Product placement in the meat substitute sector: Evidence from a spatial demand model

Stefan Hirsch
University of Hohenheim, Department of Management in Agribusiness
s.hirsch@uni-hohenheim.de

Selected Paper prepared for presentation at the 2022 Agricultural & Applied Economics Association Annual Meeting, Anaheim, CA; July 31-August 2

Product placement in the meat substitute sector: Evidence from a spatial demand model

Rising welfare and increased efficiency in livestock-farming, have led to an overconsumption of meat and dairy products in developed regions such as Europe and the U.S. Those developments have caused negative environmental and health effects as well as increased ethical concerns by consumers (Tilman and Clark 2014; Godfray et al. 2018). Due to these reasons the rise in meat consumption has recently come to a stop and even slight reductions in the amount of meat consumed could be observed in Europe and the U.S. (Hagmann et al. 2019; Petersen et al., 2021). Concurrently, a market for meat substitutes has established where products compete increasingly with traditional meat products. Meat substitutes have been recognized as a healthy alternative protein source with several benefits regarding ethical, environmental and health issues (Apostolidis and Fraser, 2016). In this article we investigate how far different strategies to market meat substitutes affect their demand. More precisely we are interested in whether designing and marketing meat substitutes by imitating their original meat counterparts as closely as possible is superior to marketing them as differentiated plant-based protein alternatives.

Previous literature focusing on the marketing and demand of meat substitutes has investigated consumers' acceptance and willingness-to-pay (WTP) for meat substitutes focusing on individual products and single attributes (e.g., front-of-package labels or organic production) using choice-based conjoined analysis (e.g., Escribano et al., 2021) or randomized control studies (e.g., Katare et al., 2022).[1] Using a treatment with information related to environmental and health externalities of meat consumption Katare et al. (2022) show that the demand for sustainable beef

[1] For a review on consumers' acceptance of different types of meat substitutes we refer to Onwezen et al. (2021).

products and plant-based alternatives is inelastic. Taylor et al. (2022) benchmark the dynamic situation ongoing in the US meat market. They show that consumers choose beef three times as often as plant-based alternatives and that consumers perceive the image of beef overall positively. Some studies have also investigated consumer spending for meat substitutes using retail and consumer scanner data. For example, Cuffey et al. (2022) use Nielsen Homescan data to analyze consumers' spending patterns for meat substitutes over time. They detect that household spending on plant-based meat substitutes drops by 75% in the months subsequent to an initial purchase of such products. Recent literature also considers the drivers of demand and consumers' acceptance of hybrid and cultured meat (e.g., Grasso, Asioli and Smith, 2022; Palmieri, Perito and Lupi, 2021; Weinrich, Strack and Neugebauer, 2020). For example, Asioli et al. (2022) focusing on the role of information messages related to health benefits or sensory and convenience characteristics for the WTP for hybrid burgers. They find that consumers are until now not ready to pay a premium for these kind of innovations and that the WTP is strongly influenced by the type of information provision and consumers' characteristics. Verbeke, Sans and van Loo (2015) show that consumers after receiving information about cultured meat in general express positive expectations about such products with up to 43% of consumers willing to try such products. Despite this extensive literature on consumers demand for meat alternatives to the best of our knowledge no study has so far investigated the relevance of product placement and design strategies for meat substitutes using a combination of comprehensive datasets on consumer purchases and product characteristics.

We add to this literature by applying a random coefficients demand model (Berry, Levinsohn, and Pakes, 1995) as well as a spatial structural model (Richards et al., 2013) to a large set of products and attributes. This allows us besides investigating consumer demand and substitution patterns for meat and meat substitutes to also consider strategic interactions among food manufacturing firms when setting the prices and product design of meat and meat substitute products (Richards et al., 2013). Our aim is to contribute to the understanding of consumers' choices in the market of differentiated meat and substitute products as well as on food manufacturers strategic product design and pricing decisions when introducing meat substitutes to the meat market. The results provide evidence on whether food manufacturing firms should aim to resemble meat products in their appearance as closely as possible when introducing meat substitutes to the market or whether a differentiated product design of meat substitutes that does not aim to resemble an original meat product is preferable. We focus on burger patties and use the German meat market as a case study where both strategies can be observed i.e., plant-based patties that are e.g., marketed as "plant-based burger" aiming to reflect real meat patties as closely as possible and plant-based alternatives that are e.g., marketed as e.g., "vegetable patty" and do not attempt to closely resemble the appearance of original meat products.

The remainder of the article is organized by first providing an overview of the methodological approaches used. Subsequently, we introduce the datasets used and present and discuss the estimation results. The article finishes with some conclusions.

2. Empirical concept

2.1 Random coefficients logit demand model

To estimate consumers' valuation of characteristics of meat and meat substitutes, we use the random coefficients logit demand model estimator proposed by Berry, Levinsohn and Pakes (1995) (henceforth BLP). BLP is a random utility approach that has been particularly applied to consumers food choices (e.g., Nevo, 2001; Hirsch, Tiboldo and Lopez, 2018; Lopez and Fantuzzi, 2012; Khanal and Lopez and 2021; Wang and Cakir, 2020) and was continuously further developed (e.g., Nevo 2000; Reynaert and Verboven. 2014). In contrast to product space approaches such as the Almost Ideal Demand System model (Deaton and Muellbauer 1980; Roosen, Staudigel and Rahbauer, 2022), the Rotterdam model (Theil, 1965) or EASI[2] models (Lewbel and Pendakur, 2009) BLP is a characteristic space approach, that allows to estimate demand using a random coefficients logit model under consideration of product characteristics (Khanal and Lopez, 2021). BLP considers heterogeneity in consumer and product characteristics, price endogeneity, and in contrast to product space approaches such as AIDS or Rotterdam models is not affected by a dimensionality problem that arises since these models use a system of demand equations for individual products leading to a large number of demand functions that each depend on the product's own price and the prices of all other products considered. This can potentially lead to an extremely large number of parameters that need to be estimated (Khanal and Lopez 2021). Modeling demand based on product characteristics (such as nutrients, brands, price, packaging, etc.) rather than the product space also enables to conduct counterfactual analysis to test alterations of characteristics and policies such as meat taxes or advertising bans (Liu, Lopez & Zhu 2014). Moreover, BLP is less restrictive with respect to consumer heterogeneity leading to more realistic substitution patterns compared to logit or nested logit discrete choice models. This allows to derive more accurate own- and cross-price elasticity estimates, and of marginal costs and resulting product-level markups (Vincent 2015; Hirsch et al., 2018; Liu, Lopez, Zhu 2014). Finally, compared to the classical approaches (e.g., Almost Ideal Demand System or linear demand models) random utility approaches have been shown to lead to lower biases in elasticities n case of incorrectly specified models (Bass et al. 2008, Bonnet et al. 2018).

[2] Abbreviation for Exact Affine Stone Index implicit Marshallian demand system (see Lewbel and Pendakur (2009) for a more detailed description of the model).

Modelling consumer choices

Consumer i's indirect utility from consuming product j in period t is defined as (e.g., Vincent, 2015)[3]:

$$U_{ijt} = \alpha_i p_{jt} + \beta_i (x_{jt} + Sub_{jt} + Sub_{jt} I_{jt}) + v_{jt} + \varepsilon_{ijt} \tag{1}$$

p_{jt} represents product j's price in period t while x_{jt} is the vector describing those product characteristics that can be observed. Those include nutrients, ingredients, labels and the volume of sales under promotion enabling us to assess the relevance of product attributes and nutrients for utility and how those vary across consumer groups[4]. In addition, we add a dummy variable (*Sub*) capturing whether j is a meat substitute or a meat product. Moreover, an interaction between *Sub* and an indicator (*I*) that takes value of one if the product aims to closely resemble an original meat product and zero otherwise is added. This allows us to investigate whether consumers value meat substitutes that aim to closely resemble their original counterpart differently than those that pursue a different strategy by rather marketing the innovation as a plant-based protein alternative. v_{jt} captures base utility of unobserved (to the econometrician but not the consumer) product characteristics i.e., deviations from observed product quality that are similar for all i while ε_{ijt} is an idiosyncratic i.i.d. error drawn from a Type I extreme value distribution. Finally, α_i and β_i are random coefficients to be estimated reflecting individual taste parameters unique to consumer i that are defined by a set of observed and unobserved demographics of the analyzed markets D_i and V_i, respectively (e.g., Vincent, 2015; Khanal and Lopez, 2021):

[3] See, for example, Vincent (2015), Hirsch et al. (2018) or Khanal and Lopez (2021) for derivations of the model.
[4] This also enables to detect adverse consumption patterns, for example, if unfavorable nutrients are positively valued (e.g., Liu Lopez Zhu 2014).

$$\alpha_i = \alpha + \lambda D_i + \omega V_i \text{ and } \beta_i = \beta + \delta D_i + \gamma V_i \,. \qquad (2)$$

D_i and V_i are standard normally distributed and have densities h(D) and g(V), respectively[5]. Substitution of (2) into (1) leads to:

$$U_{ijt} = \phi_{jt} + \mu_{ijt} + \varepsilon_{ijt}\,, \qquad (3)$$

with $\phi_{jt} = \alpha p_{jt} + \beta x_{jt} + \nu_{jt}$ and $\mu_{ijt} = \lambda D_i p_{jt} + \delta D_i x_{jt} + \omega V_i p_{jt} + \gamma V_i x_{jt}$. Based on (3), the indirect utility is divided into two parts, where the first is mean utility reflected by ϕ_{jt} which is common to all consumers *i* (with α and β being the means of random coefficients reflecting taste parameters common to all consumers). The second, μ_{ijt}, represents deviations from the mean utility specific to each consumer i.e. interactions between consumer and brand characteristics, Finally, ε_{ijt} reflects idiosyncratic consumer taste (Vincent, 2015; Hirsch et al., 2018; Khanal and Lopez, 2021).

[5] To define $\boldsymbol{D_i}$ we rely on representative census survey data from which we make 100 draws per market. According to Lopez and Fantuzzi (2012) further draws can come from a normal distribution with a mean of zero and a variance equal to one. One can then observe how the variables in $\boldsymbol{D}$ effect the taste of consumers for e.g., price. For example, the mean effect of price on demand is likely negative but richer consumers can be less sensitive. Hence it can be observed how specific consumer groups value individual product characteristics.

An outside good j = 0 with utility $U_{i0t} = 0$ $= \varepsilon_{ijt}$ is included to allow for the alternative that consumer i opts not to buy any of the J products. For each market the outside good includes all meat and meat substitute products that are not in the sample. It is assumed that in market equilibrium each consumer i either choose one unit of the option in the choice set that leads to the highest utility or the outside good. Based on logit-probabilities, the probability that in period t a consumer i chooses one unit of product j is then defined as (Vincent, 2015; Khanal and Lopez, 2021):

$$Pr_{ijt} = \frac{\exp(\phi_{jt} + \mu_{ijt})}{1 + \sum_{k=1}^{J} \exp(\phi_{kt} + \mu_{ikt})} . \quad (4)$$

The market share of j in t can be derived by aggregating across consumers which is equal to the aggregate probability that consumers jointly select j in t. This is based on integrating out as follows:

$$S_{jt} = \int\int\int I\{(D_i, V_i, \varepsilon_{ijt}) : U_{ijt} \geq U_{ikt} \forall k = 0,...J\} dH(D) dG(V) dF(\varepsilon), \quad (5)$$

with $H(D)$, $G(V)$, and $F(\varepsilon)$ being the CDFs of D_i, V_i, and ε_{ijt} (Vincent, 2015; Khanal and Lopez, 2021).

Markets are defined as a combination of time periods t and the two cities included (see description below) which implies that the estimation is based on 500 markets (250 weeks * 2 cities). For each market own- and cross-price elasticities can be derived for all individual products j using the demand parameters estimated in (5) as probability-weighted averages (Berry, Levinsohn, and

Pakes 1995). Note that this allows to consider flexible patterns of substitution (e.g., Vincent 2015; Lopez and Fantuzzi 2012). This leads to the following definition of own- and cross price elasticities at the product level (e.g., Vincent, 2015):

$$\eta_{jkt} = \frac{\partial S_{jt}}{\partial p_{kt}} \frac{p_{kt}}{S_{jt}} = \begin{cases} -\frac{p_{jt}}{S_{jt}} \iint \alpha_i Pr_{ijt}(1 - Pr_{ijt}) dH(D) dG(V) & for\ j = k, \\ \frac{p_{kt}}{S_{jt}} \iint \alpha_i Pr_{ijt} Pr_{ikt} dH(D) dG(V) & for\ j \neq k. \end{cases} \tag{6}$$

Based on (6) all consumers *i* will have different price elasticities w.r.t to the products *j*.[6] We use the averages of the derived own- and cross-price elasticities over markets to investigate substitution patterns across meat and meat substitutes. In particular, we are interested in assessing whether products that aim to closely imitate meat have for example lower own-price elasticities but higher cross-price elasticities with meat compared to more differentiated meat substitutes that do not aim to imitate original meat (e.g., Hirsch et al. 2018; Vincent 2015).

[6] For example, in the standard logit model with homogeneous consumer preferences ($\alpha_i = \alpha$ and $\beta_i = \beta$), (6) is reduced to: $\eta_{jkt} = \begin{cases} -\alpha p_{jt}(1 - Pr_{jt}) & if\ j = k \\ \alpha p_{kt} Pr_{kt} & if\ j \neq k \end{cases}$. This leads to the restriction, that given equal market shares for *j* and *k* (which are often small in real markets) the alternative with the lower price always has a lower elasticity which does not need to be the case in the real market. Additionally, the cross-price elasticities that result between *j* and *k* under the assumption of homogeneous preferences can point to unrealistic substitution patterns. For example, assume that *j* and *k* have equal market share. Cross-price elasticities of *j* and *k* with another product l, that is almost identical to *j* but unsimilar to *k*, will be similar based on the logit model elasticities. Nevertheless, it is more realistic to assume that a consumer switches to the more alike product implying that the cross-price elasticity of *j* and *l* is larger compared to the one between *k* and *l* (Hirsch et al. 2018; Vincent 2015, Shreay, Chouinard, and McCluskey 2016).

Retail competition

Based on the assumption of horizontal Bertrand-Nash price competition among firms we calculate equilibrium prices and market shares and markups (Liu, Lopez, Zhu, 2014). To derivation of markups estimates for each product *j* is based on Berry, Levinsohn, and Pakes (1995) and Nevo (2001). It is assumed that F firms operate on the market that, in period *t* supply a subset ($G_f \in J$) of the full product set J (Vincent, 2015; Hirsch et al. 2018). Profits of firm *f* are then calculated by:

$$\Pi_{ft} = \sum_{j \in G_f} S_{jt}(\mathbf{p})(p_{jt} - MC_{jt})M - C_f \tag{7}$$

where $S_j(\mathbf{p})$ is j's share of the market derived from (5). S is depends on the $J \times 1$ price vector $\mathbf{p}$ which includes prices of the entire product set J. Marginal costs are reflected by MC_j, fixed costs by C_f, and the size of the market in *t* by M.

Under the reasonable assumption that in a market with differentiated but still substitutable products firms engage in Bertrand price competition the following FOC of profit maximization for f results (Vincent 2015) where retailers maximize profits by setting prices (Wang and Cakir, 2020):

$$0 = S_{jt}(\mathbf{p}) + \sum_{r \in G_f} (p_{rt} - MC_{rt}) \frac{\partial S_{rt}(\mathbf{p})}{\partial p_{jt}} \tag{8}$$

where $S_j(\mathbf{p})$ is derived from (5) and $\frac{\partial s_{rt(\mathbf{p})}}{\partial p_{jt}}$ from (6). (8) leads to J markup equations which can be written in matrix form as follows (Vincent, 2015; Hirsch et al., 2018; Khanal and Lopez, 2021):

$$\mathbf{p} - \mathbf{MC} = -\boldsymbol{\Omega}^{-1}\mathbf{S(p)} \tag{9}$$

where $\boldsymbol{\Omega}$ is a ($J \times J$) block diagonal matrix that contains the derivatives of $S_r(\mathbf{p})$ w.r.t. the prices p_j. The $J \times 1$ vectors **p**, **MC**, and **S(p)** capture prices, the products' marginal costs, and market shares, respectively. S are predicted shares from (5) and equilibrium prices can be derived from (6). The equations defined by (9) can then serve to calculate marginal costs (MC) and price-cost margins (p-MC) for all *j*. This information can then be used to calculate Lerner indices of market power for individual products j in each *t* as follows:

$$L_{jt} = (p_{jt} - MC_{jt}) / p_{jt} = \left|\frac{1}{\eta_{jt}}\right|. \tag{10}$$

Hence the estimation of the demand model allows to derive own- and cross-price elasticities as well as markups for each product in all markets and over time. Note that it is not required that the same products are used in each market which helps to estimate substitution effects more accurately for relevant products and markets (Vincent 2015; Khanal and Lopez, 2021).

Endogeneity of prices, identification, and estimation

BLP is built on estimating a closed form of the demand model (5) with Generalized Method of Moments (GMM) estimation based on a set of "optimal" instrumentals variables and the constraint that the predicted market shares are equal to the observed shares (e.g., Vincent, 2015; Hirsch et al., 2018). Using GMM we can solve the integral defined for the moment function with an algorithm to minimize differences between the observed market shares and their estimated counterparts (Nevo 2000; Vincent 2015). Note that the estimation of the demand function is affected by endogeneity of product prices since prices reflect the value attached to the products' characteristics. However, not all product characteristics are observed by the researchers (but potentially by producers) and included in the demand model which implies correlation of product prices and errors terms (Wang and Cakir, 2020; Berry, Levinsohn and Pakes, 1995). Nevo (2012) states that the instruments used in the estimation not only enable to control for endogeneity of prices but also endow the generation of moment conditions for the identification of the random coefficients. (Vincent 2015). According to Reynaert and Verboven (2014) and Berry, Levinsohn and Pakes (1995), "optimal" instruments can be used to increase estimation efficiency leading to estimates with smaller standard errors that more closely reflect true values (Vincent, 2015).[7] The set of optimal instruments is composed of a subset of standard suboptimal instruments that includes i) exogenous cost drivers and ii) exogenous product characteristics. Costs drivers are proxied by processing costs of meat, dairy and their substitutes using producer price and labor cost indices from Eurostat for the respective 3-digit NACE codes (Eurostat 2012, 2022a, 2022b). Moreover, Hausman-type instruments consisting for a market A in period *t* of prices of the same goods in another market B are added. The latter are correlated with prices in A because of common marginal costs but not with demand in A due to uncommon demand shifters making them valid instrumental variables (Nevo, 2000)[8]. Exogenous product characteristic are all non-price variables in x_{jt} since

[7] According to Chamberlain (1987), under conditional moment restrictions we can derive the set of efficient instruments by calculating the derivatives of the conditional moment condition with respect to the parameters and then calculating the expected values. Moreover, Reynaert and Verboven (2014) investigate differences in the performance between the approximated set of optimal instruments and the exact implementation. They show that both alternatives are suited to mitigate specific problems related to the estimation of the BLP model. They also show that both options substantially increase the efficiency and stability of the estimation.

[8] Note that prices of the same products in the other cities/markets are suitable IVs if demand shocks do not correlate across cities. For example, if advertising or promotion is city specific and not at the same time started across several cities. Hence one should use markets that are outside a large enough range. However, if there is for example a nationwide promotion or scandal or some kind of nutritional awareness campaign that suddenly arises (nationwide)

those are independent of ε_{ijt}. The set of instruments is completed by the squared values and interactions of the IVs and the summed characteristics of the other products in the choice set (Vincent 2015). We first assess the exogeneity of prices using the Davidson-MacKinnon test and evaluate the exogeneity and validity of instruments via a standard logit model using 2SLS estimation, Sargan tests of overidentification and minimum eigenvalue statistics (Hirsch et al., 2020)[9].

2.2 Spatial Demand Model

To further investigate the effect that product proximity in the meat market has on demand we estimate a spatial demand model (Richards et al., 2013). The structural model consists of a random utility demand equation that based on a spatial autoregressive framework considers the proximity of products in the attribute space (Richards et al., 2013):

$$\ln\mathbf{S} - \ln S_0 = (\mathbf{I} - \lambda\mathbf{W})^{-1}(\beta'\mathbf{x} - \alpha\mathbf{p} + \boldsymbol{\xi}) \qquad (11)$$

S includes products' market shares, **x** reflects brand dummies and promotion activities, and **p** captures product prices. The matrix **W** consist of proximity measures between each pair of products in the characteristics space. Hence consumers assess the utility from selecting a specific product in comparison to the utility that can potentially be achieved from buying other products provided in the choice set. We define proximity as the inverse of the Euclidean distance between

the assumption is violated. We therefore check for the presence of such events and similar to Wang and Cakir (2020) also add time dummies to the demand function to control for time-variant nationwide shocks (Hausmann et al., 1994; Wand and Cakir, 2020).

[9] See also Liu and Lopez (2015) on how to test validity of instruments in the BLP model.

product pairs using the following holistic set of attributes: appearance (measured by a subjective inspection of the product package to reveal whether the product aims to imitate an original meat counterpart), nutritional composition, package design/material (e.g., eco-friendly or plastic free), labelling (e.g., animal welfare, regional, high in protein, low in sodium).[10] This implies that a higher value in $\mathbf{W}$ reflects greater similarity between products so that a positive $\hat{\lambda}$ indicates that higher similarity between products has a positive effect on demand (Richards et al., 2013). However, it must be noted that the demand function in (11) considers overall proximity between all combinations of products in the market (meat products and meat substitutes). Hence based on (11) $\hat{\lambda}$ only provides an overall measure for the effect of product proximity in the meat and meat substitute market. Our aim is to extend (11) to allow for a particular consideration of the proximity between meat substitutes and traditional meat products.

The spatial demand equation (11) is extended by a pricing equation which is derived based on manufacturers profit maximization problem (Richards et al., 2013):

$$\mathbf{p} - \mathbf{MC} = -\left(\mathbf{I} - \lambda\,(\mathbf{Wb} * \mathbf{I})\right)\left(\mathbf{S}_{\mathbf{p}}^{-\mathbf{1}}\right)\mathbf{S} = -\left(\boldsymbol{\theta}\mathbf{S}_{\mathbf{p}}^{-\mathbf{1}}\right)\mathbf{S} + \lambda(\mathbf{Wb} * \mathbf{I})\left(\mathbf{S}_{\mathbf{p}}^{-\mathbf{1}}\right)\mathbf{S} \qquad (12)$$

where $\mathbf{S}_{\mathbf{p}}^{-\mathbf{1}}$ is the inverse of the matrix containing the logit-share derivatives and $\boldsymbol{\theta}$ is a conduct parameter measuring the type of price competition in the market with $\boldsymbol{\theta} = 1$ reflecting Bertrand-Nash competition[11].

[10] Since the attributes consist of a mixture of binary and continuous variables, we first calculate the inverse Euclidian distance for the continuous variables and the Jaccard similarity measure for the binary characteristics. Subsequently we take the average of both measures to derive the inverse distance used in $\mathbf{W}$.

[11] $\boldsymbol{\theta}$ <1 indicates stronger competition compared to Bertrand while $\boldsymbol{\theta}$ >1 indicates a less competitive situation.

Finally, a product design (location) equation which is derived based on the assumption that similar to the pricing decision the design/location decision results from a Nash equilibrium in which manufacturing firms decide on the average distance of their product innovation j from competitors' products (Richards et al., 2013):

$$Q\left(p_j - MC_j\right)S_j\left(1 - S_j\right) + Q\sum_{l \neq j}\left(p_l - MC_l\right)S_j S_l = (1/\lambda)(\rho_1 \overline{w}_j)^2 \qquad (13)$$

The system of equations is then estimated jointly using the GMM approach. This also enables us to account for endogeneity of prices and product attributes by applying a suitable identification strategy. The results provide evidence on the effect of product proximity on consumer demand[12].

3. Data

As a case study we use Germany, the largest EU market for meat products with an annual per capita consumption of 60kg (Statista, 2018, 2019). Moreover, by accounting for around 20% of total EU food industry turnover Germany represents one of the largest EU food industries (Eurostat, 2021). As data sources we merge Information Resources Inc. (IRI) weekly retail scanner data on sales, prices and promotion activities of meat and meat substitute products over the period 2017-2021 with information on product attributes from Mintel's Global New Product Database (GNPD) on food product innovations. IRI provides data at the European Article Number (EAN) level[13] from several thousand stores at the two-digit postcode level across Germany. The GNPD comprises detailed product information including appearance, package type, nutritional values, production methods (e.g., organic) and marketing (e.g., FOP labels and claims) allowing us to

[12] See Richards et al. (2013) for a detailed derivation of the model.
[13] Similar to the UPC level.

define a holistic attribute space. Since GNPD only includes product innovations (i.e., products newly introduced to the market or product extensions) we collect the missing data for established products by scanning retailers only stores using the respective EAN code. This leads to a comprehensive sample of burger patties sold and consumed in the German market. As markets we focus on two German cities Munich and Berlin that represent two interesting populations with cultural differences related to the consumption of meat. This leads to around 500 markets included in the estimation (250 weeks * 2 cities). Finally, to measure manufacturer costs we rely on average personal costs for each NACE 2-digit code (Eurostat, 2022a) and the producer price index (PPI) available on a monthly basis for meat and dairy provided by Eurostat as well as energy costs (Eurostat, 2022b).[14]

4. Primary and Expected Results

4.1 BLP results

The BLP demand function will allow us to quantify the effect of meat substitutes closely imitating traditional meat products via the effect of the interaction term $Sub_{jt}I_{jt}$. Moreover, the own- and cross price elasticities derived from the BLP model allow us to investigate substitution pattern between meat and meat substitutes by focusing on differences in own price elasticities of meat substitutes that closely imitate meat and those that pursue a different strategy. Moreover, differences in cross price elasticities of meat and meat substitutes that closely imitate meat and meat and those substitutes that pursue a different strategy will allow to generate insights on which type of meat substitutes offers more fruitful option for substituting meat. For example, Khanal and

[14] See Eurostsat (2012) for a description.

Lopez (2021) find for the fluid milk marked that own price elasticities of plant-based milk alternatives are partially higher than those of cow milk. Moreover, they find that plant-based alternatives are close substitutes to each other (high cross-price elasticities) while cross price elasticities with milk products are lower. Similarly, we will investigate substitution potential of plant-based meat alternatives particularly focusing on the importance of close proximity of meat alternatives to their traditional meat counterparts.

4.2 Spatial Demand Model Results

Preliminary results reveal positive spatial lag coefficients ($\hat{\lambda}$) indicating that meat and meat substitute products close to each other in the attribute space lead to reinforcing effects on consumer demand. Moreover, by uncovering substitution effects between meat substitutes and meat products the demand model results enable to identify drivers of the long-term economic viability of meat substitutes. Next steps include simulating the effect of λ on prices, location, consumer and producer surplus (Richards et al, 2013). Moreover, we aim to extend the model to arrive at λ values particularly capturing the effect of proximity between meat substitutes and traditional meat products on consumer demand.

In addition, from a policy perspective we will use the estimation results to simulate the effect of restrictions in bargain advertising of meat which are currently on the policy agenda in Germany as well as the effect of meat taxes on substitution between meat and meat substitutes. From the manufacturers' perspective the model provides equilibrium results regarding product placement and pricing and allows to simulate effects of product design and pricing on the firms' economic performance.

References

Apostolidis, C. and McLeay, F. (2016). Should we stop meating like this? Reducing meat consumption through substitution. *Food Policy* 65: 74-89.

Asioli, D., Banovic, M., Barone, A.M., Grasso, S., Nayga, R.M. (2022). European consumers' valuation for hybrid meat: Does information matter? *Applied Economic Perspectives and Policy*, 2022: 1–19.

Bass, F., Huang, D., Rojas, C., 2008. What happens when demand is estimated with a misspecified model. Journal of Industrial Economics, 56: 809–839.

Berry, S., Levinsohn, J., and Pakes, A. (1995). Automobile Prices in Market Equilibrium. *Econometrica*, 63 (4): 841–890.

Bonnet, C., Bouamra-Mechemache, Z. and Corre, T. (2018). An Environmental Tax Towards More Sustainable Food: Empirical Evidence of the Consumption of Animal Products in France. *Ecological Economics* 147: 48-61.

Chamberlain, G. (1987). Asymptotic Efficiency in Estimation with Conditional Moment Restrictions. Journal of Econometrics 34: 305–334.

Cuffey, J., Chenarides, L., Li, W., Zhao, S. (2022). Consumer spending patterns for plant-based meat alternatives. *Applied Economic Perspectives and Policy*, 2022: 1–23.

Deaton, A. and J. Muellbauer. 1980. "An almost ideal demand system." The American Economic Review 70: 312-326.

Escibando et al. (2021). Stated Preferences for Plant-Based and Cultured Meat: A Choice Experiment Study of Spanish Consumers. *Sustainability* 13, 8235

Eurostat (2012). Handbook on Industrial Producer Price Indices (PPI). Luxembourg: European Commission.

Eurostat (2022a). Labour cost index - recent trends. https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Labour_cost_index_-_recent_trends

Eurostat (2022). Industrial producer price index. https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Industrial_producer_price_index_overview

Godfray, H. C. J., Aveyard, P., Garnett, T., Hall, J. W., Key, T. J., Lorimer, J., . . . Jebb, S. A. (2018). Meat consumption, health, and the environment. Science (New York, N.Y.), 361(6399).

Grasso, S., Asioli, D., Smith, R. (2022). Consumer co-creation of hybrid meat products: A cross-country European survey. *Food Quality and Preference*, 100: 104586.

Hagmann, D., Siegrist, M., & Hartmann, C. (2019). Meat avoidance: Motives, alternative proteins and diet quality in a sample of Swiss consumers. *Public Health Nutrition*, 1–12.

Hirsch, S. Tiboldo, G. & Lopez, R.A. (2018) A tale of two Italian cities: brand-level milk demand and price competition, Applied Economics, 50:49, 5239-5252.

Hirsch, S., Mishra, A., Möhring, N., Finger, R. (2020). Revisiting firm flexibility and efficiency: evidence from the EU dairy processing industry. European Review of Agricultural Economics, 47(3): 971-1008.

Hoek, A.C., van Boekel, M.A.J.S., Voordouw, J., Luning, P.A. (2011). Identification of new food alternatives: How do consumers categorize meat and meat substitutes? *Food Quality and Preference* 22: 371-383.

Katare, B. Yim, H., Byrne, A., Wang, H.H., Wetzstein, M. (2022). Consumer willingness to pay for environmentally sustainable meat and a plant-based meat substitute. *Applied Economic Perspectives and Policy*, 2022: 1–19.

Khanal, B. and Lopez, R.A. (2021). Demand for Plant-Based Beverages and Competition in Fluid Milk Markets. Available at SSRN: https://ssrn.com/abstract=3888564 or http://dx.doi.org/10.2139/ssrn.3888564.

Lewbel, Arthur, and Krishna Pendakur. 2009. "Tricks with Hicks: The EASI Demand System." American Economic Review, 99 (3): 827-63.

Liu, Y., Lopez, R.A., Zhu, C. (2014). The Impact of Four Alternative Policies to Decrease Soda Consumption. *Agricultural and Resource Economics Review*, 43(1): 53 – 68.

Lopez, R. A., and K. L. Fantuzzi. 2012. "Demand for Carbonated Soft Drinks: Implications for Obesity Policy." Applied Economics 44 (22): 2859–2865.

Nevo, A. 2000. "A Practitioner's Guide to Estimation of Random-Coefficients Logit Models of Demand." Journal of Economics and Management Strategy 9 (4): 513–548.

Nevo, A. 2001. "Measuring market power in the ready-to-eat cereal industry." Econometrica 69 (2): 307–342.

Nevo, A. 2012. "Applications and Choice of IVs, NBER Methods Lectures." Accessed 9 May 2017). http://www.nber.org/econometrics_minicourse_2012/aviv_l3.pdf

Onwezen, M.C., Bouwman, E.P., Reinders, M.J., Dagevos, H. (2021). A systematic review on consumer acceptance of alternative proteins: Pulses, algae, insects, plant-based meat alternatives, and cultured meat. *Appetite*, 105058.

Palmieri, N., Perito, M.A., Lupi, C. (2021). Consumer acceptance of cultured meat: some hints from Italy. *British Food Journal*, 123(1): 109-123.

Petersen, T., Hartmann, M., and Hirsch, S. (2021). Which meat (substitute) to buy? Is front of package information reliable to identify the healthier and more natural choice? *Food Quality and Preference* 94: 104298.

Reynaert, M., and F. Verboven. 2014. Improving the Performance of Random Coefficients Demand Models: The Role of Optimal Instruments. Journal of Econometrics 179: 83–98

Richards, T.J., Allender, W.J., and Hamilton, S.F. (2013). Rivalry in Price and Location by Differentiated Product Manufacturers. *American Journal of Agricultural Economics* 95(3): 650-668.

Roosen J., Staudigel, M., Rahbauer, S. (2022). Demand elasticities for fresh meat and welfare effects of meat taxes in Germany. *Food Policy* 106: 102194.

Shreay, S., H. H. Chouinard, and J. J. McCluskey. 2016. "Product Differentiation by Package Size." Agribusiness: an International Journal 32(1): 3-15.

Statista. (2018). Per capita consumption of meat products in Germany in 2016 and 2018, by type (in kilograms). Retrieved from https://www.statista.com.

Statista. (2019). Meat substitutes market size in selected countries Europe in 2018 (in million euros). Retrieved from www.statista.com.

Taylor, H., Tonsor, G.T., Lusk, J.L., Schroeder, T.C. (2022). Benchmarking US consumption and perceptions of beef and plant-based proteins *Applied Economic Perspectives and Policy*, 2022: 1–22.

Theil, H. 1965. The information approach to demand analysis. Econometrica 33: 67–87.

Tilman, D., & Clark, M. (2014). Global diets link environmental sustainability and human health. *Nature*, 515(7528), 518–522.

Verbeke, W., Sans, P., van Loo, E.J. (2015). Challenges and prospects for consumer acceptance of cultured meat. *Journal of Integrative Agriculture*, 14(2): 285–294.

Vincent, D. W. 2015. "The Berry-Levinsohn-Pakes estimator of the random-coefficients logit demand model." The Stata Journal 15(3): 854-880.

Wang, Y. and Cakir, M. (2020). Welfare impacts of new demand-enhancing agricultural products: The case of Honeycrisp apples. *Agricultural Economics*, 51: 445-457.

Weinrich, R., Strack, M., Neugebauer, F. (2020). Consumer acceptance of cultured meat in Germany. *Meat Science*, 162: 107924.