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The Determinants of Plant-Based Meat Alternative Purchases in the U.S.: A Double Hurdle Latent Class Growth Model

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The Determinants of Plant-Based Meat Alternative Purchases in the U.S.: A Double Hurdle Latent Class Growth Model

Abstract: Plant-Based Meat Alternative (PBMA) products, as an alternative protein source, are designed to mimic the test and texture of conventional meat and claim to remove the detrimental health effects associated with consuming animal meat. PBMA is still not a substitute for red meat, although the U.S. market is experiencing substantial growth in PBMA products. In this study, we combine socioeconomic and demographic characteristics using household-level consumer panel data covering the entire U.S. to determine the factors influencing PBMA consumption. Using a double hurdle model, we find household size, marital status, age, education, race, and ethnicity play a significant role in PBMA consumption. Price and income do not influence PBMA consumption for the newly participating households. The latent class growth model indicates that most households are occasional consumers while only 11.5% consume PMBA consistently during the study period, although showing a downward trajectory. This indicates that the demand for PBMA has been declining in recent periods. Our results call for more investment in research and development focusing on the PBMA industry so that consumers can decide for themselves if PBMA could be a staple on their plate.

Keywords: plant-based meat, panel-double hurdle model, latent class growth model, demand elasticity, meat

1. Introduction:

Animal agriculture has derived worldwide criticism from environmental, animal welfare, and public health perspectives. It is a major concern as around 14.5% of global greenhouse gas emissions originated from livestock production, and particularly in the U.S., this sector is responsible for almost half of the total greenhouse gas emissions from agricultural activities. The U.S. is one of the heaviest beef-consuming countries (57.2 lb. per capita in 2018), although many consumers reported a desire to reduce their consumption (Neff et al., 2018) and try new alternative protein options (Van Loo et al., 2020). The growing demand and consumption of red and processed meat also exacerbate detrimental health outcomes, forcing many national and international food-based dietary guidelines to advise the reduction of meat consumption (USDA, 2020).

The demand for plant-based protein sources such as soy chunks, tofu, tempeh, and such like other plant products is substantially lower than animal meat products, especially in Western countries like the U.S. Plant-Based Meat Alternative (PBMA) can be a suitable option that is designed not only to replicate the test and texture of conventional meat but also to avoid the detrimental health effects (e.g., cholesterol, saturated fat content) as it is fully plant-based (Lacy-Nichols et al., 2021). The raw ingredients of PBMA are originated from soy, pea, and wheat protein, and the production process has noticeable advantages over the animal meat industry by generating lower greenhouse gas emissions and minimal use of water and land (Heller & Keoleian, 2018; Tilman & Clark, 2014; Zhao et al., 2022).

However, there are some concerns regarding the PBMA being a substitute for animal meat as the cultural identity is deeply bonded with conventional meat, and some concern about nutritional loss during the ultra-processing of PBMA still exists (Hu et al., 2019; Slade, 2018; Zhao et al., 2022). Additionally, there is a lack of clear understanding of the long-run health effects of PBMA as it is a relatively new product. Although the nutritional positioning of PBMA is a matter of debate, if producers promote it as an ‘ultra-processed’ food, then there is a concern regarding some adverse health effects, including obesity, CVD, cancer, and type 2 diabetes (Lacy-Nichols et al., 2021). Hence, meat proponents and some nutrition experts have expressed doubts regarding the potential health benefits the product claims due to its ultra-processing nature (Bohrer, 2019; Khandpur et al., 2021; Santo et al., 2020).

The recent growth of the PBMA industry creates a dire need to identify whether PBMA is only attracting the meat reducers-flexitarians and nonmeat consumers or whether the majority of the PBMA demand is originated from conventional meat consumers (Zhao et al., 2022). To become a mainstream product and an ideal substitute for animal meat, PBMA price needs to be very competitive with conventional meat products. However, due to the lack of research and development and technological advancement, expensive processing methods make the PBMA price higher than some of the conventional meat products (e.g., ground meats). Hence, most consumers may be reluctant to shift from animal meat apart from testing the PBMA once or twice. Based on the focus group discussion in Germany, France, and the Netherlands, Weinrich (2018) identified that consumers may consume meat alternatives once or twice a week but are unlikely to substitute animal meat as consumers prefer the test of conventional meat products. Also, eating habits and convenience are major factors in consuming animal meat instead of meat substitutes. According to the market demand study of PBMA by Zhao et al. (2022), the demand and market share of PBMA in the U.S. is substantially lower than conventional meat. The authors found that consumers consider PBMA as a substitute for chicken, turkey, and fish but as a complement to beef and pork.

Although some consumers were skeptical regarding plant-based meat products' taste, price, safety, and naturalness at the beginning, the uprising market demand shows a promising trajectory for plant-based meat to become viable alternatives to animal meat in the long term. Indeed, the market segment of plant-based meat was worth $939 million in 2019, and it is estimated that by 2025 the market value will be around $27.9 billion in the U.S. (Choudhury et al., 2020). However, the PBMA market may face issues related to sustainable growth in the future, considering consumers' unfamiliarity with the processing nature and the nutritional aspects of the product. Several surveys have been conducted to determine the consumption pattern of plant-based meat among different countries, and the results vary widely. The survey results are dependent on the questionnaire design and terminology that may not necessarily be a true reflection of consumers' purchasing behavior, and thus the result varies significantly even within countries (Bryant et al., 2019).

In this study, we combine a comprehensive list of socioeconomic and demographic characteristics of household-level data covering the entire U.S. rather than focusing only on the own and cross-price elasticity of PBMA. To our best knowledge, there is no study conducted in the U.S. utilizing micro-level household characteristics that determines PBMA consumption using a double hurdle latent class growth model. Moreover, we use retail-level consumer purchase data that accurately represent the market demand for PBMA instead of surveys and questionnaires that create a hypothetical market condition. We also use an instrumental variable and control function approach to depict the price elasticity more accurately, which is the first of its kind in a panel-double hurdle framework. Hence, this study will shed light on the determinants of household PBMA consumption with a class-specific predicted growth trajectory that will eventually help to implement suitable policies for the betterment of both consumers and the PBMA industry.

2. Data and Preliminary Analysis:

Our primary source of data is the Nielsen Scantrack scanner panel data. The enriched dataset contains around 40,000 to 60,0000 active participant households and 35,000 to 55,000 grocery, drug, mass merchandise, and other stores representing the entire U.S. (divided into 52 markets). We compiled plant-based meat price, quantity, household income, and other demographic variables of 6,941 newly participating households during 2019 and 2020 for this study. PBMA consists of various categories of products, whereas Beyond Meat and Impossible Meat brands contribute a substantial proportion of total sales. The household scanner data contains observations of repeated purchasing behavior, including quantities and total expenditure of each household. Hence, the enriched data source is widely used to analyze consumer demand and purchasing behavior (Zare & Zheng, 2021; Zhao et al., 2022; Zhen et al., 2011; Zheng et al., 2016; Cuffee et al., 2022). We select the households that agree to scan and transmit the store-bought items for every month of 2019 and 2020, totaling 24 observations for each household.

The unit price of PBMA cannot be observed directly in the household scanner panel data. Hence, we derive the unit price of purchasing households by dividing the total PBMA expenditure by the total quantity purchased. There is a substantial percentage of households that do not consume PBMA. We thus follow an alternative approach used by Dong & Kaiser (2008) to calculate the unit price. The imputed unit price of non-purchased households is obtained by averaging the unit price of households that purchased PBMA.

One of the major limitations of formulating the unit price following the above approach is the high possibility of price endogeneity that may cause bias in estimates. To address the endogeneity problem, we use an instrumental variable (IV) as an identification strategy. This is the first study to deal with price endogeneity in a panel-double hurdle framework. Let us consider a bivariate model:

$$y = \alpha + \beta x + \varepsilon \tag{1}$$

where x is an endogenous variable and $cov(x, \varepsilon) \neq 0$. We consider an instrumental variable z such that it is correlated with x but not correlated with ε. Hence, to remove the price (p) endogeneity problem, we need to use an IV where $cov(z, p) \neq 0$ but $cov(z, \varepsilon) = 0$. Although satisfying the first requirement $cov(z, p) \neq 0$ is not a concern, in practice fulfilling the second requirement $cov(z, \varepsilon) = 0$ is challenging as ε is unobserved. Thus, we must rely on the economic intuition to meet the assumption. In this study, we are using the average unit price of all the counties within a state, excluding the county the households purchased from, as an IV to solve the price endogeneity problem.

We implement a two-stage residual inclusion approach as a solution for the biased estimate of price. In this method, we first regress the unit price of PBM with the price IV and extract the residual. If we include the residual as a regressor in the econometric model, then the estimators are called two-stage residual inclusion estimators (Palmer et al., 2017). This can be written as:

$$\text{Stage 1: } p = \alpha + \beta p_{iv} + \varepsilon, \qquad \varepsilon \sim N[0, \sigma^2]$$
$$\text{Stage 2: } h(E[Y]) = \beta_0 + \beta_1 p + \beta_2 \hat{\varepsilon} \tag{2}$$

Table 1 represents the descriptive statistics of explanatory variables, including price, income, household size, marital status, age, education, presence of children, race, and ethnicity. We find that 24.46% of households (1698 out of 6941 households) consumed PBMA at least once during 2019 and 2020. The average unit price of PBMA and average household income are \$4.179 and \$64,516.32, respectively. The average household size is 3.168, with a standard deviation of 1.279. Also, a majority of the household head age is more than 45 years regardless of male and female. Only 3.2% and 34.6% of male head age are less than 30 and between 30-45 years. Also, 56.9% household do not have any members less than 18 years old, and 96% household head is married. Our dataset contains 78.1% Caucasian households followed by African American (9.7%), Asian (5.7%), and other races (6.5%). Also, most of the households are from non-Hispanic ethnicity.

3. Econometric Model:

The double hurdle latent class growth model is based on a two-step procedure. In the first stage, we estimate the double hurdle model that contains participation and consumption equations. In the second stage, we use the household socio-demographic categorical variables to define class membership and model latent class growth trajectory framework. In that case, we only consider the households that consume PBMA at least once during 2019 and disregard households that never consume PBMA (the so-called serial nonparticipant households). This is because serial nonparticipant households will not have any trajectory of consumption as they are not evaluating the tradeoff and have a linear zero line with respect to the observed timeframe.

3.1 Double hurdle model

The determinants of plant-based meat consumption embody the idea of a two-stage budgeting decision known as the double hurdle model (Cragg, 1971) due to the presence of a significant percentage of zero-quantity purchases in the dataset. The first stage is called the participation equation, which identifies the households' decision on whether to purchase or not. The second stage is called the consumption equation, which determines the households' decision on the quantity of purchases from the retail market given the circumstances. If y_i denotes the consumption amount of household i, then we can model it as

$$y_i = \begin{cases} x_i\beta + \epsilon_i & if \min(x_i\beta + \epsilon_i, z_i\gamma + u_i) > 0 \\ 0, & otherwise \end{cases}$$

$$\begin{pmatrix} \epsilon_i \\ u_i \end{pmatrix} \sim N(0, \Sigma), \Sigma = \begin{pmatrix} 1 & \sigma_{12} \\ \sigma_{12} & 1 \end{pmatrix} \tag{3}$$

The above equation holds true for cross-sectional data where each household has only one time period observation. However, our household consumption data is in a panel format where each household has 12 months' observations between 2019 and 2020. Hence, we adopt the panel-hurdle framework developed by Dong and Kaiser (2008) and use Engel & Moffatt (2014)'s notations of constructing panel-double hurdle model.

Let us consider observations of i $(i = 1, \dots, n)$ number of households each containing t $(t = 1, \dots, T)$ time period and denote y_{it} as the decision of i^{th} household at time t. Hence, we can write the two hurdles as following:

First hurdle

$$d_i^* = z_i'\alpha + \varepsilon_{1,i}$$
$$d_i = 1 \; if \; d_i^* > 0, d_i = 0 \; otherwise$$
$$\varepsilon_{1,i} \sim N(0,1) \tag{4}$$

The most essential feature of constructing a panel-double hurdle model is to configure the first hurdle that contains only one outcome for each household for all the time periods. It means $d_i = 0$ for i^{th} household indicates all the observations on y along the timeframe must be 0 for that household.

Second hurdle

$$y_{it}^{**} = x_{it}'\alpha + u_i + \varepsilon_{2,it}$$
$$y_{it}^* = \max(y_{it}^{**}, 0)$$
$$\begin{pmatrix} \varepsilon_{1,i} \\ u_i \\ \varepsilon_{2,it} \end{pmatrix} \sim N\left[\begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho\sigma_u & 0 \\ \rho\sigma_u & \sigma_u^2 & 0 \\ 0 & 0 & \sigma^2 \end{pmatrix}\right] \tag{5}$$

Observed

$$y_{it} = d_i y_{it}^* \tag{6}$$

The second hurdle is similar to a standard Tobit model, where y_{it} is the PBM consumption of i^{th} household at time t, y_{it}^{**} is the latent variable that cannot be observed directly but has an effect on y_{it} (Tshabalala & Sidique, 2020), and u_i is the random effect that is subject-specific. We assume that the error term is normally distributed with zero mean in the joint distribution, and ρ indicates the correlation between $\varepsilon_{1,i}$ and u_i.

The model can be estimated using two stages where the first stage evaluates β_1 (probit model) and the second stage β_2 (OLS) (Tshabalala & Sidique, 2020). If $\varphi(.)$ is the distribution function, then probit log-likelihood function can be written as:

$$lnL_i = \sum \ln\big(1 - \varphi(-x_1\beta_1)\big) + (1 - d).\ln(\varphi(-x_1\beta_1)) \tag{7}$$

The OLS log-likelihood function is:

$$lnL_i = \sum \ln\big(1 - \varphi(y_i^* > 0)\big) + \sum \ln(\varphi(y_i^* > 0))g(y_i^*|y_i^* > 0) \tag{8}$$

The panel-double hurdle estimates are generated by Maximum simulated likelihood (MSL) method that uses the Halton draws technique and hence the probabilities are not exact. We further calculate the average marginal effect of exogenous variables on three quantities of interest: (i) the probability of consumption (equation 9), (ii) the expected quantity of consumption given the household consume PBM (equation 8), and (iii) the expected quantity of consumption at unconditional level (equation 7). These three conditions can be written as:

$$E(q_{it}) = Prob(d_i = 1).\left\{\varphi\left(\frac{x_{it}\beta}{\sqrt{\sigma_1^2 + \sigma_2^2}}\right).x_{it}\beta + \sqrt{\sigma_1^2 + \sigma_2^2}.\theta\left(\frac{x_{it}\beta}{\sqrt{\sigma_1^2 + \sigma_2^2}}\right)\right\} \tag{9}$$

$$E(q_{it}|q_{it} > 0) = x_{it}\beta + \sqrt{\sigma_1^2 + \sigma_2^2}.\frac{\theta\left(\frac{x_{it}\beta}{\sqrt{\sigma_1^2 + \sigma_2^2}}\right)}{\varphi\left(\frac{x_{it}\beta}{\sqrt{\sigma_1^2 + \sigma_2^2}}\right)} \tag{10}$$

$$Prob(q_{it} > 0) = Prob(d_i = 1).\varphi\left(\frac{x_{it}\beta}{\sqrt{\sigma_1^2 + \sigma_2^2}}\right) \tag{11}$$

$$Prob(d_i = 1) = \varphi(z_i\gamma) \tag{12}$$

where $\varphi(.)$ is the cumulative distribution function and $\theta(.)$ is the probability distribution function.

3.2 Latent class growth model

We adopt the latent class growth framework following Bacci et al. (2017). A matrix of covariates X_i representing socio-demographic variables are included to explain the conditional distribution of Y_{it} which can be written as follows:

$$f(y_{it}|l, x_{it}) = f(y_{it}|L_i = l, x_{it}) = \begin{cases} \gamma(x_{it})\varphi(y_{it}; \mu_{it}, \sigma^2) & if\ y_{it} > 0 \\ 1 - \gamma(x_{it}) & if\ y_{it} = 0 \end{cases} \tag{13}$$

where l is the latent classes and L_i individual specific latent variables and $\varphi(y_{it}; \mu_{it}, \sigma^2)$ is the density of normal distribution. We assume:

$$\gamma(x_{it}) = \frac{\exp\,(x'_{it}\beta_l)}{1 + \exp\,(x'_{it}\beta_l)} \tag{14}$$

where β_l captures the effect on covariates in x_{it} on the event that household i consumes PBMA at month t. All the households contain 24 months of observations, and we include a polynomial sequence of degree 2 on the number of months to allow the inverse U-shape trajectories with semiparametric splines formulation (Green & Silverman, 1994). The proposed latent class growth model can be written as follows:

$$f(y_i|X_i, z_i) = \sum_{l=1}^{k} \pi_l(z_i) f(y_i|l, X_i) \tag{15}$$

where k is the maximum number of latent classes based on minimum Bayes information criterion (BIC). We can define this as:

$$f(y_i|l, X_i) = \prod_{t:y_{it} \neq NA}^{T} f(y_{it}|l, x_{it}) \tag{16}$$

Here, 'NA' denotes the values that are not used in this model. As it is stated earlier that we only consider the household which consumed PBMA at least once during 2019 and 2020. In this model, we include only the households' observations starting from the fast month of purchasing PBMA and subsequent months regardless of consumption. For instance, if a household purchased PBMA for the first time during April 2019, then the consumption for all the months before April 2019 is considered as 'NA,' and all the subsequent months since April 2019 are taken into account. In this way, we can remove the serial nonparticipants from the model and only consider household PBMA consumption behavior who at least choose PBMA even once as an alternative option. Also, $\pi_l(z_i)$ is the conditional probability of being in latent class l where z_i computed through multinomial logit parameterization, $log\left\{\frac{\pi_l(z_i)}{\pi_1(z_i)}\right\} = z_i'\delta_l$.

We use the Bayes formula to calculate the posterior probability for household class membership allocation, which can be written as follows:

$$\pi_l'(X_i z_i, y_i) = \frac{\pi_l(z_i) f(y_i|l, X_i)}{f(y_i|X_i, z_i)} \tag{17}$$

4. Results and Discussion:

Table 2 shows the estimated coefficients of the double hurdle model. We find several factors that determine the participation of PBMA consumption, such as income, household size, age, education level, race, and ethnicity. Regarding consumption equations, almost all the socio-demographic variables are statistically significant except for price, income, African American, and other races.

Table 3 shows the average marginal effects of independent variables on PBMA consumption based on three properties. The participation equation measures the probability that a household consumes plant-based meat. The consumption equation represents the expected quantity consumed given that the household consumed plant-based meat (conditional) and the expected quantity of plant-based meat consumed by a household (unconditional).

Results indicate that price and income have no significant effect on participation and consumption decisions. This result is expected as PBMA is not a mainstream product and is still far away from becoming a substitute for conventional meat products. Most households consume PBMA to test the product for the first time and then switch back to animal meat. Thus, the probability and the quantity of consumption are not affected by the change in the unit price of PBMA and household income level. Zhao et al. (2022) adopted a similar demand system model to investigate PBMA and animal meat products demand elasticity. They found that the own-price elasticity of PBMA (-1.5) is the highest among all conventional animal protein sources such as beef, chicken, pork, fish, lamb, and duck.

Household demographic characteristics play a significant role in determining PBMA consumption. For example, household size has a positive significant effect on participation and consumption decisions. A 1% increase in household size results in a 0.3% higher probability of PBMA consumption and increased consumption of 0.016 at the unconditional level. The age of the male head also plays a significant role in PBMA consumption. The results suggest that households with male head aged between 30-45 years have a 0.5% higher probability of consumption and tend to consume 0.06 and 0.02 quantities more at conditional and unconditional levels, respectively, compared to older male-headed households. It is also true for female-headed households where younger females like to consume PBMA more than older females. Households with female head aged under 30 and between 30-45 years are 1.8% and 1.2% more likely to consume PBMA compared to elderly female age above 45 years. In terms of consumption equation, female age under 30 consume 0.21 and 0.079 more quantity at conditional and unconditional levels, respectively compared to older female. Middle aged female (age between 30-45) also consume significant higher quantity than older female. Siegrist & Hartmann (2019) also identified that younger, female, and people with better education are likely to consume meat alternatives than their counterparts.

The presence of children (age < 18) also plays a vital role in household PBMA consumption decisions. The results indicate that households with children have a 0.7% lower probability of participating, and if they consume, they consume 0.096 less quantity at the conditional level and 0.031 less quantity at the unconditional level with respect to their counterpart. Although male education level does not affect consumption, the education level of females has a significant positive effect. Highly educated females (having more than a high school degree) are more likely to consume PBMA, and if they consume, they tend to purchase more compared to less educated females at the unconditional level.

Moreover, married households not only have a higher probability of consumption, but also they consume more quantity at both conditional and unconditional levels than households with other marital statuses. Race is also an important factor in determining PBMA consumption. Asian, African American, and other race households are not only more likely to consume but also quantity demand for PBMA is higher at conditional (not for Asian) and unconditional levels compared to Caucasian households. Hispanic households also have a 0.3% higher probability of consuming PBMA than non-Hispanic households.

Although PBMA is one of the fastest-growing products compared to conventional meat in the U.S., consumers' acceptance of PBMA as a substitute for animal protein remains unsatisfactory. Most consumers are willing to try the product once or twice rather than a permanent shift. In that case, promotion has played a positive role in deriving consumer demand for PBMA in recent years (Zhao et al., 2022). Most households started to consume PBMA since 2019, but 75% of them tried it only once before dropping out (Cuffey et al., 2022). This indicates there is a dire need for improving the product in terms of quality, appearance, and flavor to attract new consumers and provide a better incentive to continue consumption for the existing ones.

Table 4 reports the maximum log-likelihood, BIC, and average weights of the two-class model. In this study, we restrict the model to a maximum of two classes because of our interest in distinguishing the growth trajectory of households who consumed PBMA once or twice from the households that consumed consistently throughout the selected timeframe. We find the BIC value is substantially lower for $K = 2$, and 88.5% of the households represent class 2. Table 5 shows the concomitant variables that characterize class membership of individual households. The class membership coefficients indicate the significance of covariates in the multinomial logit model to belong in latent class 1 against latent class 2 as reference. We do not include price and income in this latent class growth model as both price and income do not have significant effects on participation and consumption decision. Hence, we only use binary variables to define class memberships and find that females aged between 30-45 years and Asian households have significant effects for latent class 1.

Figure 1 represents the estimated trajectories for $K = 2$ classes that take into account unobserved heterogeneity. By allowing for two classes, we can clearly separate the households that consumed once or twice during the last 24 months, account for 88.5% of observations, and fall in class 2. Only 11.5% of the households in class 1 consistently consumed PBMA. The trajectory of class 2 exhibits a U-shape where the consumption quantity is close to one unit till the first five months and then drops down to zero. This indicates class one households tried PBMA for the first five months (may not consistently) and then decided not to consume. Class 1 includes all the households that consumed PBMA for most of the observed periods but show a downward trajectory. Class 1 consumes almost 4 quantities during the first five months of consumption with a declining trend. This indicates that even for the consistent consumers of PBMA, the preference is shifting to other sources of animal protein in recent periods.

Table 6 indicates the class membership posterior probability to identify the household characteristics of latent classes conditional on each concomitant covariate. Class 2 contains most of the weights because most households consumed PBMA once or twice and fall under class 2. The results suggest that there is a higher probability of males aged between 30-45 years to represent class 1, indicating middle-aged male-headed households consumed PBMA more often than both young and elderly male-headed households. Young- and middle-aged females also have a substantially higher posterior probability of being in class 1 than elderly females. Married households are also more likely to fall under class 1, while Asian households mostly represent class 2. This result is very similar to the double hurdle model consumption equation estimates except for Asians.

PBMA has shown a promising consumption pattern since 2019 in the U.S. market, but our study indicates a downward trajectory in the recent period. Cuffey et al. (2022), Michel et al. (2021), and Taylor et al. (2023) also identified that PBMA consumption dropped dramatically since the first purchase making PBMA an occupational consumed products in the U.S. There could be numerous reasons for the inconsistency of PBMA consumptions where some of the notable factors can be taste and texture, price, availability, limited product range, consumer resistance to change, and marketing and perception. It is also worth noting that the purchase of PBMA has no negative influence on the spending of conventional meat products (Cuffey et al., 2022; Zhao et al., 2022) that bolsters the fact that PBMA is not considered a substitute for conventional meat.

5. Conclusion:

PBMA is designed to replicate the test and texture of conventional meat products by removing the detrimental health effects of red meat. Although the PBMA industry is growing at an exponential rate, still now the demand for PBMA compared to animal meat products is substantially lower. The lower demand may be associated with the consumers' unfamiliarity and barrier to consuming new products. Also, the average price of PBMA is comparatively higher than most animal meat products which may be one of the major reasons for lower demand. So far, we do not have a clear understanding of the factors influencing household determinants of PBMA consumption in the United States. Hence, in this study, we utilize a panel-double hurdle framework using retail-level consumer scanner data instead of stated preference data collected from surveys and questionnaires to shed light on the household socioeconomic and demographic characteristics that influence PBMA consumption.

We find household size, marital status, age, education, race, and ethnicity play a significant role in PBMA consumption. Price and income do not influence PBMA consumption for the newly participating households. The result is expected as PBMA is still not a mainstream product and is far from becoming a perfect substitute for animal meat. In fact, Zhao et al. (2022) found that PBMA is a complement for beef and pork. Consumers prefer to try the product once or twice rather than permanently shifting to PBMA, and thus promotion plays a vital role in increasing the demand (Zhao et al., 2022).

We also find large households are not only more likely to consume PBMA but also the quantity demanded is significantly higher than large households. Hence, an increase in household members positively influences PBMA consumption. Male-headed households have no influence on PBMA consumption regardless of age (except for middle-aged males) and education. However, young and educated females have a higher probability of consuming the product. Also, Asian, African American, and other races are more prone to consume PBMA than Caucasian.

For the latent class growth model, we find that a majority of the households consume only once or twice, while 11.5% of households consume the product consistently throughout the selected time period. However, the most consistent consumers also indicate a downward trajectory of consumption, indicating a decrease in demand for PBMA in the U.S. Although the findings of this study are consistent with the existing literature, this study quantifies the consumption growth trajectory with class membership posterior probability. Hence, we can identify which households have a higher probability of consuming PBMA with two separate classes and serial non-participant households with higher precision.

The findings of this study will play an essential role in implementing suitable policies for the betterment of both consumers and the PBMA industry. To become a mainstream product in the near future, attracting not only meat reducers-flexitarians but also traditional meat consumers and becoming a substitute for animal meat, PBMA price needs to be lower than its counterparts. The product needs more promotional activities and increased quality, appearance, and flavor to mimic animal meat products. Hence, it is necessary to invest more in research and development in the PBMA industry so that consumers can decide for themselves if PBMA could be a staple on their plate.

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Table 1: Descriptive statistics

Variables	Unit	Mean	SD
Price	$/unit	4.179	0.405
Household income	Continuous ($/year)	64516.320	26823.660
Household size	Continuous (integer)	3.168	1.279
Male age under 30	Binary	0.032	0.188
Male age between 30-45	Binary	0.346	0.479
Male > 45 years	Binary	0.617	0.486
Female age under 30	Binary	0.052	0.221
Female age between 30-45	Binary	0.391	0.488
Female > 45 years	Binary	0.557	0.497
With Children (age <18)	Binary	0.431	0.495
Without Children (age <18)	Binary	0.569	0.495
Male > high school degree	Binary	0.335	0.472
Male ≤ high school degree	Binary	0.665	0.472
Female > high school degree	Binary	0.212	0.409
Female ≤ high school degree	Binary	0.788	0.409
Married	Binary	0.960	0.196
Other than married	Binary	0.040	0.196
Caucasian	Binary	0.781	0.414
African American	Binary	0.097	0.296
Asian	Binary	0.057	0.233
Other	Binary	0.065	0.247
Hispanic	Binary	0.113	0.317
Non-Hispanic	Binary	0.887	0.317

Table 2: Estimated parameters of double hurdle model (Maximum likelihood Estimates)

Variables	**Participation equation**		**Consumption equation**	
	Estimate	Standard Error	Estimate	Standard Error
Price	-5.662	3.760	6.503	5.957
Income	0.000*	0.000	-0.000	0.000
Household size	-0.302***	0.098	0.658***	0.190
Male age under 30	0.907**	0.358	-1.400***	0.466
Male age between 30-45	-0.066	0.097	0.539***	0.191
Female age under 30	-0.570***	0.190	2.388***	0.371
Female age between 30-45	0.029	0.103	1.149***	0.200
With Children (age <18)	0.027	0.066	-0.744***	0.138
Male > high school degree	6.709	4.080	-2.374***	0.610
Female > high school degree	-0.350***	0.089	1.848***	0.205
Married	-0.005	0.148	0.763**	0.357
African American	0.648***	0.157	-0.069	0.200
Asian	1.248**	0.497	-0.462**	0.229
Other	0.192	0.151	0.363	0.260
Hispanic	0.728***	0.174	-0.461**	0.214
Constant	1.254***	0.262	-16.180***	0.733

Notes: ***, **, and * represent rejecting the null hypothesis at 1%, 5%, and 10% level of significance, respectively.

Table 3: Estimated Elasticities

Variables	**First Hurdle**	**Second Hurdle**	
	Probability	Conditional Level	Unconditional Level
Price	0.006	-0.257	0.050
	(0.055)	(0.873)	(0.239)
Income	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Household size	0.003**	0.029	0.016**
	(0.002)	(0.024)	(0.007)
Male age under 30	-0.004	-0.008	-0.023
	(0.003)	(0.062)	(0.015)
Male age between 30-45	0.005***	0.060***	0.020***
	(0.002)	(0.022)	(0.007)
Female age under 30	0.018***	0.210***	0.079***
	(0.003)	(0.045)	(0.013)
Female age between 30-45	0.012***	0.163***	0.050***
	(0.002)	(0.022)	(0.007)
With Children (age <18)	-0.007***	-0.096***	-0.031***
	(0.001)	(0.016)	(0.005)
Male > high school degree	0.045	1.031	0.169
	(0.042)	(0.840)	(0.164)
Female > high school degree	0.015***	0.181***	0.065***
	(0.002)	(0.021)	(0.007)
Married	0.007***	0.103***	0.032***
	(0.003)	(0.037)	(0.012)
African American	0.006***	0.122***	0.023***
	(0.002)	(0.029)	(0.007)
Asian	0.008*	0.189**	0.031*
	(0.004)	(0.091)	(0.017)
Other	0.006***	0.088***	0.024**
	(0.002)	(0.031)	(0.009)
Hispanic	0.003*	0.084***	0.010
	(0.002)	(0.032)	(0.007)

Notes: ***, **, and * represent rejecting null hypothesis at 1%, 5%, and 10% level of significance, respectively. Standard errors inside the parenthesis.

Table 4: Maximum log-likelihood, BIC index and average weights for each class (K)

Class	**Log-likelihood**	**BIC**	**Average weights (%)**	
			Class 1	**Class 2**
$K = 1$	-41052.95	82168.83	100	
$K = 2$	-36178.98	72532.73	11.5	88.5

Table 5: Estimated coefficients of class membership model with $K = 2$ classes

Covariates	**Results for class 1**
Male age under 30	-0.357
Male age between 30-45	-0.134
Female age under 30	0.542
Female age between 30-45	0.686**
With Children (age <18)	-0.153
Male ≤ high school degree	-0.064
Female ≤ high school degree	-0.039
Married	0.701
African American	0.124
Asian	-1.141**
Other	-0.215
Hispanic	-0.245

Notes: Class 2 is the reference. ** represents significant at the 5% level.

Table 6: Class membership posterior probabilities at conditional level

Covariates	**Results for class 1**	**Results for class 2**
Male age under 30	0.107	0.892
Male age between 30-45	0.129	0.870
Male > 45 years	0.105	0.894
Female age under 30	0.113	0.886
Female age between 30-45	0.138	0.861
Female > 45 years	0.094	0.905
With Children (age <18)	0.123	0.876
Without Children (age <18)	0.108	0.891
Male ≤ high school degree	0.107	0.892
Male > high school degree	0.117	0.882
Female ≤ high school degree	0.107	0.892
Female > high school degree	0.116	0.883
Married	0.117	0.882
Other than married	0.057	0.942
Caucasian	0.119	0.880
African American	0.133	0.866
Asian	0.049	0.950
Other	0.114	0.885
Hispanic	0.100	0.900

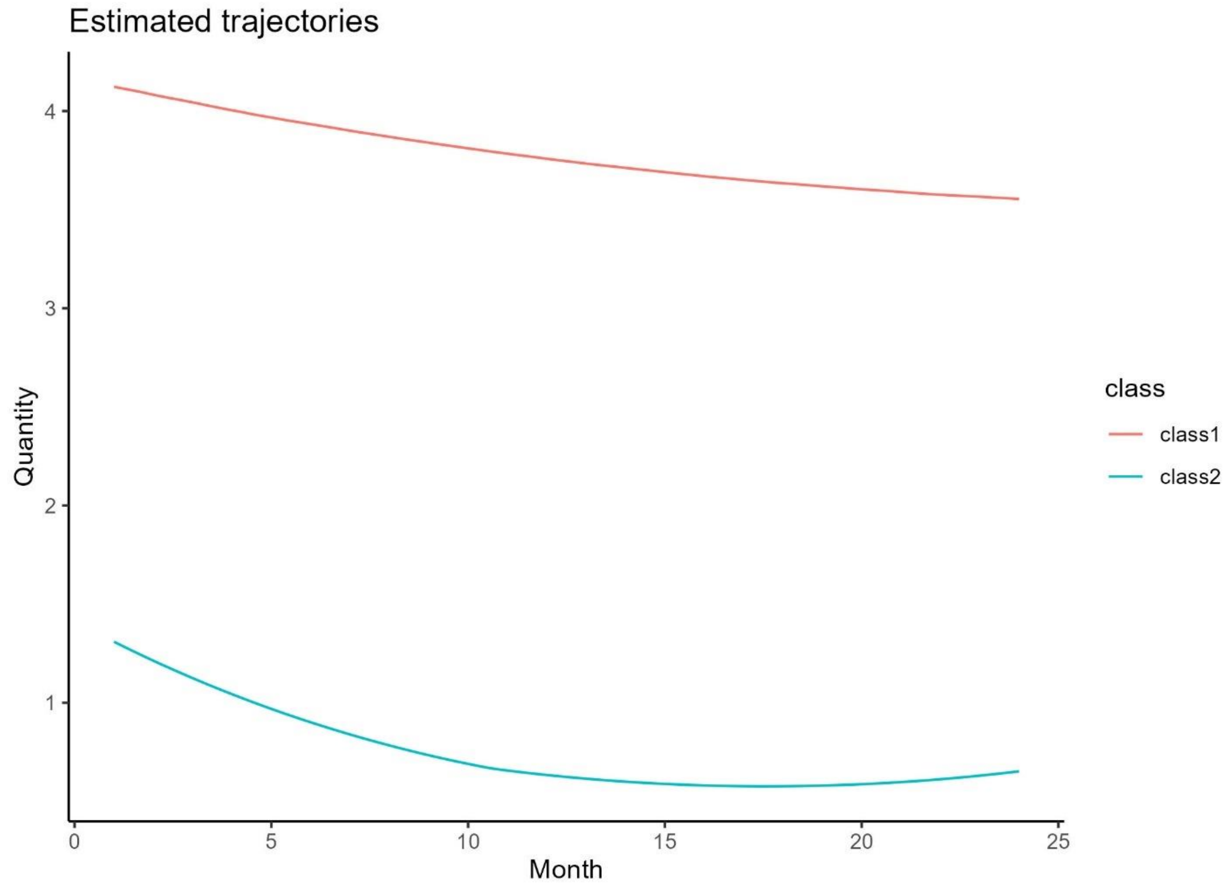

Figure 1: Estimated trajectories of latent class 1 and class 2.