. MVL Estimates with Demographics, Time Fixed-Effects, Cross-Product Relationships, and Prior Three Period Lag

Utility/Product	Turkey	Beef	Chicken	PBMA	None
Cross Product Relationships					
Ground Turkey	—	−0.012 (0.010)	0.838* (0.022)	0.246* (0.023)	—
Ground Beef	−0.012 (0.010)	—	0.244* (0.021)	−0.316* (0.021)	—
Ground Chicken	0.838* (0.022)	0.244* (0.021)	—	0.065 (0.054)	—
PBMA	0.246* (0.023)	−0.316* (0.021)	0.065 (0.054)	—	—

(*Continued*)

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Table A3. (*Continued*)

Utility/Product	Turkey	Beef	Chicken	PBMA	None
Base Utilities					
Constant	−1.355* (0.127)	0.538* (0.147)	−2.854* (0.152)	−0.528* (0.252)	1.184* (0.013)
Price	−0.557* (0.036)	−0.557* (0.036)	−0.557* (0.036)	−0.557* (0.036)	—
Residuals	0.533* (0.039)	0.595* (0.039)	0.601* (0.058)	0.545* (0.038)	—
Q1	−0.015 (0.019)	−0.154* (0.015)	−0.161* (0.045)	−0.560* (0.042)	0.021* (0.010)
Q2	0.003 (0.019)	−0.153* (0.016)	−0.120* (0.044)	−0.530* (0.042)	−0.019 (0.010)
Q3	−0.022 (0.019)	−0.143* (0.016)	−0.102* (0.044)	−0.322* (0.038)	−0.032* (0.010)
Q4	0.000 (0.019)	−0.141* (0.016)	−0.072 (0.044)	−0.199* (0.034)	−0.034* (0.010)
Q5	0.011 (0.019)	−0.149* (0.014)	−0.094* (0.044)	−0.154* (0.034)	0.006 (0.010)
Q6	0.142* (0.019)	0.065* (0.012)	0.042 (0.043)	−0.063 (0.033)	−0.124* (0.010)
Q7	0.090* (0.019)	0.045* (0.012)	0.001 (0.044)	0.054 (0.032)	−0.061* (0.010)
Single Female	0.107* (0.013)	−0.085* (0.009)	0.105* (0.032)	0.136* (0.025)	0.016* (0.007)
Single Male	0.150* (0.025)	−0.061* (0.015)	0.041 (0.060)	0.623* (0.036)	−0.086* (0.013)
Household Size	0.020* (0.006)	0.090* (0.004)	−0.099* (0.015)	0.011 (0.012)	−0.055* (0.003)
College	0.159* (0.010)	−0.158* (0.006)	0.067* (0.024)	0.165* (0.019)	0.041* (0.005)
Employed	0.138* (0.014)	−0.014 (0.008)	0.346* (0.035)	0.169* (0.026)	−0.057* (0.007)
High Income	0.086* (0.011)	−0.004 (0.007)	0.034 (0.027)	0.023 (0.021)	−0.016* (0.006)
Children	0.076* (0.015)	−0.139* (0.010)	0.148* (0.037)	−0.070* (0.029)	0.052* (0.009)
Low Income	−0.087* (0.012)	0.010 (0.007)	−0.103* (0.030)	−0.064* (0.022)	0.011 (0.006)
Young	0.194* (0.018)	−0.056* (0.014)	0.022 (0.044)	0.153* (0.034)	−0.051* (0.011)
Old	−0.072* (0.013)	0.018* (0.007)	−0.186* (0.032)	−0.157* (0.024)	0.018* (0.007)
Non-white	0.141* (0.011)	−0.223* (0.008)	0.196* (0.026)	0.055* (0.021)	0.063* (0.007)
Prior Purchase Effects					
Prior Ground Turkey Purchases over last 3 weeks	1.743* (0.009)	−0.775* (0.010)	0.055* (0.026)	−0.364* (0.025)	—
Prior Ground Beef Purchases over last 3 weeks	−0.768* (0.011)	0.525* (0.006)	−0.547* (0.025)	−0.949* (0.023)	—

(*Continued*)

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Table A3. (*Continued*)

Utility/Product	Turkey	Beef	Chicken	PBMA	None
Prior Ground Chicken Purchases over last 3 weeks	0.131* (0.023)	−0.382* (0.021)	3.151* (0.023)	−0.141* (0.054)	—
Prior PBMA Purchases over last 3 weeks	−0.314* (0.023)	−0.907* (0.021)	0.034 (0.050)	2.946* (0.018)	—
Log-Likelihood				−2,292,559	
AIC				2,292,803	

A* denotes significance at the 5% level. The values are relative to 2020 Q4, married, not college educated, not employed, middle income, without children, middle age, and white. This model uses a habit formation and variety seeking specification with a dummy variable rather than the chosen specification of Number of selections/Week. The dummy variable takes a value of 1 if the product has been selected in the last three weeks. The model was not selected due to a higher AIC value.

Table A4. MVL Estimates with Demographics, Time Fixed-Effects, Cross-Product Relationships, and Cumulative Prior Purchases of Products without bootstrapped standard errors

Variable	Turkey	Beef	Chicken	PBMA	None
Cross-Product Relationships					
Ground Turkey	—	0.352* (0.01)	0.752* (0.025)	0.331* (0.025)	—
Ground Beef	0.352* (0.01)	—	0.469* (0.022)	0.152* (0.022)	—
Ground Chicken	0.752* (0.025)	0.469* (0.022)	—	0.033 (0.062)	—
PBMA	0.331* (0.025)	0.152* (0.022)	0.033 (0.062)	—	—
Base Utilities					
Constant	−0.881* (5.104)	0.651* (5.984)	−2.163* (5.690)	0.839* (0.256)	1.184* (0.013)
Price	−0.72* (0.037)	−0.72* (0.037)	−0.72* (0.037)	−0.72* (0.037)	—
Residuals	0.679* (0.039)	0.727* (0.04)	0.58* (0.058)	0.704* (0.038)	—
Q1	−0.102* (0.02)	−0.149* (0.015)	−0.417* (0.049)	−1.043* (0.045)	0.022* (0.01)
Q2	−0.035 (0.02)	−0.182* (0.016)	−0.228* (0.047)	−0.816* (0.044)	−0.019 (0.01)
Q3	−0.078* (0.02)	−0.178* (0.017)	−0.201* (0.047)	−0.49* (0.04)	−0.032* (0.01)
Q4	−0.018 (0.02)	−0.181* (0.016)	−0.107* (0.046)	−0.321* (0.037)	−0.034* (0.01)
Q5	0.001 (0.02)	−0.18* (0.015)	−0.146* (0.047)	−0.25* (0.036)	0.006 (0.01)
Q6	0.166* (0.02)	0.064* (0.012)	0.061 (0.045)	−0.123* (0.035)	−0.124* (0.01)
Q7	0.111* (0.02)	0.044* (0.012)	−0.019 (0.046)	0.042 (0.034)	−0.061* (0.01)
Single Female	0.126* (0.014)	−0.042* (0.009)	0.167* (0.034)	0.097* (0.026)	0.016* (0.007)

(*Continued*)

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Table A4. (*Continued*)

Variable	Turkey	Beef	Chicken	PBMA	None
Single Male	0.048 (0.028)	−0.051* (0.016)	−0.073 (0.07)	0.028 (0.043)	−0.085* (0.013)
Household Size	0.033* (0.007)	0.037* (0.004)	−0.007 (0.016)	0.042* (0.013)	−0.055* (0.003)
College	0.087* (0.011)	−0.063* (0.007)	0.106* (0.026)	0.138* (0.02)	0.041* (0.005)
Employed	0.061* (0.015)	0.003 (0.008)	0.103* (0.037)	0.078* (0.027)	−0.057* (0.007)
High Income	0.05* (0.012)	0.02* (0.008)	0.16* (0.028)	0.132* (0.023)	−0.016* (0.006)
Children	−0.009 (0.016)	−0.051* (0.01)	0.067 (0.038)	−0.057 (0.031)	0.052* (0.009)
Low Income	−0.09* (0.013)	−0.01 (0.007)	−0.142* (0.032)	0.002 (0.023)	0.01 (0.006)
Young	0.113* (0.02)	−0.032* (0.014)	0.152* (0.047)	0.018 (0.037)	−0.051* (0.011)
Old	−0.035* (0.014)	0.013 (0.008)	−0.195* (0.034)	−0.069* (0.025)	0.018* (0.007)
Non-White	0.081* (0.012)	−0.107* (0.008)	−0.032 (0.029)	0.021 (0.023)	0.063* (0.007)
Prior Purchase Effects					
Cumulative Prior Ground Turkey Purchases	6.906* (0.031)	−2.513* (0.039)	0.21* (0.088)	−0.672* (0.084)	—
Cumulative Prior Ground Beef Purchases	−3.029* (0.046)	4.051* (0.02)	−2.251* (0.106)	−4.82* (0.106)	—
Cumulative Prior Ground Chicken Purchases	0.193* (0.094)	−1.442* (0.094)	12.125* (0.09)	0.272 (0.175)	—
Cumulative Prior PBMA Purchases	−1.72* (0.098)	−3.604* (0.091)	−1.25* (0.233)	9.555* (0.063)	—
Log-Likelihood				−2,194,953	
AIC				2,195,197	

A* denotes significance at the 5% level. Base utility estimates are relative to 2020 Q4, married, not college educated, not employed, middle income, without children, middle age, and white. This model has the safe coefficient values as in table 4, but the standard errors are not bootstrapped.

Table A5. First stage regressions of price determinants

Variables/Dependent Variable	Ground Turkey Price	Ground Beef Price	Ground Chicken Price	PBMA Price
Intercept	2.704* (0.02)	3.843* (0.014)	2.999* (0.01)	1.022* (0.029)
Wholesale Prices Lagged Two Weeks				
Average Beef Wholesale Price	−0.015* (0.001)	-0.018* (0.001)	−0.017* (0.000)	0.163* (0.002)
Soybean Meal	1.714* (0.048)	−3.129* (0.035)	1.888* (0.027)	10.131* (0.077)
Turkey Hens	0.398* (0.016)	0.559* (0.011)	0.372* (0.008)	3.319* (0.023)

(*Continued*)

Table A5. (*Continued*)

Variables/Dependent Variable	Ground Turkey Price	Ground Beef Price	Ground Chicken Price	PBMA Price
Average Chicken Wholesale Price	−0.020* (0.005)	0.034* (0.004)	0.136* (0.003)	−0.339* (0.007)
Time Period Fixed Effects				
Q1	−0.016* (0.002)	−0.171* (0.002)	−0.068* (0.001)	−0.007 (0.004)
Q2	−0.011* (0.003)	−0.215* (0.002)	−0.101* (0.001)	−0.018* (0.004)
Q3	−0.009* (0.003)	−0.220* (0.002)	−0.041* (0.002)	0.245* (0.004)
Q4	−0.006* (0.002)	−0.239* (0.002)	−0.026* (0.001)	0.371* (0.003)
Q5	0.062* (0.002)	−0.201* (0.001)	−0.070* (0.001)	0.189* (0.003)
Q6	0.121* (0.001)	−0.094* (0.001)	0.019* (0.001)	0.199* (0.002)
Q7	0.081* (0.002)	−0.022* (0.001)	0.099* (0.001)	0.088* (0.002)
Base Demographics				
Single Female	−0.00001 (0.00017)	−0.0003 (0.00035)	0.00007 (0.00038)	0.00021 (0.00073)
Single Male	0.00009 (0.0003)	−0.001 (0.001)	−0.00023 (0.00068)	0.00037 (0.00132)
Household Size	0.00006 (0.00008)	0.00023 (0.00016)	−0.00001 (0.00018)	0.00025 (0.00034)
College	0.00006 (0.00012)	−0.001* (0.00026)	0.00011 (0.00028)	−0.00026 (0.00054)
Employed	0.00008 (0.00016)	−0.00044 (0.00033)	−0.00011 (0.00036)	0.00008 (0.00068)
High Income	0.00000 (0.00015)	−0.00036 (0.0003)	−0.00016 (0.00033)	0.00006 (0.00064)
Children	−0.00007 (0.0002)	−0.001 (0.00041)	−0.0002 (0.00045)	−0.00002 (0.00087)
Low Income	0.00003 (0.00014)	0.00027 (0.0003)	0.00004 (0.00033)	−0.00008 (0.00063)
Young	0.0001 (0.00027)	−0.001 (0.001)	−0.00005 (0.0006)	0.00065 (0.00115)
Old	−0.00005 (0.00015)	0.00026 (0.00031)	−0.0002 (0.00034)	0.00025 (0.00065)
Non-White	0.00017 (0.00015)	−0.001* (0.00000)	0.00012 (0.00034)	−0.00024 (0.00066)
Non-Imputed Price Observations and Demographic Interactions				
Non-Imputed Price Observation (NP)	0.074* (0.024)	0.060 (0.041)	0.220* (0.059)	−0.118 (0.100)
NP* Single Female	0.127* (0.014)	0.073* (0.030)	0.184* (0.035)	−0.023 (0.056)

(*Continued*)

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Table A5. (*Continued*)

Variables/Dependent Variable	Ground Turkey Price	Ground Beef Price	Ground Chicken Price	PBMA Price
NP* Single Male	0.172* (0.025)	−0.095 (0.052)	0.011 (0.058)	0.279* (0.082)
NP* Household Size	−0.078* (0.006)	−0.063* (0.011)	−0.104* (0.017)	0.041 (0.026)
NP* College	0.090* (0.010)	0.035 (0.021)	0.070* (0.027)	0.124* (0.043)
NP* Employed	0.033* (0.015)	0.154* (0.026)	−0.044 (0.039)	0.067 (0.059)
NP* High Income	0.262* (0.012)	0.255* (0.024)	0.187* (0.03)	0.129* (0.051)
NP* Children	0.057* (0.015)	−0.030 (0.028)	0.168* (0.043)	−0.248* (0.065)
NP* Low Income	−0.205* (0.013)	−0.281* (0.022)	−0.329* (0.029)	−0.233* (0.048)
NP* Young	0.091* (0.018)	−0.105* (0.041)	0.063 (0.048)	−0.035 (0.079)
NP* Old	0.103* (0.014)	0.208* (0.025)	0.201* (0.035)	−0.355* (0.055)
NP* Non-White	−0.185* (0.011)	−0.129* (0.023)	−0.212* (0.026)	0.200* (0.050)

A* denotes significance at the 5% level. These regressions are the average estimates from the first stage price regressions. The residual value from these models is then input into the second stage MVL mode.

Table A6. Share of Price Imputation for the different products

Product Type	Share 1	Share 2
Ground Turkey	94%	11%
Ground Beef	98%	90%
Ground Chicken	99%	24%
Ground Meat Alternatives	98%	2%

*Share 1 is the share of imputed price when accounting for all potential purchase occasions 1-(non-random weight purchases)/(104*7,975 households)
*Share 2 is the share of the imputed price of the actual purchased product (1-(non-random weight purchases/total purchases)

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