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Plant-based meat complements

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PLANT-BASED MEAT COMPLEMENTS*

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Abstract

Reducing meat consumption is a global policy priority due to environmental, health, and animal welfare concerns. Meat taxation is often proposed as a policy tool, with price elasticities as key inputs for ex ante evaluations. We estimate own- and cross-price elasticities for major meat categories and plant-based meat substitutes (PBMS) using weekly transaction data from approximately 1,500 products across several retail chains and 884 Dutch stores (2015–2018). We estimate a Quadratic Almost Ideal Demand System and find that most meat categories have inelastic own-price elasticities, except pork, which is elastic. Surprisingly, PBMS exhibit a positive own-price elasticity and negative cross-price elasticities with most meat prices, suggesting that PBMS function as complements rather than substitutes. We discuss potential drivers, including the growing availability of high-quality PBMS. Finally, we simulate meat tax scenarios and show that a simple VAT increase achieves meaningful reductions in demand and environmental impact.

Keywords: Consumer demand; meat; plant-based meat substitutes; QAIDS; price elasticity

JEL Codes: D12, H23, Q18

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1 Introduction

The transition from animal-based to plant-based protein is attracting increasing policy attention due to environmental, health, and animal welfare concerns (e.g., Godfray et al.) 2018; De Boer and Aiking, 2019; Bonnet et al., 2020). Food systems account for 34% of global anthropogenic greenhouse gas (GHG) emissions (Crippa et al., 2021), with meat production being significantly more carbon-intensive than plant-based foods (Tilman and Clark) 2014; Godfray et al., 2018). The recent IPCC special report on climate change and land (IPCC, 2019) identifies dietary change towards low-GHG diets, with a higher share of plant-based food, as a major opportunity for climate change mitigation and adaptation. While meat is a key source of protein, high consumption – especially of red and processed meat – is strongly linked to health risks such as colorectal cancer, cardiovascular diseases, and diabetes (e.g., Norat et al.) 2005; Rohrmann et al., 2013; Wolk, 2017). Beyond its environmental and health impacts, animal welfare is a rising concern. Intensive livestock production may be morally problematic due to its disregard for the living conditions of animals; an issue gaining attention in economic research (Lusk and Norwood, 2011; Hestermann et al., 2020; Espinosa and Treich, 2024).

Many countries have set targets to transition toward more sustainable protein sources, aiming to reduce environmental impacts, enhance food security, and diversify protein production. In the Netherlands, the government set a food policy goal to shift the current consumption pattern from 60% animal-based and 40% plant-based proteins to an equal split of 50–50 by 2030, and potentially an even larger transition to 40% animal-based and 60% plant-based proteins (Health Council of the Netherlands, 2023). Other countries are also developing protein transition strategies, but few have articulated such explicit consumption targets.

Altering meat consumption patterns relies on individual dietary behavioral change. Several policy interventions are under discussion to help consumers change their dietary behavior, including fiscal policies, informational interventions, and nudges (Bonnet et al.) 2020). There is a growing interest in using a Pigovian meat tax to reduce meat consumption (e.g., Nordgren, 2012; Jarka et al., 2018; Funke et al., 2022), supported by recent research suggesting that fiscal policies are necessary to achieve substantially lower levels of meat consumption (Katare et al., 2020). The effectiveness of meat taxation depends on consumers' response to price changes, making price elasticities key parameters for ex ante policy evaluations. Previous studies have estimated such meat price elasticities in countries such as Sweden, France, and Germany (e.g., Säll and Gren, 2015; Säll, 2018; Bonnet et al., 2018; Roosen et al., 2022) and used these elasticities to simulate the environmental impacts of different meat tax designs. These estimates are hindered, however, by a lack of detailed meat consumption data, and it remains unclear whether price incentives can effectively drive substitution towards plant-based proteins (Hassett et al., 2025). In this paper we address both issues.

One approach to estimate price elasticities for meat consumption is to use time-series data on aggregate demand at the country level (e.g., Säll and Gren, 2015). However, this approach can only provide a rough indication of consumption patterns, as it relies on data from production and trade. An alternative approach is to use scanner data acquired from household surveys or sample stores (e.g., Capps Jr, 1989; Dong et al., 2015; Caillavet et al., 2016). These data allow controlling for consumer characteristics but face potential selection bias due to sampling and measurement errors due to the difficulty of observing the prices and expenditure of fresh meat products (Lensing and Purcell, 2006; Zhen et al., 2009; Einav et al., 2010; Taylor and Tonsor, 2013). A meta study by Cornelsen et al. (2016) compared studies using aggregate time-series data, cross-sectional and longitudinal household survey data, and found that the level of detail in the data can significantly affect the estimated price elasticities.

In this paper, we use a detailed store- and item-level supermarket scanner dataset to estimate (own- and cross-) price elasticities of meat, fish, and, importantly, PBMS. The barcode scanner data contain weekly observations on prices and sales from 884 supermarket stores across the Netherlands, belonging to several chains, for the period between 2015 and 2018. The original dataset includes more than 265 million observations and covers products from all animal protein categories, as well as the category including PBMS products. Our weekly store-level dataset is much more disaggregated than time-series data, enabling us to exploit variations in prices and demand across stores, chains, and time. Furthermore, it does not suffer from potential sampling and measurement errors compared to studies based on market survey scanner data. We include both traditional and novel PBMS in a newly constructed PBMS category for our analysis. Over the last decades, novel plantbased products such as veggie burgers have been developed to imitate the appearance, taste, and texture of meat products, positioning them as a new and trending alternative source of protein intake (Tziva et al., 2020). Accordingly, we provide a more comprehensive and precise estimation of price elasticities, while including PBMS as a separate category.

To our knowledge, only the recent study by Zhao et al. (2023) has used supermarket scanner data to estimate the cross-price elasticities between meat and PBMS. However, their data are aggregated at the state level which does not allow them to use variation in prices and products between stores. Additionally, although their data cover the period 2017–2020, the study was conducted in the United States where the market share of PBMS is relatively low, ranging from 0.05% to 0.34% across different states, compared to 4% in the Netherlands. The Netherlands is a pioneer country in the market for PBMS with the largest consumption share among European countries. Therefore, empirical evidence from the Netherlands is particularly instructive for understanding how consumers behave when PBMS are both widely available and easily accessible.

Supermarket consumption plays a key role in Dutch food policy because it closely reflects overall household food consumption. There are two main reasons. First, unlike many other countries where eating out is more common, the Dutch consume a high share (about 80%) of their food at home (Van Rossum et al., 2023). Second, Dutch consumers purchase the majority of their groceries from supermarkets rather than specialized stores or other retail channels. Supermarkets account for around 60% of total food expenditure (Berkhout et al., 2024).

We use a quadratic version of the Almost Ideal Demand System (QAIDS) (Banks et al.), [1997] to model store-level consumer demand. The widely used Almost Ideal Demand System (AIDS) method has the advantage of providing intuitive price elasticities while satisfying the theoretical assumptions of consumer demand (Deaton and Muellbauer, 1980a). The quadratic extension by (Banks et al.) [1997] also allows for non-linear total expenditure. Recent countryspecific studies have used (Q)AIDS models to estimate price elasticities of meat (Smed et al., 2007; Säll and Gren, 2015; Dong et al., 2015; Caillavet et al., 2016) with data sources ranging from aggregated per capita consumption and price data to individual or household panel survey data. In terms of food groups, most studies focus exclusively on meat categories and do not include a separate category for PBMS, with the exception of Caillavet et al. (2016) who group food items based on environmental impacts, nutritional contents, and substitution options within the group.

Although prices are (indirectly) observed in our store-level data, as opposed to household survey data where prices are usually missing, we still face the identification challenge of endogenous prices, which may result in biased and inconsistent estimates. This concern is especially relevant when using aggregate retail data (Chintagunta, 2001). Retailers may set prices based on historical demand and on consumer characteristics unobserved by the researcher. The resulting price endogeneity can lead to an underestimation of price elasticities. We follow the industrial organization literature (Hausman et al., 1997; Nevo, 2003) and apply Hausman instrumental variables to address this endogeneity. Nevo (2003) argues that the average price of the same product in other markets can serve as a valid instrument given that prices in different markets are correlated due to common cost shocks, while any specific demand shock in one market should not directly affect prices in another. Similarly, we use the weighted average prices of the same food category in nearby stores – that are not from the same chain – as a proxy for actual prices.

This paper has two main contributions. First, we provide new evidence on how price changes affect the demand for meat, fish, and PBMS based on current market conditions and consumer preferences. Our estimates of price elasticities for beef, pork, poultry, and fish are consistent with the extant literature. However, we find a surprising positive price elasticity for PBMS, suggesting that PBMS act as a complement to meat. We discuss this result in the context of an emerging market where the supply side is changing in terms of both quality and prices. Second, we use these new elasticities to simulate the impact of possible meat taxation schemes on meat consumption as well as resulting reductions in related GHGs. We find that a simple increase in the VAT on meat (from 9% to 21%) results in a similar environmental outcome when compared to a Pigovian tax scheme in which each meat category is taxed based on (a lower bound of) its environmental social cost.

The remainder of the paper is structured as follows. We begin by introducing the supermarket scanner data in Section 2. In section 3, we describe the methodology of estimating price elasticities using a QAIDS model. Section 4 presents our results on price elasticities and the subsequent simulations of two meat taxation schemes. The final section provides conclusions.

2 Data

We use a large supermarket scanner dataset from Statistics Netherlands which covers 884 stores from several supermarket chains over the period from 2015 to 2018. The stores in our data are geographically dispersed across the country. The dataset contains weekly observations on sales and quantity for each product in the food domain. Each item is uniquely identified by either a thirteen-digit European Article Number or a supermarket's own barcode, linked to its product description which includes the brand, name, and package size. All items are categorized using the Classification of Individual Consumption according to Purpose (COICOP), a system for classifying consumer expenditure managed by the United

 $^{^{1}}$ We also have data for the years 2019–2020 that we decided not to include because from 2019 onward substantial changes occurred in the data reporting procedure.

Nations. The five-digit COICOP code categorizes items belonging to meat and its subcategories. For our analysis, we focus on three meat groups – beef, pork, and poultry – while lamb and other meats are excluded from the analysis since they constitute only a small percentage of turnover. In addition to these three meat groups, we include fish as a separate category, as it is both a key source of animal-based protein and an integral part of the Dutch diet. Finally, because the COICOP classification does not feature a separate PBMS category, we manually construct one based on product descriptions. Most products included in this category are novel PBMS products, which are easily identified because they tend to be explicitly marketed as meat replacements. Unlike Zhao et al. (2023) who only include novel PBMS, we also include traditional PBMS, such as tofu and tempeh. These products are a major source of plant-based proteins, and are typically displayed alongside novel PBMS in Dutch supermarkets.²

For each item, we observe weekly aggregate sales and quantities at the supermarket chain-store level. We use this data to calculate the unit prices (euro/kg) of each product, and then the unit prices (euro/kg) of each category for our demand system estimation. Unit prices of each product category are weighted by the number of units sold of each product within that category. One concern with unit prices is the quality bias suggested by Deaton (1988), and also discussed in the meta-analysis on food price elasticities by Cornelsen et al. (2016). Specifically, unit price changes do not solely reflect changes in product prices within a category but also substitution within that category between more expensive and cheaper products (usually reflecting quality differences). For example, price changes may affect both how much beef is purchased and whether consumers opt for expensive beef steaks or cheaper minced beef. As a result, the price variation captured by unit prices for categories tends to be smaller than the actual variation. This suggests that actual price changes may be somewhat underestimated, which could potentially lead to an overestimation of price elasticities (Cornelsen et al., 2016).

The major data problem we face is related to the calculation of unit prices. There are measurement errors in prices (euro/g or euro/piece) and missing values for quantities (weight) in some meat and fish products.³ We use a two-step procedure to address both issues. First, for products that have quantity data available but where it is unclear whether the price is in euro/g or euro/piece, we calculate average prices and then use cutoff prices to determine

 $^{^{2}}$ Although beans are also an important source of plant-based proteins, we did not include them in our PBMS category as beans are less commonly marketed as meat substitutes in Dutch supermarkets.

³These problems do not exist for PBMS. Unlike meat, they typically have standard package sizes, and this information is usually available in the product description.

the price type.⁴ Next, we convert gram prices to kilogram prices. Second, for products that only have per-piece prices as well as those with missing quantity data, we use a text-based algorithm to fill in the correct quantity information. Regular expressions are applied to identify quantity details in the product descriptions, such as "100 g", "1 kg", "1000gr", etc. If such information is available, we extract the quantity data and convert it to kilograms. Next, we calculate the unit price for each item, which represents the average weekly price of the item in a store within a particular supermarket chain.

This two-step procedure means that we drop observations where measurement errors are suspected – i.e. items for which we cannot identify gram prices or per-piece prices – and for which we cannot determine a consistent package size. In total, around 15% of observations are dropped in this procedure. Upon inspecting product names and descriptions, we did not find evidence of systematic bias in the characteristics of the dropped products. We further trim outliers within each food category, removing products in the top 1% highest and bottom 1% lowest prices within a category. Next, we construct the unit price, representing the average weekly price per food category in a store within a particular supermarket chain, and again we trim the top 1% and bottom 1% observations as outliers.

We identify the unique location of each store using its 4-digit postcode (PC4) address. Since the exact address is not available, we use the coordinates of the center of the PC4 as a proxy for the store's location. These coordinates are then used to calculate the distances between store pairs, which are used in constructing our instrumental variables, as explained further in Section 3

Overall, we observe that for each product item, prices vary substantially across chains and over time, but less so across locations and individual stores. More specifically, at the same time point, the main source of price variation is price differences between chains, while the within-chain price variation among stores is relatively small. Price variations also occur over time, driven by both baseline price differences between supermarket chains as well as weekly promotions. Unobserved promotions may introduce potential bias when estimating price elasticities, as they can lead to hoarding behavior by consumers. Hoarding implies that the demand response to prices during the week of a promotion might be overestimated while the demand response in subsequent weeks might be underestimated. To address this potential bias, we calculate demand using a 2-week moving average, which helps eliminate most short-term hoarding induced by promotions. As a robustness check (see Appendix B.4),

 $^{^{4}}$ We use prices below 0.07 Euro as an indication for gram prices and prices above 1 Euro as an indication for per-piece prices. For products with gram prices, we drop the bottom 0.5% of observations.

we also provide an alternative specification that does not use a moving average.

Figure 1 illustrates weekly aggregate price-quantity combinations for four randomly selected stores from our sample. The figure shows predominantly downward-sloping correlations between quantities and (endogenous) prices. Importantly, there is substantial variation in prices and quantities, across stores and over time, which we exploit in our analysis. Due to the computational limitations of Stata, we restrict our sample to half the stores of the full dataset. We apply stratified sampling based on supermarket chains. The data description below is based on this subsample, while a description of the full sample is provided in Appendix A



Figure 1: Plots of weekly price-quantity combinations for five product categories (different colors) in four stores (different subplots).

Figure 2 shows the price distributions for the three categories of meat, as well as fish and PBMS. Differences in aggregated prices arise from both the prices set by supermarkets as well as consumer choices for specific items within a category (such as different cuts of meat), given that the unit price per category is a weighted average of all products in the category. The histogram of beef prices is the only one to display a bimodal distribution; beef products show a clear price difference between low-quality beef, such as minced beef, and high-quality beef, such as rib-eye steaks. Figure 3 illustrates the weighted (by sales) category prices of different product categories between 2015 and 2018 (adjusted for CPI). The prices of pork, poultry, and fish follow an increasing trend over the sample period. Beef prices remain relatively stable, with seasonal fluctuations in the first four years followed by a price drop at the end of 2018. In contrast, the prices of PBMS exhibit a slight downward trend over time. Figure 4 shows the market shares of different product categories between 2015 and 2018. Among all categories, the market share of PBMS is small and stable at about 4%. Both poultry and fish show slightly increasing market shares, while the shares of beef and pork remain stable over the sample period. Finally, Table 1 presents the descriptive statistics of the subsample used for the demand system estimation. For comparison, we also provide the distributions, trends and descriptive statistics for the full sample in Appendix A.



Figure 2: Price histograms by product category



Figure 3: Weighted (by sales) category prices, adjusted for CPI

P P P						
	Mean	SD	Min	Max		
Beef price (Euro)	11.57	2.53	6.67	16.63		
Pork price (Euro)	7.85	0.57	6.40	9.79		
Poultry price (Euro)	8.21	0.63	6.56	10.04		
Fish price (Euro)	13.39	1.56	9.35	17.93		
PBMS price (Euro)	12.38	0.96	8.12	14.64		
Beef share	0.20	0.07	0.08	0.40		
Pork share	0.21	0.05	0.08	0.37		
Poultry share	0.36	0.06	0.19	0.49		
Fish share	0.19	0.04	0.09	0.31		
PBMS share	0.04	0.02	0.01	0.12		
Observations	55,438					

Table	1:	Г	escriptive)	e statistics
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3 Methods

We model supermarket consumers' demand and estimate own- and cross-price elasticities for beef, pork, poultry, fish, and PBMS using a QAIDS model as proposed by Banks et al. (1997). This model is an extension of the original AIDS model developed by Deaton and Muellbauer (1980a). The AIDS model and its variations have been widely applied to estimate priceand income elasticities, including in the food domain (see for instance the meta-analyses by Gallet, 2010b,a; Cornelsen et al., 2016).⁵ Although this model was originally applied

⁵Different demand models have been used to estimate price elasticities, each with its own advantages and disadvantages. Alternative popular approaches include the Exact Affine Stone Index (EASI) demand system (Lewbel and Pendakur, 2009), and random utility models, such as the multinomial logit, nested logit, or random coefficient logit models (McFadden, 1974; Berry, 1994; Berry et al., 1995). Random utility models



Figure 4: Market shares by product category

to household survey data to model individual or household preferences, it has also been applied to aggregate retail scanner data, such as store-level retail data (Jones et al., 2003; Bronnmann, 2016; Lindström, 2022). In this case, the model captures the behavior of the representative consumer.

The QAIDS model addresses a key limitation of the original AIDS model, which does not allow nonlinear Engel curves. Expenditure on animal-based products likely exhibits a nonlinear relationship with income, as meat and fish may become necessities for wealthier households. Given their relatively high price, PBMS may be considered luxury goods for poorer households but necessities for wealthier ones. Therefore, the QAIDS model appears to be a suitable choice for our data.

We use the QAIDS model to estimate how product price, other products' prices, and total expenditure affect aggregated consumer choices regarding the budget share spent on a product category. The product categories included in the demand system are beef, pork,

have the advantage of avoiding a large number of parameter estimates in demand systems when there are many food groups and multiple stages (McFadden, 1974), allowing for flexibility in substitution behavior due to heterogeneity in consumer characteristics. As a result, estimation biases are smaller compared to demand systems when the model is mis-specified (Huang et al., 2008). However, a disadvantage of this approach is that it only accounts for discrete choices.

poultry, fish, and PBMS. The model is expressed using the following system of equations:

$$s_{ikt} = \alpha_i + \sum_{j=1}^n \beta_{ij} \ln p_{jkt} + \gamma_i \ln \left(\frac{X_{kt}}{P_{kt}}\right) + \tau_i \ln \left(\frac{X_{kt}}{P_{kt}}\right)^2 + \mu_{ikt},\tag{1}$$

$$\ln P_{kt} = \alpha_0 + \sum_{j=1}^n \alpha_j \ln p_{jkt} + \frac{1}{2} \sum_{j=1}^n \sum_{i=1}^n \beta_{ij} \ln p_{ikt} \ln p_{jkt}.$$
 (2)

The dependent variable s_{ikt} represents the expenditure share of total expenditure for product category i (i = 1, 2, ..., n) in store k in week t. It is defined as $s_{ikt} = p_{ikt}q_{ikt}/X_{kt}$, where X_{kt} is the total expenditure on the n product categories included in the demand system, $X_{kt} = \sum_{i=1}^{n} p_{ikt}q_{ikt}$. P_{kt} is a price index and μ_{ikt} denotes the error term. We estimate four parameters from the above system, α_i , β_{ij} , γ_i , and τ_i . Our main interest lies with β_{ij} , γ_i , and τ_i . These parameters measure the effects of a price change of product j on the expenditure share of product i, and the effect of a real income change on this expenditure share. To account for heterogeneity among supermarket chains, time trends, and differences across stores, we include chain indicators, month and year fixed effects, and store fixed effects (captured by the α parameters) following the approach of Leccoq and Robin (2015).

Estimating the above system of equations requires satisfying certain properties for the model to be consistent with utility maximization. The first assumption is adding-up, expressed as $\sum_{i=1}^{n} \alpha_i = 1$ and $\sum_{i=1}^{n} \beta_{ij} = \sum_{j=1}^{n} \beta_{ji} = 0$, which states that the sum of expenditures on each product equals total expenditures, implying that the sum of expenditures cannot exceed total income. The second assumption is homogeneity, given by $\sum_{i=1}^{n} \gamma_i = 0$, which states that the demand remains unchanged if all prices as well as total expenditure increase by the same positive proportion. The final assumption is symmetry of the Slutsky equation, given by $\beta_{ij} = \beta_{ji}$. While all three assumptions are theoretically required for utility maximization, in practice, the symmetry and homogeneity assumptions can be relaxed when using aggregated store-level data, as supported by Deaton and Muellbauer (1980b) and Christensen et al. (1975).

Using scanner data to conduct demand system analysis implies a potential endogeneity issue due to the classic simultaneity of demand and supply. While consumers decide their consumption quantities based on market prices, retailers may simultaneously adjust prices in response to market demand. This joint determination of prices and consumption is particularly relevant for aggregated store scanner data, as opposed to household-level data. While the influence of a single household on prices can be ignored, the aggregated behavior of all customers at a specific store may induce price adjustments from the supply side. We use instrumental variables to address this price endogeneity. Because our dataset includes observations from multiple supermarket chains, we follow the approach of Hausman et al. (1997) and Nevo (2003) and use average prices of neighboring stores from different chains as instruments for own store prices. This instrument relies on the idea that a product's price in a specific region and supermarket chain reflects not only general product costs and chain-level factors, but also other costs related to the region, as well as consumer characteristics in that region. Since general product costs are shared across regions, average prices from other chains in the region are correlated with own store prices. This approach assumes that region-specific and chain-specific costs are uncorrelated. In the Netherlands, this assumption is plausible due to the country's small size, well-integrated infrastructure, and relatively homogeneous regions, which minimize regional cost differences. Additionally, centralized pricing strategies for standardized goods like meat and fish further reduce the influence of regional factors.

To construct the instrument, we first calculate the Euclidean distances from the center of the PC4 area where each store is located to the PC4 areas of all other stores, as a proxy for the distances between a store and other stores. Next, we select only those stores that are within 10 km radius and do not belong to the same supermarket chain. The weighted average price of a particular product category from this selection of stores is then used as an instrument for the price of the same category in the own store. On average, there are 4.6 competing stores within this 10 km radius.⁶

We are ultimately interested in estimating elasticities. The price and expenditure elasticities follow directly from the estimated parameters. The expenditure elasticities e_i are given by

$$e_i = 1 + \frac{\gamma_i}{s_i}.\tag{3}$$

The uncompensated Marshallian elasticities e_{ij}^M , which account for both income and substitution effects, are given by

$$e_{ij}^{M} = \frac{\beta_{ij} - \gamma_i s_j}{s_i} - \delta_{ij},\tag{4}$$

where $\delta_{ij} = 1$ if i = j, and otherwise $\delta_{ij} = 0$.

 $^{^{6}}$ We explore the sensitivity of our results to the size of this area in a robustness check provided in Appendix B.3

	Beef price (ln)	Pork price (ln)	Poultry price (ln)	Fish price (ln)	PBMS price (ln)
IV beef price	-0.014^{***}	0.000	0.001^{***}	0.008***	-0.007^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
IV pork price	0.000	0.001^{**}	0.001^{***}	0.015^{***}	0.007^{***}
	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
IV poultry price	-0.005^{***}	0.001	-0.005^{***}	0.028^{***}	-0.006^{***}
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
IV fish price	0.008^{***}	0.005^{***}	0.004^{***}	-0.001^{***}	0.001^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
IV PBMS price	-0.004^{***}	0.003^{***}	-0.003^{***}	0.002^{***}	-0.007^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Total consumption (ln)	-0.069^{***}	0.011^{***}	-0.003^{**}	0.047^{***}	0.002
	(0.003)	(0.002)	(0.001)	(0.002)	(0.002)
Constant	3.222^{***}	1.757^{***}	2.120^{***}	1.831^{***}	2.477^{***}
	(0.027)	(0.019)	(0.012)	(0.024)	(0.024)
Observations	55438	55438	55438	55438	55438
Adjusted R^2	0.895	0.466	0.821	0.673	0.300
F	1127.617	116.527	606.046	273.622	57.776

Table 2: QAIDS model first-stage results

Note: Standard errors in parentheses.

* p < 0.1, ** p < 0.05, *** p < 0.01.

4 Results

4.1 Main results

Table 2 reports the first-stage results of the QAIDS model. Nearly all IV prices are significantly correlated with the original prices. For the same product category, all IV prices exhibit a significant negative coefficient, except for pork. The first-stage results demonstrate strong statistical power with F statistics ranging from 57 to 1127.

Table 3 presents the main results of the QAIDS model. The significance of the coefficients of the quadratic expenditure terms suggest that the QAIDS version is preferred. Coefficients from the QAIDS model can be used to calculate the price elasticities, in which we are ultimately interested. These elasticities highlight the potential substitution effects between product categories.

Table 4 reports these elasticities. We report the uncompensated (own- and cross-) price elasticities instead of compensated price elasticities to facilitate comparison with the existing literature. The own-price elasticities are presented on the diagonal and represent the per-

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	Beef	Pork	Poultry	Fish	PBMS
	share	share	share	share	share
Beef price (ln)	0.054	0.043	0.043	-0.095^{***}	-0.046***
	(0.028)	(0.026)	(0.024)	(0.020)	(0.010)
Pork price (ln)	0.043	-0.222^{***}	0.057	0.092**	0.029
	(0.044)	(0.040)	(0.036)	(0.031)	(0.016)
Poultry price (ln)	0.043	0.057	-0.078^{*}	0.032	-0.054^{**}
	(0.047)	(0.043)	(0.039)	(0.034)	(0.017)
Fish price (ln)	-0.095^{***}	0.092^{***}	0.032^{*}	0.003	-0.032^{***}
	(0.017)	(0.016)	(0.015)	(0.013)	(0.006)
PBMS price (ln)	-0.046	0.029	-0.054	-0.032	0.103^{***}
	(0.041)	(0.038)	(0.033)	(0.029)	(0.015)
Total consumption (\ln)	-0.101^{***}	-0.020	0.159^{***}	-0.042^{***}	0.004
	(0.012)	(0.014)	(0.011)	(0.010)	(0.003)
Squared total consumption (\ln)	0.009^{***}	0.003^{**}	-0.013^{***}	0.001	-0.001^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Observations 5	55438				

Table 3: QAIDS model regression results

Note: Standard errors in parentheses.

* p < 0.1, ** p < 0.05, *** p < 0.01.

centage change in the expenditure share of a product category in response to a 1% change in its price. All own-price elasticities are statistically significant. We expect all own-price elasticities to be negative, which we find confirmed for all product categories except for PBMS. The own-price elasticities for beef, pork, poultry, and fish are estimated at -0.56, -2.06, -0.94, and -0.92, respectively, suggesting that the price elasticity for pork is notably higher than for the other categories.

Our estimates are broadly consistent with those of Andreyeva et al. (2010), Gallet (2010b), and Säll and Gren (2015), who all report an average own-price elasticity for meat of around -0.7. However, some studies using household scanner data report higher elasticities. For example, Smed et al. (2007) reports own-price elasticities for all meat categories ranging from -2.02 to -1.01 in Denmark. Similarly, Bonnet et al. (2018) estimate own-price elasticities for 23 groups of animal-based products in France, finding values between -1.61 and -1.18. One possible explanation for the relatively high price elasticity of pork in our estimates is that, compared to other meat categories, pork is more commonly consumed by lower-income Dutch households, possibly making its demand more sensitive to price changes.

Surprisingly, the own-price elasticity for PBMS is positive at 1.49; a 1% price increase for PBMS results in a 1.49% increase in demand. This result is counterintuitive, as one would

	Beef	Pork	Poultry	Fish	PBMS
	price	price	price	price	price
Share of beef	-0.560^{***}	0.234	-0.138	-0.455^{***}	-0.252
	(0.133)	(0.223)	(0.237)	(0.085)	(0.207)
Share of pork	0.228 (0.118)	-2.064^{***} (0.193)	0.164 (0.206)	0.421^{***}	0.131 (0.181)
Share of poultry	-0.025 (0.057)	0.134 (0.096)	-0.944^{***}	0.046	-0.136
Share of fish	(0.007)	(0.050)	0.102)	(0.050)	(0.003)
	-0.430^{***}	0.537^{**}	0.113	-0.919^{***}	-0.173
	(0.104)	(0.173)	(0.182)	(0.065)	(0.161)
Share of PBMS	(0.104) -1.118^{***} (0.234)	(0.173) 0.720 (0.389)	(0.133) -1.170^{**} (0.413)	(0.003) -0.747^{***} (0.147)	$\begin{array}{c} (0.101) \\ 1.486^{***} \\ (0.361) \end{array}$

Table 4: Uncompensated own- and cross-price elasticities

Note: Standard errors in parentheses.

* p < 0.1, ** p < 0.05, *** p < 0.01.

typically expect a negative own-price elasticity. This expectation aligns with Zhao et al. (2023) who estimate an own-price elasticity for PBMS of -1.48. One possible explanation for the positive price elasticity for PBMS in the current study is the changing composition of this category over the 4-year sample period. The variety and quality of PBMS products in the Dutch market have been increasing steadily over this period, while prices of newly introduced products did not necessarily decrease. Unlike the *sales-weighted* category price for PBMS, which decreases over time (Figure 3), the average *unweighted* product prices show a slight increase for much of the sample period. Both price trends are illustrated in Figure 5. This difference in trends between weighted and unweighted PBMS prices reflects the introduction of more higher-priced PBMS products to the market over the sample period. Similar trends have been observed in other markets, such as the electric vehicle (EV) market: while sales-weighted prices remain relatively constant, unweighted prices increase steadily as more high-priced EVs are introduced (Gillingham et al., 2023). In our case, consumers may respond to the novel (higher-priced) PBMS products with higher demand due to their preferences for attributes like taste, texture, etc. Thus, price elasticities in a market in its early stages of development may evolve over time as the supply side changes in terms of both quality and prices.

Further support for this argument comes from a model variant that uses a narrower PBMS category, excluding novel PBMS and retaining only traditional ones such as tofu and tempeh. This yields a strongly negative own-price elasticity of -4.45. However, due to limited price variation in traditional PBMS, the model has difficulties converging. When replacing store



Figure 5: Weighted and unweighted PBM prices (with trend-lines), adjusted for CPI

dummies with broader urbanity and province dummies (data otherwise unused in this paper), we obtain a statistically significant elasticity of -0.83. This implies that the counterintuitive positive price elasticity is driven by novel PBMS, not traditional ones, because the latter are less affected by changing category composition.

For the cross-price elasticities we expect positive coefficients, indicating that consumers often substitute between animal-based product categories. This expectation is confirmed for substitution between beef and pork, as well as between fish and pork. However, we also observe some negative or statistically insignificant cross-price elasticities between animalbased products. Similar findings have been reported by Roosen et al. (2022) for Germany, Säll and Gren (2015) for Sweden, and Rickertsen (1996) for Norway and Scotland.

Regarding our main interests in the substitution from animal-based to plant-based proteins, we find that PBMS are complements to beef, poultry, and fish, but substitutes to pork. This finding challenges the general notion that PBMS are suitable replacements for animal products. Nevertheless, it is consistent with the estimates of Zhao et al. (2023) who also report negative cross-price elasticities between the prices of beef, pork, and other meat types, and the demand for PBMS (see also Caputo et al.) 2025). Our estimates indicate that a 1% increase in the price of beef, poultry or fish will respectively lead to a 1.12%, 1.17%, or 0.75% decrease in the demand for PBMS. Overall, our findings provide evidence that plantbased meat substitutes are better characterized as *complements* rather than *substitutes* for animal-based proteins.

4.2 Robustness checks

We perform a set of robustness checks to assess whether our results are sensitive to model selection, sample selection, and the construction of the instruments. Results from these tests are presented in the appendix. Overall, we find that our results are robust to these alternative choices in model setup. In Appendix B.1, we present the results from a linear AIDS model. In Appendix B.2, we use an alternative randomly selected subsample comprising 50% of the stores in the full sample. In Appendix B.3, we run the QAIDS model with alternative IVs to examine whether our results are sensitive to the radius used for inclusion of competing stores. Specifically, we first decrease and then increase the original 10 km radius by 2 km. In Appendix B.4, we run the QAIDS model without using a 2-week moving average for demand. Recall that moving averages for market shares were used to control for potential hoarding behavior, so one would expect larger responses to prices when moving averages are not applied. Indeed, we find that the resulting price elasticities are more elastic than in our main results, confirming the presence of hoarding behavior in response to discounts. Finally, In Appendix B.5, we estimate an alternative model that excludes PBMS. This alternative demand system addresses the concern that a demand system may not perform well when one or more groups account for only a small share of total demand, as is the case for PBMS in our study. We find that the own-price elasticities align closely with our main results, see Table B1 in Appendix B.

4.3 Effects of an environmental meat tax

We use the price elasticities estimated from the QAIDS model to simulate changes in demand and the resulting environmental impacts of a potential meat tax. We consider two meat taxation schemes. The first is an ad valorem tax based on an increase in the VAT rate for all meat categories (beef, pork, and poultry) from 9% to 21%, the two rates under the current Dutch VAT regime. At present, the lower VAT rate applies to food products, including meat. A recent policy proposal suggests applying the higher VAT rate of 21% to all meat categories. This scenario is comparable to the German study by Roosen et al. (2022) which evaluates a VAT increase from 7% to 19% (see also Springmann et al., 2025).

The second meat taxation scheme we consider is a differentiated Pigovian excise tax based on the carbon emissions associated with each meat category (beef, pork, and poultry). Our Pigovian tax is rather conservative for three reasons: (a) we include only the climate change impacts of meat consumption, ignoring aspects such as biodiversity, nutrient pollution, health, and animal welfare (see e.g. [Funke et al.] [2022]); (b) we use a conservative estimate of the Social Cost of Carbon, specifically the lower bound in Rennert et al. (2022); and (c) we account for the fact that 80% of beef in the Netherlands originates from dairy herd, with only a small portion of their GHG emissions attributed to meat under current accounting rules (CE Delft, 2018). The rationale behind this conservative design of the Pigovian tax is twofold. First, implementing a relatively high tax rate appears unfeasible in the current Dutch political climate. Second, higher tax rates would stretch the validity of our estimated price elasticities, which are more reliable for smaller price changes. Elasticities derived from the QAIDS model may not hold under very large price shifts, as they are based on observed data within a limited price range. Moreover, such high rates could reduce consumption of certain meat categories to near-zero levels, which appears unrealistic (we briefly describe the impact of applying the mean estimate of the Social Cost of Carbon from Rennert et al.] (2022) at the end of this section).

The associated tax levels for both meat taxation schemes are summarized in Table 1 Note that this table excludes fish and PBMS, as these products are not taxed under either scheme. However, their consumption is indirectly affected due to cross-price elasticities. Coincidentally, the average tax on meat across all meat categories is identical at 1 Euro/kg under both tax schemes. Because of this similarity, any differential impacts between the two tax schemes arise from differences in tax rates across individual meat categories. As expected, under the Pigovian tax scheme, beef is taxed higher due to its larger climate impact. Consequently, we might expect the Pigovian tax scheme to result in sharper reductions in meat-related GHG emissions. However, as we will see below, this is not the case. This outcome is primarily due to the differences in price elasticities between the meat categories.

We combine the full set of (own- and cross-price) elasticities from Table 4 with the tax schemes and other data from Table 5 to calculate the impact of the tax schemes on changes in demand for each meat category (see Figure 6). Next, we use the carbon emissions data by meat category from Table 5 to calculate the corresponding overall impact on GHG emissions (see Figure 7).

Figure **6** shows that both tax schemes lead to considerable reductions in meat consumption, particularly for pork. This outcome is explained by the relatively high price elasticity of pork compared to the other meat types. While beef, due to its high environmental impact, is taxed heavily under the Pigovian tax, its low price elasticity results in a relatively modest reduction in consumption compared to the VAT increase. The differential impact of the two tax schemes on poultry falls somewhere in between those observed for beef and

	Beef	Pork	Poultry
Average price incl VAT $(Euro/kg)^a$	11.64	7.84	8.21
Consumption $(kg/year per person)^b$	7.42	15.22	8.98
(a) Ad valorem tax via VAT			
Original VAT (%)	9	9	9
New VAT (%)	21	21	21
Tax $(Euro/kg)$	1.28~(11.0%)	0.86~(11.0%)	0.90~(11.0%)
(b) Excise tax on carbon emissions			
Carbon emissions (kg CO2eq per kg meat) ^{c}	54.3	15.3	11.7
Carbon price $(Euro/ton CO2eq)^d$	37.40	37.40	37.40
Tax (Euro/kg)	2.03~(17.4%)	0.57~(7.3%)	0.44~(5.4%)
^a This study.			

Table 5: Data used for simulating the effects of two meat taxation schemes

^b Based on the ratios of meat types from (Dagevos et al., 2022), applied to survey results on meat consumption by Van Rossum et al. (2023).

^c Derived from Poore and Nemecek (2018), converted from data per 100g protein using RIVM (2024) and assuming 80% dairy herd and 20% beef herd composition (CE Delft, 2018).

 d Based on the lower bound estimate from Rennert et al. (2022), converted to Euros using the 2020 exchange rate.

pork. Given poultry's unit price elasticity, the lower tax under the Pigovian scheme results in a proportionally smaller reduction in consumption. Through cross-price elasticities, the tax on meat also affects the consumption of both fish and PBMS. While fish consumption remains largely unchanged, PBMS consumption decreases, consistent with our results that this category acts as a complement to meat.

Figure 6 shows the overall impact of both meat taxation schemes on meat consumptionrelated GHG emissions. Surprisingly, there is no statistical difference between the two outcomes, despite the Pigovian tax scheme being designed to tax more polluting meat categories at higher rates. This similarity in outcomes can be attributed to the relatively elastic demand for pork combined with the relatively inelastic demand for beef. As a result, the higher Pigovian tax rate on beef does not lead to a significant decline in its consumption compared to a VAT increase. Likewise, the relatively low Pigovian tax rate on pork results in a much more modest reduction in pork consumption compared to the VAT increase. Consequently,

⁷Note that this calculation also requires data on carbon emissions for both fish and PBMS, which are not included in Table 5. For fish we again use Poore and Nemecek (2018), converted from data per 100g protein using RIVM (2024), resulting in 12.0 kg CO2eq per kg fish. For PBMS we rely on the review by Shanmugam et al. (2023) who report 1.7 kg CO2eq per kg PBMS.

any environmental gains from the higher Pigovian tax on beef (relative to the VAT increase) are offset by the relatively small reduction in pork consumption (again, relative to the VAT increase). This finding has positive implications: a VAT increase is simpler to implement, both politically and administratively, compared to a Pigovian tax scheme. From an environmental perspective, there is no compelling need to design a complex scheme with differential tax rates for different meat categories.



Figure 6: Change in meat consumption per category

At the start of this section, we listed three reasons why the Pigovian tax that we use is rather conservative. To check the impact of this conservative design, we also examined the effect on meat demand and related environmental impact of using the mean estimate for the Social Cost of Carbon from Rennert et al. (2022) (162.80 EUR/ton CO2eq). Compared to the changes in meat consumption reported for the Pigovian tax scheme in Figure 6, there is one notable difference: the reduction in beef consumption would be four times larger, while the decrease in pork consumption is nullified. This last result is due to the sizable cross-price elasticity from the beef price to pork consumption. Compared to the changes in CO2eq emissions due to meat taxation reported in Figure 7 using the mean Social Cost of Carbon implies that the reduction is about three times larger at -25%, although the standard deviation of this estimate also increases by a factor of three.



Figure 7: Change in CO2eq emissions due to meat taxation (with 95% confidence interval)

5 Conclusion

In this paper, we estimate the price elasticities of demand for beef, pork, poultry, fish, and PBMS using a unique store-level supermarket scanner dataset for the Netherlands. Food consumption is highly context-specific, underscoring the need for country-specific evidence to inform national food policies. This study is set in the Netherlands, where earlier studies mostly relied on meta-analysis based on data from other countries. Most of our estimates align with the literature. For example, we confirm that beef, poultry, and fish exhibit rather inelastic own-price elasticities. We newly document the high price elasticity of pork and the positive elasticity for PBMS, providing evidence that plant-based meats are better characterized as *complements* rather than *substitutes*.

Our simulation results provide new insights for policy-making in the domain of the protein transition. We show that potential meat taxation schemes are more effective at reducing pork consumption compared to beef or poultry. Importantly, a simple VAT increase achieves emission reductions comparable to a differentiated Pigovian tax. Finally, in the context of policy goals for the protein transition, our finding that PBMS are complements to meat suggests that meat taxation alone may not be sufficient to drive consumers to switch to PBMS.

A limitation of our analysis is that we do not examine the distributional effects of the proposed meat taxation schemes. Meat taxes may have disproportionate impacts on lowincome households, as these consumers tend to spend a larger share of their income on food, including meat products. This raises equity concerns that merit policy attention. Future research could explore the design of complementary measures, such as subsidies for plant-based alternatives or targeted income support, to mitigate the regressive effects while achieving the environmental and health objectives of meat taxation. Understanding these distributional consequences is crucial for ensuring that meat taxation policies are both effective and socially equitable.

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A Data description for full sample

Table A1 shows the descriptive statistics (mean, standard error, min, and max) of the full sample. We do not find any significant difference compared to the subsample descriptive statistics of Table 1. Figure A1 shows the price distributions of the five product categories and Figure A2 A3 show the trends of average prices and market shares. Again, these are similar to those of the subsample, compare Figures 2.4.

	I I I I I I I I I I I I I I I I I I I		I I	
	Mean	SD	Min	Max
Beef price (Euro)	11.48	2.50	6.67	16.63
Pork price (Euro)	7.84	0.57	6.40	9.79
Poultry price (Euro)	8.22	0.63	6.56	10.04
Fish price (Euro)	13.40	1.55	9.35	17.93
PBMS price (Euro)	12.39	0.96	8.12	14.64
Beef share	0.20	0.07	0.08	0.40
Pork share	0.21	0.06	0.08	0.37
Poultry share	0.36	0.06	0.19	0.49
Fish share	0.18	0.04	0.09	0.31
PBMS share	0.04	0.02	0.01	0.12
Observations	106,404			

Table A1: Descriptive statistics (full sample)



Figure A1: Price histograms by product category (full sample)



Figure A2: Weighted (by sales) category prices, adjusted for CPI (full sample)

B Robustness checks

We conduct five robustness checks. They are described below. For simplicity, we report for each check only the own-price elasticities. These are combined in Table B1 for easy comparison to the main results from Table 4. In column 'Main results' we repeat the own-price elasticities from the diagonal of Table 4. while subsequent columns present the corresponding elasticities for each of the individual robustness checks (RBC). Comparing columns for each meat type using difference-in-coefficients tests, the price elasticities reported are statistically similar to our main model, with only one exception: in RBC 5 (only animal products) pork becomes more elastic.

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	Main results	RBC 1 Linear	RBC 2 Sample	$ m RBC \ 3 m 8 \ km$	$\begin{array}{c} \mathrm{RBC} \ 3\\ 12 \ \mathrm{km} \end{array}$	RBC 4 Moving	RBC 5 Animal
Beef	-0.560 (0.133)	-0.607 (0.128)	-0.732 (0.101)	-0.644 (0.131)	-0.592 (0.126)	-0.531 (0.158)	-0.569 (0.067)
Pork	-2.064 (0.193)	-2.071 (0.191)	-1.814 (0.145)	-2.173 (0.211)	-1.982 (0.177)	-2.308	-2.648 (0.130)
Poultry	(0.193) -0.944 (0.102)	-0.963	-0.840	-0.956	-0.912	(0.233) -0.699 (0.102)	-0.891
Fish	(0.102) -0.919	(0.105) -0.891	(0.090) -0.857	(0.109) -0.913	(0.098) -0.869	(0.123) -0.883	(0.062) -0.978
PBMS	(0.065) 1.486 (0.361)	(0.064) 1.558 (0.370)	(0.048) 1.157 (0.270)	(0.068) 1.251 (0.339)	$(0.063) \\ 1.561 \\ (0.363)$	(0.078) 2.360 (0.500)	(0.054)
	× /	× /	· /	· /	· /	· /	

Table B1: Uncompensated own-price elasticities for robustness checks (RBC) 1–5

Note: Standard errors in parentheses, all estimates significant with p < 0.01.



Figure A3: Market shares by product category (full sample)

B.1 Linear AIDS model

In this robustness check (RBC 1, 'Linear'), we conduct a standard, linear, AIDS model estimation instead of its quadratic version.

B.2 Alternative subsample

In this robustness check (RBC 2, 'Sample'), we run the QAIDS model on an alternative subsample of 50% of the stores in the total sample. Descriptive statistics on average prices and budget shares are shown in Table B2, which are very similar to the summary statistics of the subsample that is used for the main results, see Table 1.

B.3 Choice of distance in IV construction

In this robustness check (RBC 3, '8 km' and '12 km'), we run the QAIDS model using alternative IVs to check if the results are sensitive to the choice of distance to nearby stores. Recall that we used a 10 km radius for competing stores in the construction of our instruments. Next, we adjust this radius to, respectively, 8 and 12 km. Choosing a narrower definition of neighboring stores results in a smaller sample, but it also means that these stores are competing for more similar consumers and hence the prices they offer will also be more similar. The inverse argument holds for the broader definition of neighboring stores.

		(1 /
	Mean	SD	Min	Max
Beef price (Euro)	11.50	2.50	6.67	16.63
Pork price (Euro)	7.85	0.58	6.40	9.79
Poultry price (Euro)	8.21	0.63	6.56	10.03
Fish price (Euro)	13.42	1.55	9.35	17.93
PBMS price (Euro)	12.40	0.95	8.12	14.64
Beef share	0.20	0.07	0.08	0.40
Pork share	0.21	0.06	0.08	0.37
Poultry share	0.36	0.06	0.19	0.49
Fish share	0.18	0.04	0.09	0.31
PBMS share	0.04	0.02	0.01	0.12
Observations	53,874			

Table B2: Descriptive statistics (alternative subsample)

B.4 Without moving average

In this robustness check (RBC 4, 'Moving'), we run the QAIDS model without using the 2-week moving averages for market shares.

B.5 Only animal products

In this robustness check (RBC 5, 'Animal'), we run an alternative QAIDS model without PBMS. Note that due to the exclusion of PBMS, the last entry in the column is empty.