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Price elasticities of meat, fish and plant-based meat substitutes: evidence from store-level Dutch supermarket scanner data*

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Abstract

Reducing meat consumption has become a global policy target due to rising environmental, health, and animal welfare concerns. We provide novel evidence on how price change in real life affects grocery shopping behavior in the Netherlands. We focus on price-induced behavioral response among major meat categories (beef, pork, and poultry), fish, and the emerging product category of plant-based meat substitutes (PBMS). Our analysis is based on detailed weekly transaction data from approximately 1,500 products in 884 stores from several retail chains between 2015 and 2018. The own- and cross-price elasticities are estimated via a Quadratic Almost Ideal Demand System model, where we instrument the endogenous prices by the average prices from nearby stores. Our results show that all animal products have inelastic own-price elasticities, except for pork (-2.1). PBMS have a significant positive own-price elasticity (1.52), which we explain by the increasing variety of high-quality PBMS products. We also show that PBMS are price complements for beef, poultry, and fish. This study contributes to the policy discussions on a carbon meat tax and the protein transition by providing key statistics on price elasticities.

Keywords: Consumer demand; meat; fish; plant-based meat substitutes; price elasticity
JEL Codes: Q1, D1, D4

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1 Introduction

The transition from animal-based to plant-based protein is high on the policy agenda for reasons related to environmental impacts of food production, health concerns, and animal welfare (e.g., Godfray et al., 2018; De Boer and Aiking, 2019; Bonnet et al., 2020). Food systems account for 34% of global greenhouse gas (GHG) emissions (Crippa et al., 2021). Meat production is much more carbon-intensive compared with plant-based foods (Tilman and Clark, 2014; Godfray et al., 2018). The recent IPCC special report on climate change and land (Mbow et al., 2019) suggests that a dietary transition towards low-GHG emission diets, with a higher share of plant-based food, can be a major opportunity for climate change adaption and mitigation. Although meat has its nutritional values as a good protein source, high meat intake in the Western diet, particularly red and processed meat consumption, is strongly associated with health risks for colorectal cancer, cardiovascular diseases, and diabetes (e.g., Norat et al., 2005; Rohrmann et al., 2013; Wolk, 2017). Besides environmental and health impacts, animal welfare is a rising concern. Intensive livestock production may be morally problematic considering that it ignores the living conditions of animals (Hestermann et al., 2020). A growing economics literature suggests that when maximizing the utility from the consumption of meat, animal welfare has been ignored (e.g., Lusk and Norwood, 2011; Espinosa and Treich, 2024).

Many Western countries have launched protein transition targets, while the exact policy instruments to be implemented are still under discussion. In the EU, fourteen Member States signed the 'European Soya Declaration' in 2017, in which they committed to promote healthy sustainable diets using plant-based proteins, while the Commission also calls for developing national strategies from Member States (EU, 2018). In the Netherlands, the government announced a food policy target of changing the current consumption pattern from 40% animal-based and 60% plant-based proteins to 50% animal-based and 50% plant-based proteins by 2030, and potentially an even larger transition to 40% animal-based and 60% plant-based proteins (Health Council of the Netherlands, 2023).

Altering meat consumption patterns relies on individual dietary behavioral change. Several types of policy interventions that may assist consumers in changing dietary behavior are under discussion, including fiscal policies, informational interventions, and nudges (Bonnet et al., 2020). There is a rising interest in using a Pigouvian meat tax to reduce meat consumption (e.g., Nordgren, 2012; Jarka et al., 2018; Funke et al., 2022). This interest is backed up by recent theoretical research suggesting that fiscal policies are necessary to achieve substantially lower levels of meat consumption (Katare et al., 2020). Nevertheless, the effectiveness of meat taxation depends on consumers' response to price changes, which makes price elasticities key parameters for ex ante policy evaluations. Previous studies have estimated such price elasticties of meat in Sweden, France, and Germany (e.g., Säll and Gren, 2015; Säll, 2018; Bonnet et al., 2018; Roosen et al., 2022) as well as their environmental impacts under different meat tax designs. These estimates are hampered, however, by the lack of detailed meat consumption data, and it remains unclear if price incentives can lead to substitution towards plant-based proteins. The latter question is challenging to answer due to the lack of necessary data on the consumption of plant-based proteins and the difficulty of defining the potential substitutes for meat.

Estimating meat price elasticities has been a popular topic in the agricultural economics literature (e.g., Purcell and Raunikar, 1971; Rickertsen, 1996; Smed et al., 2007; Gallet, 2010b) as meat is a major food consumption group. It gradually gained more attention also in the environmental economics literature due to the rising concerns about the external costs of meat consumption (e.g., Säll and Gren, 2015; Säll, 2018). Attention for cross-price elasticities between meat and plant-based meat substitutes (PBMS) has only shown up in very recent years. However, the challenge of data availability and quality has always existed in estimating these price elasticities. One approach is to use time-series data on aggregate demand at the country level (e.g., Säll and Gren, 2015). This can only provide a rough indication of consumption based on production and trade. A more recent 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 from Cornelsen et al. (2016) compared studies using aggregate time-series data, cross-sectional and longitudinal household survey data, and suggests that the level of detail in the data can significantly affect the estimated price elasticties.

Besides the aforementioned two sources of revealed preference data, an alternative data source is stated preference data collected from choice experiments. Discrete choice experiments (DCE) (e.g., Apostolidis and McLeay, 2016; Lusk and Tonsor, 2016; Van Loo et al., 2020; Tonsor et al., 2023) make it easy to vary prices exogenously, and also overcomes other identification issues such as measurement errors on prices that observational data face. However, the method is based on the tradeoff between discrete choices, while in real life, particularly in food consumption, consumers do not only decide which product to buy, but also how much of the product to buy. Besides, consumers can also decide to buy multiple products at the same time. A growing literature has extended the DCEs to make them more suitable for food consumption choices. Caputo and Lusk (2022) provide a Basket-Based Choice Experiment (BBCE) approach which allows for joint choices of different food products. Neill and Lahne (2022) further extend it to a Basket and Expenditure Based Choice Experiment (BEBCE) approach which allows for continuous choice. Nevertheless, hypothetical bias is still a major concern for stated preference data, because these choices are usually made in a hypothetical setting and are not incentivized (Louviere et al., 2000; Holmes and Adamowicz, 2003; Carlsson et al., 2011).

In this paper, we use a detailed store-item-level supermarket scanner dataset to estimate cross-price elasticities of meat, fish, and, importantly, also PBMS. The barcode scanner data has weekly observations on prices and sales from 884 supermarket stores all over the country that belong to several chains between 2015 and 2018. The data set has more than 265 million observations and covers all products that belong to meat, fish, and PBMS available in the supermarkets. Our weekly store-level dataset is much more disaggregate than the time-series data which allows us to exploit variations in prices and demand across stores, chains, and time. It does not suffer from potential sampling and measurement errors as compared to studies based on market survey scanner data. We include both traditional and novel PBMS in the PBMS category in our analysis because we consider both of them are important substitutes to meat. Traditional plant-based products such as tofu and tempeh have existed for many years in non-Western countries (Asgar et al., 2010). In Western countries, only in the last decades, novel plant-based products such as veggie burgers have been developed to imitate the appearance, taste, and texture of meat products, and they are regarded as a new trending alternative source of protein intake (Tziva et al., 2020). The market share of these products has been increasing rapidly over the past few years.[1] Because our data is available at the item level, we could select both traditional and novel PBMS food product items and construct a complete PBMS category including both of them. As such, 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 is aggregated at the state level which does not allow for between-store price and product variations. Additionally, although their data covers 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% in different states, compared to 4% in the Netherlands. Although overall PBMS is an emerging market, the Netherlands is a pioneer country in this market. Among European countries, it has the largest share in consumption of PBMS as well as a relatively developed market given that PBMS products are available in all supermarket stores. Therefore, empirical evidence from the Netherlands can be a good case study to understand how consumers behave when PBMS are largely available and easily accessible.

Understanding supermarket consumption behavior is essential for designing food policies in the Netherlands as it is representative for household food consumption. There are two main reasons. First, unlike in other countries and cultures where eating out is more common, the Dutch have a high share of food-at-home consumption. According to the Dutch National Food Consumption Survey 2012-2016 survey (Van Rossum et al., 2016), 80% of the foods and drinks are consumed at home. Second, Dutch consumers purchase the majority of their groceries from supermarkets rather than specialized stores, and other retail channels. Supermarkets cover around 50% of total food revenues (Foodservice Instituut, 2019).[2]

We use a quadratic version of the Almost Ideal Demand System (QAIDS) (Banks et al., 1997) to model demand at the store level. The widely used Almost Ideal Demand System (AIDS) method has the advantage of providing intuitive price elasticities and satisfying the

[1] Allied Market Research (2019) predicts that the global plant-based meat substitute market size, including products prepared from tofu, tempeh, textured vegetable protein, seitan, Quorn, and other plant-based sources, will grow from 4.1 billion dollars in 2017 to 8.1 billions dollars by 2026.

[2] Based on data from The Food Research Company, Foodstep, FSIN Food500, Information Resources, Incorporated (IRI), GfK, Nielsen and CBS, in 2018 the overall revenues from food-at-home consumption are 41.34 million, where supermarkets account for 32.35 million, new retail account for 3.17 million, and specialized stores (such as butchers, bakeries, etc.) account for 5.82 million; out-of-home food consumption generates 20.10 million revenues in total (Foodservice Instituut, 2019)

theoretical assumptions about consumer demand (Deaton and Muellbauer, 1980a), while the quadratic version by (Banks et al., 1997) further improved on allowing non-linear total expenditure. Recent country-specific studies have used the AIDS models to estimate price elasticities of meat (Smed et al., 2007; Säll and Gren, 2015; Dong et al., 2015; Caillavet et al., 2016). Their data sources range from aggregated per capita consumption and price data to individual or household panel survey data. In terms of food groups, most only focus on meat groups and do not have a separate group for PBMS, with the exception of Caillavet et al. (2016) who group food items based on both environmental impacts and nutritional contents as well as substitution options within the group.

Although prices are indirectly observed in our store-level data rather than in household survey data where prices are usually missing, we still face the identification challenge of endogenous prices that may result in biased and inconsistent estimates. This concern is especially relevant when using aggregate retail data (e.g., Chintagunta, 2001). Retailers may set prices based on both historical demand and other consumer characteristics that are known to retailers but unobserved to researchers. The resulting price endogeneity would lead to an underestimation of price elasticities. Hence, we apply the Hausman instrumental variables to deal with the endogeneity issue following the industrial organization literature (Hausman et al., 1997; Nevo, 2003). Nevo (2003) argues that the average price of the same product in other markets can be 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 market. Likewise, we use the weighted average prices of the same food category of nearby stores that are not from the same chain are used as a proxy for the actual prices of a store.

This paper has three main contributions. First, we provide new evidence on how price changes affect the demand response of meat, fish, and PBMS based on current market conditions and consumer preferences. Understanding consumer preferences for PBMS over conventional animal-based products using recent data is particularly interesting because both the introduction of new food products as well as consumer trends have started to shift in recent years. The taste, texture, and appearance of PBMS have become more similar to meat products than their prior versions. Nevertheless, they are still on average more expensive than conventional meat products. Second, we exploit detailed price and quantity variations in supermarket sales across stores, chains, and time, and estimate price elasticities based on timely demand response. The rich observations in terms of time frequency and spatial distribution reduce the potential selection bias from imbalanced store selection with regard to their geographical or other characteristics, and enable us to estimate demand system models in a more reliable way than studies using other types of observational data (Meyer et al., 2011). Third, our study contributes to a large strand of literature that predicts the environmental impacts of economic policies on food consumption (Smed et al., 2007; Säll and Gren, 2015; Dong et al., 2015; Caillavet et al., 2016). Current studies conduct simulations based on either price elasticities from a general meta-analysis, or estimated in a way which may contain identification issues. The price elasticities we estimate will provide a more reliable source for further studies which are based on price elasticities of meat and meat substitutes.

The remainder of the paper is structured as follows. We proceed first with introducing the supermarket scanner data in Section 2 as our main contribution lies in the data used. In section 3, we describe the methodology of estimating price elasticities through a QAIDS model. Section 4 presents the empirical results. The final section concludes.

2 Data

We use a large supermarket scanner data set from Statistics Netherlands which covers 884 stores from several supermarket chains over the period from 2015 to 2018.[3] The stores in our data are geographically dispersed across the whole country. The data set contains weekly observations on sales and quantity for each product in the food domain. Each item is uniquely identified with either a thirteen-digit European Article Number (EAN) or a supermarket's own barcode, linked to the product description including brand, name, and package size. All items are categorized by the Classification of Individual Consumption according to Purpose (COICOP), which is a classification of consumer expenditure managed by the United Nations. The five-digit COICOP allows to categorize items belonging to meat and subcategories of meat. For our analysis, we focus on three meat groups – beef, pork, and poultry – while lamb and other meat are not included in 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 another source of

[3]We also have data from 2019 - 2020. However, we decided not to include data from 2019 because from that year onward there were some changes in the data reporting procedure.

animal-based protein given that fish consumption is an important part of Dutch people's diet. Finally, we manually construct a category for PBMS based on product descriptions because the COICOP classification does not feature this separate category. The majority of products that are included in this category are the novel PBMS products, while traditional PBMS products, such as tofu and tempeh only account for 2.2% of the number of total products. Unlike Zhao et al. (2023) which only focuses on the novel PBMS, we decide to also include the traditional PBMS as they are a major source of plant-based proteins, and in Dutch supermarket stores, these products are usually displayed together with the novel PBMS, and next to meat and fish shelves.[4]

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 prices that 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 by the meta-analysis on food price elasticities by Cornelsen et al. (2016). That is, unit price changes do not only reflect changes in product prices within a product category, but also substitution within that category between more expensive and cheaper products, which usually is an indication of quality differences. For example, price changes could affect both decisions on how much beef to buy, and buying expensive beef steaks or cheap minced beef. Hence, the price variation captured by unit values is usually smaller than the actual one. Cox and Wohlgenant (1986) suggest to regress unit values on household socio-demographic characteristics to adjust for this bias, however, our data does not allow for that as consumer characteristics of different stores are unobserved. Alternatively, Deaton (1988) suggest using a joint estimation of quantity and quality demand functions. This is also not so suitable in our study as our major interests lie in the price elasticities between the product categories instead of subcategory price elasticities. Having the major product categories also make our study more comparable to other price elasticities. Nevertheless, without adjusting for the quality change in consumption means that we may underestimate actual price changes, which results in an overestimation of price elasticities (Cornelsen et al., 2016).

[4] Although beans are also an important source of plant-based proteins, we did not include them in our PBMS category because beans are not typically used as a meat substitute.

The major data problem we face is related to the calculation of unit prices. There are some measurement errors in prices (euro/g or euro/piece) and missing values on quantity (weight) for meat and fish products. [5] We use a two-step procedure to correct for such missing information. First, for products that have data available on quantity but it is not clear whether price is euro/g or euro/piece, we calculate average prices and then use cutoff prices to select the price type.[6] Then we correct the gram prices to kilogram prices. Second, for products that only have per piece price as well as products that have missing data in quantity, we use a text-based algorithm to fill in the correct data of a quantity. We use regular expressions to identify if the product description has information on quantities, such as "100 g", "1 kg", "1000gr", etc. If so, we acquire the data on quantities and convert them to a consistent measure of kilograms. After that, we calculate the unit price for the products which only had per piece price or did not have a price. The unit price per item represents the average weekly price of an item in a store within a particular supermarket chain. This two-step procedure implies that we drop observations for which we believe there are measurement errors - cannot be identified as a gram price or a per piece price, and for which we cannot identify a consistent package size. In total, around 25% of observations are dropped in this procedure. We further clean the outliers within a food category, that are products considered to be too expensive (top 1%) or too cheap (bottom 1%) for that category. After that, we construct the unit price per food category, which represents the average weekly price of a food category in a store of a chain, and again we trim the top 1% and bottom 1% observations as outliers.

We identify the unique location of each store given by their 4-digit postcode (PC4) address. Because the exact address is unknown, we use the coordinates of the center of a PC4 as a proxy for the store location. These coordinates are used to calculate the distance between each pair of stores which are useful when constructing our instrumental variables, which will be further explained in the method section.

Overall, we observe that for each product item, prices vary substantially across chains and across time, but less so across locations and stores. More specifically, at the same time point, the main source of price variation is price differences between chains, while the within-chain price

[5] These problems do not exist in PBMS, as unlike meat, they usually have standard package sizes, and this information is available in the product description.

[6] We use prices below 0.07 euro as an indication of the gram price and prices above 1 euro as an indication for the per piece price. For products with a gram price, we drop the bottom 0.5% of observations which are too low to be considered as gram prices for meat and fish.

variation among stores is relatively small. Price variations also occur across time. These price differences are caused both by baseline price differences between supermarket chains as well as weekly promotions. The (unobserved) promotions may cause potential bias when estimating price elasticities given that there might be hoarding behavior by consumers. Hoarding implies that the demand response to prices in the week of promotion might be overestimated while the demand response in later weeks might be underestimated. In order to deal with this possible source of bias, we calculate the average share of demand using a 2-week moving average, which allows us to eliminate most short-term hoarding induced by promotions. We also offer an alternative specification without using a moving average as a robustness check.

Figure 1 illustrates the aggregated prices and quantities in five randomly selected stores in our sample. The figure shows mostly downward-sloping correlations between quantities and (endogenous) prices. Importantly, there is substantial variation in prices and quantities, both within and between stores, that we will exploit. We restrict the sample to half of the stores in the full sample due to the computational limitations of Stata. We use 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 the appendix.

Figure 2 shows the price distributions of the three types of meat as well as fish and plant-based meat substitutes. Differences in aggregated prices are due to the prices set by supermarkets as well as the choices of consumers for particular items within a group (such as different cuts of meat) given that the unit price per group is a weighted average price among all the products in the category. The histogram of beef prices is the only one to display a bimodal distribution; beef products have a clear price difference between low-quality beef, such as minced beef, and high-quality beef, such as rib-eye steaks. Figure 3 shows the average prices of different product categories between 2015 and 2018 (adjusted for CPI, 2015 = 100). The prices of pork, poultry, and fish have an increasing trend over the period. Beef prices seem to be relatively stable with seasonal fluctuations in the first four years, while the prices drop in the end of 2018. The prices of PBMS show a slightly decreasing trend over time, which may be explained by the overall costs dropping down in this emerging market. Figure 4 shows the market shares of different product categories between 2015 and 2018. Compared to all other groups, the market share of plant-based meat substitutes is very small and almost stable at around 4% of the market share. Both poultry and fish show a slightly increasing market share, while the market share of beef and pork is stable over the period. Finally, Table 1 shows the descriptive statistics of the subsample on which the demand system estimation is based. As a comparison, we also show the distributions, trends and descriptive statistics of the full sample in Appendix A, Figures A1–A3, and Table A1, which are very similar to the subsample.

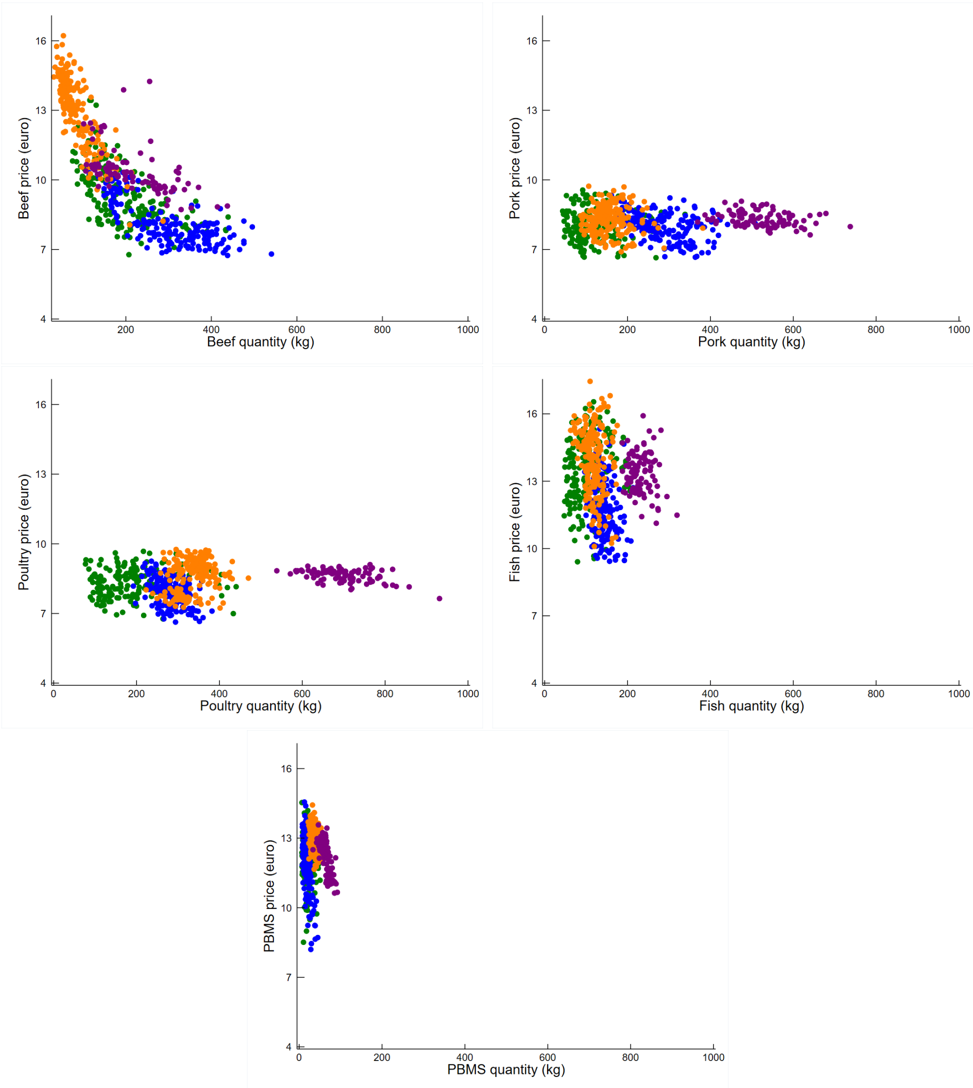

Figure 1: Plots of weekly prices and quantities of some randomly chosen sample stores. Each color represents a store.

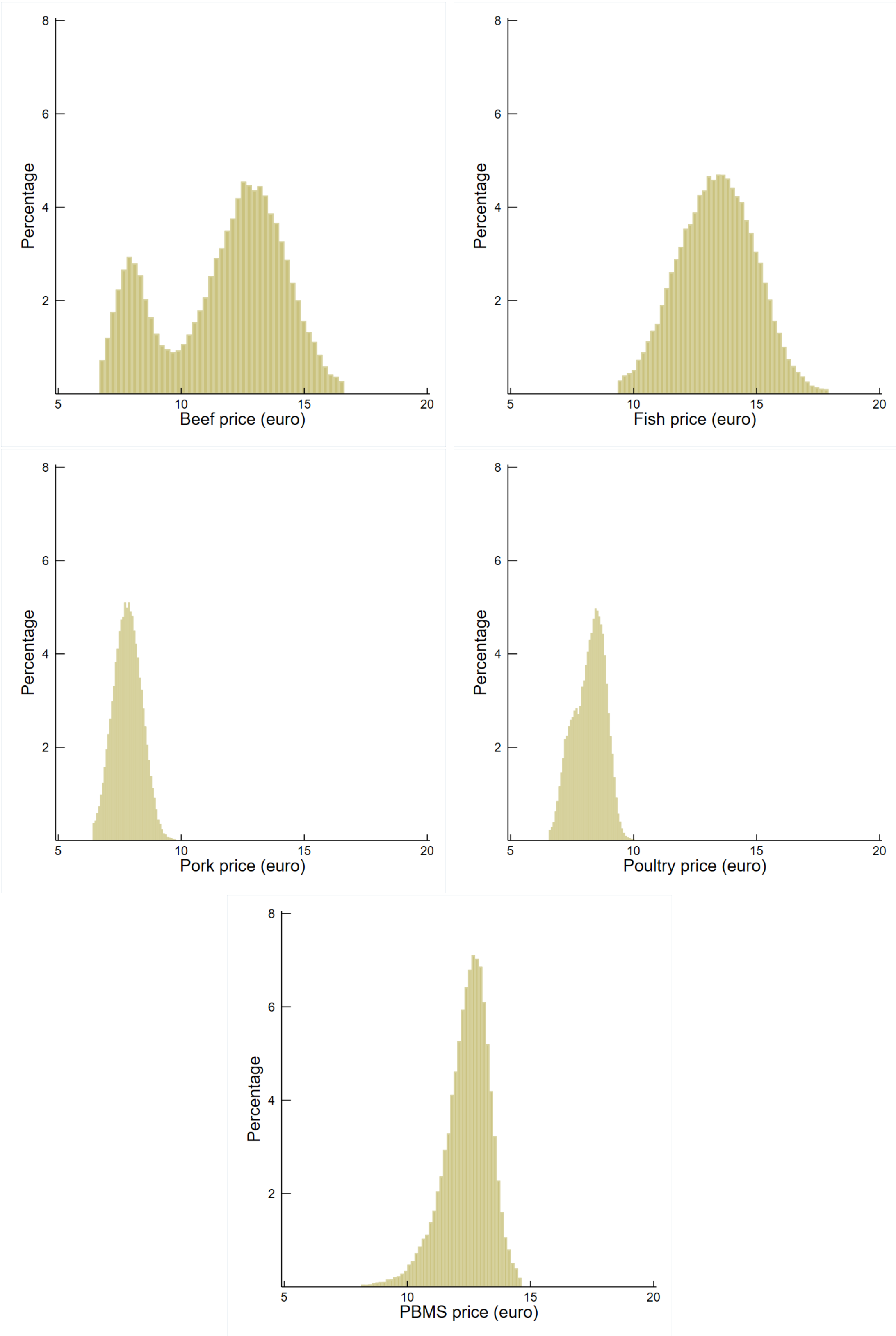

Figure 2: Histograms of price distribution, by category of products

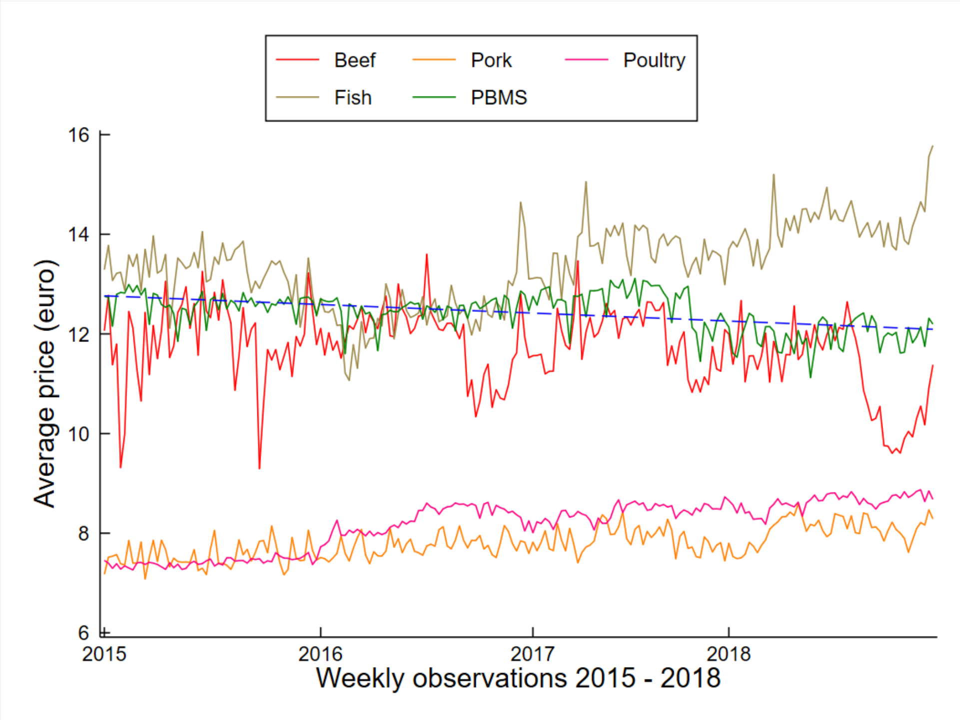

Figure 3: Average prices 2015-2018, adjusted for CPI (2015 = 100)

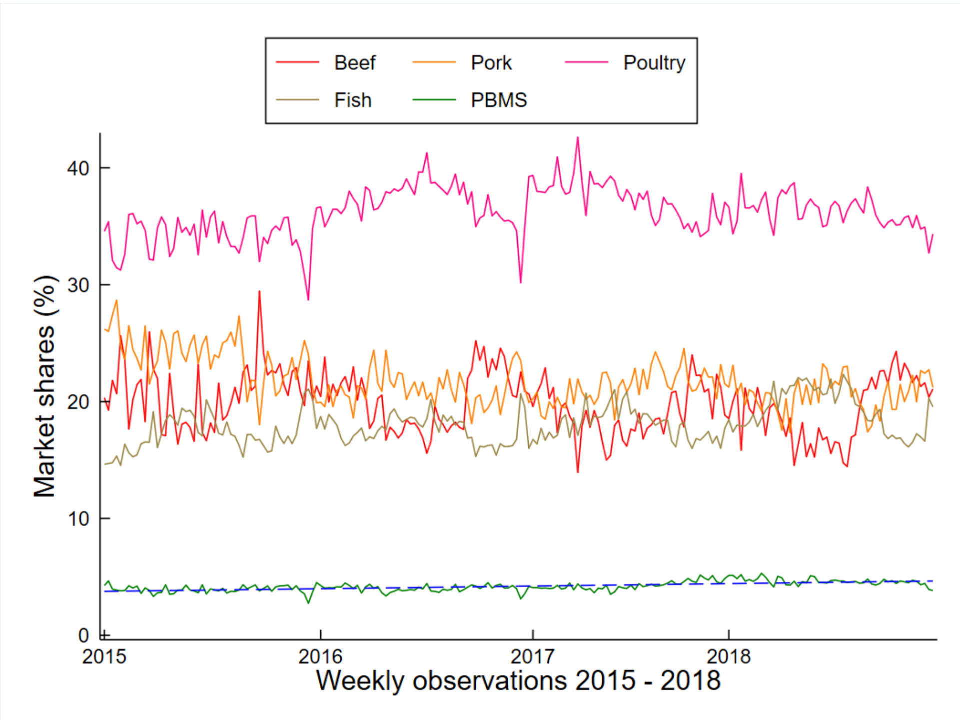

Figure 4: Market shares (%) 2015-2018

Table 1: Descriptive statistics on average prices and budget shares

	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	55439			

3 Methods

We model supermarket consumers' demand and estimate own- and cross-price elasticities of demand for beef, pork, poultry, fish, and PBMS using a QAIDS model by Banks et al. (1997) which is an extension of the original AIDS developed by Deaton and Muellbauer (1980a). The AIDS models and their variations have been widely applied for estimating price and income elasticities, especially in the food domain, as shown in the meta-analyses by (Gallet, 2010b,a; Cornelsen et al., 2016) summarize studies on meat.[7] Although originally the approach has been applied often to household survey data to model individual/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, it models the behavior of the representative consumer.

The QAIDS model considers the limitation of the original AIDS model that it does not take into account the existence of nonlinear Engel curves. The expenditure on animal-based products is likely to have a nonlinear relationship with income, given that for richer households meat and fish may become necessities. As for PBMS, they are relatively expensive food products and may be luxury goods for poorer households while they may be necessities among richer households. Hence, the QAIDS model is more suitable in our case.

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

[7]Different demand models have been used to estimate price elasticities, but each of these has 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). The random utility models are becoming popular, as it has the advantage of avoiding a large number of parameter estimations in demand systems when there are many food groups and multiple stages (McFadden, 1974), allowing for flexibility in substitution behavior due to the heterogeneity in consumer characteristics. As a result, estimation biases are smaller compared to demand systems when the model is misspecified (Huang et al., 2008). However, a disadvantage of this approach is that only discrete choices but not continuous choices are taken into account.

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

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

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

The dependent variable s_{ikt} represents the expenditure share of total expenditure for product category i ($i = 1, 2, 3, ..., n$) in store k in week t. It is defined as $s_{ikt} = \frac{p_{ikt}q_{ikt}}{X_{kt}}$, where X_{kt} is the total expenditure on n types of 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 an 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.

Estimating the above functional form requires satisfying certain properties to be consistent with utility maximization. The first assumption is adding-up, given by $\sum_{i=1}^{n} \alpha_i = 1$ 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 will remain unchanged if all prices as well as total expenditure increase by any positive proportion. The last assumption is symmetry of the Slutsky equation, given by $\beta_{ij} = \beta_{ji}$. Nevertheless, because we use aggregated store-level data, we can drop the symmetry and homogeneity properties, following Deaton and Muellbauer (1980b) and Christensen et al. (1975).

Using store scanner data to conduct demand system analysis faces potential endogeneity issue due to the classic demand and supply simultaneity. While consumers decide their consumption quantities based on market prices, retailers may also adjust prices based on market demand. The joint determination of prices and consumption might be especially problematic for aggregated store scanner data compared to household data. While the influence from a single household on prices could be ignored, the aggregated influence from all customers at a particular store could induce potential price changes from the supply side.

We use instrumental variables to deal with this price endogeneity. Because our dataset includes observations from multiple supermarket chains, we can 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. The idea of the instrument is that the price for a product sold in a certain region in a certain supermarket chain not only reflects the general costs of the product and costs related to the supermarket chain, but also other costs related to the region, as well as consumer characteristics in that region. Given that general costs of a specific product is shared among different regions, average prices of a product from stores from other supermarket chains in the neighboring region are correlated to own store prices. This assumes that the region-specific and chain-specific costs are uncorrelated. The regional-specific costs are unlikely to be correlated to each other, especially for meat and fish products, because retailers tend to find local suppliers. Sometimes due to an outbreak of animal disease, the supply costs will change but it will only affect a certain region. The chain-specific costs are mainly revealed by discounts at the chain level. We do not see national discounts for the same product in the same week, thus this is not a concern.

To construct the instrument, we first calculate the point distances from the center of the PC4 area where each store is located, to the PC4 areas where all other stores are located as a proxy for the distances between a store to all the other stores. Then, we select only those stores that are within 10 km Euclidean distance and do not belong to the same supermarket chain. The weighted average of the prices for a particular product category in this selection of stores is then used as an instrument for the price of the same item in the own store. On average, there are 4.6 stores that do not belong to the same supermarket chain within this area with a 10 km radius.[8]

To control for heterogeneity among supermarket chains, time trends, and heterogeneity among stores, we include chain indicators, month and year fixed effects, as well as store fixed effects through the α parameters as suggested by Lecocq and Robin (2015).

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 consider both income and substitution ef-

[8]We explore the sensitivity of our results to the size of this area in a robustness check provided in Appendix D.

fects and 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 $\delta_{ij} = 0$.

The compensated Hicksian elasticities e_{ij}^{H} consider only substitution effects and are given by

$$e_{ij}^{H} = \frac{\beta_{ij}}{s_i} + s_j - \delta_{ij}. \tag{5}$$

4 Results

4.1 Main results

Table 2 presents the first-stage results of the QAIDS model. Almost all IV prices are significantly correlated with the original prices. All IV prices for the same product category have a significant negative coefficient, except for pork. The first-stage results have strong statistical power with F statistics ranging between 57 and 1127.

Table 2: QAIDS Model First-stage Results

	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	55439	55439	55439	55439	55439
R^2	0.896	0.470	0.822	0.676	0.306
Adjusted R^2	0.895	0.466	0.821	0.673	0.300
F	1127.638	116.539	606.073	273.623	57.777

Note: Standard errors in parenthesis.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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.

Table 4 reports the uncompensated own- and cross-price elasticities which highlight the potential substitution effects between product categories. We report the uncompensated price elasticities instead of compensated price elasticities to allow comparison with the existing literature. The own-price elasticities are presented on the diagonal, and they represent the percentage change of the expenditure share of a certain product category responding 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. We find that the own-price elasticities for beef, pork, poultry, and fish are given by -0.59, -2.1, -0.98, and -0.89 respectively, which suggest that only the demand for pork is price elastic.

Our estimates are rather similar to Andreyeva et al. (2010), Gallet (2010b), and Säll and Gren (2015) who all find an average own-price elasticity for meat of around -0.70. However, a few country-specific studies that use household scanner data found higher levels of price-elasticity for meat. For example, Smed et al. (2007) shows that the own-price elasticities for all meat groups range from -2.02 to -1.01 for different age groups in Denmark. Bonnet et al. (2018) estimate 23 groups of animal-based products in France and find own-price elasticities between

Table 3: QAIDS Model Regression Results

	Beef share	Pork share	Poultry share	Fish share	PBMS share
Beef price (ln)	0.090***	0.046	-0.008	-0.080***	-0.049***
	(0.027)	(0.025)	(0.022)	(0.019)	(0.010)
Pork price (ln)	0.046	-0.223***	0.056	0.090**	0.031
	(0.043)	(0.040)	(0.035)	(0.031)	(0.016)
Poultry price (ln)	-0.008	0.056	-0.000	0.006	-0.055**
	(0.047)	(0.043)	(0.038)	(0.034)	(0.017)
Fish price (ln)	-0.080***	0.090***	0.006	0.016	-0.033***
	(0.017)	(0.015)	(0.013)	(0.012)	(0.006)
PBMS price (ln)	-0.049	0.031	-0.055	-0.033	0.105***
	(0.041)	(0.038)	(0.033)	(0.029)	(0.015)
Total consumption (ln)	0.047***	0.035***	-0.051***	-0.022***	-0.010***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.001)
Squared total consumption (ln)	0.009***	0.007***	-0.015***	0.001	-0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Observations	55439				

Note: Standard errors in parenthesis.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

-1.61 and -1.18. One possible explanation for price elastic demand for pork is that, compared to other meat types, pork is often consumed in lower-income Dutch households, and thus demand may be more sensitive to price changes.

Surprisingly, the own-price elasticity for PBMS is positive at 1.52; a 1% price increase in meat substitutes will result in an 1.52% increase in its demand. This result is counterintuitive because one would expect a negative own-price elasticity, which is also found by Zhao et al. (2023) who estimate that the own-price elasticity for PBMS is -1.48. A plausible explanation for the positive price elasticity for PBMS estimated by our study is the change in the composition of this category over the 4-year period that we study. The variety and quality of PBMS products in the Dutch market have been increasing steadily over this period. Simultaneously, the prices of new products were not necessarily decreasing. Unlike the weighted category price for PBMS displayed in Figure 3, average product prices were actually increasing over most of our study period, as shown in Figure 5). This difference reflects that more higher-priced PBMS products are introduced to the market over the study period. Similar trends in the differences in unweighted and weighted prices have been found in, for instance, the electric vehicle market: sales-weighted price is relatively constant while the unweighted price is increasing steadily, because more high-priced EVs are offered but few of them are sold (Gillingham et al., 2023). In our case, consumers may respond to the higher-priced products with higher demand due to their preferences in taste, texture, etc. Therefore, price elasticities in a market in its early stages of development will change over time if the supply side is changing both in terms of quality and prices.

Table 4: Uncompensated Own- and Cross-price Elasticities

	Beef price	Pork price	Poultry price	Fish price	PBMS price
Share of beef	-0.594***	0.189	-0.092	-0.423***	-0.247
	(0.130)	(0.216)	(0.231)	(0.081)	(0.202)
Share of pork	0.190	-2.090***	0.229	0.406***	0.143
	(0.118)	(0.192)	(0.205)	(0.073)	(0.182)
Share of poultry	-0.002	0.175	-0.976***	0.030	-0.149
	(0.059)	(0.097)	(0.104)	(0.037)	(0.091)
Share of fish	-0.401***	0.514**	0.076	-0.891***	-0.172
	(0.102)	(0.168)	(0.180)	(0.064)	(0.158)
Share of PBMS	-1.121***	0.787*	-1.252**	-0.754***	1.520***
	(0.236)	(0.389)	(0.415)	(0.147)	(0.364)

Note: Standard errors in parenthesis.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

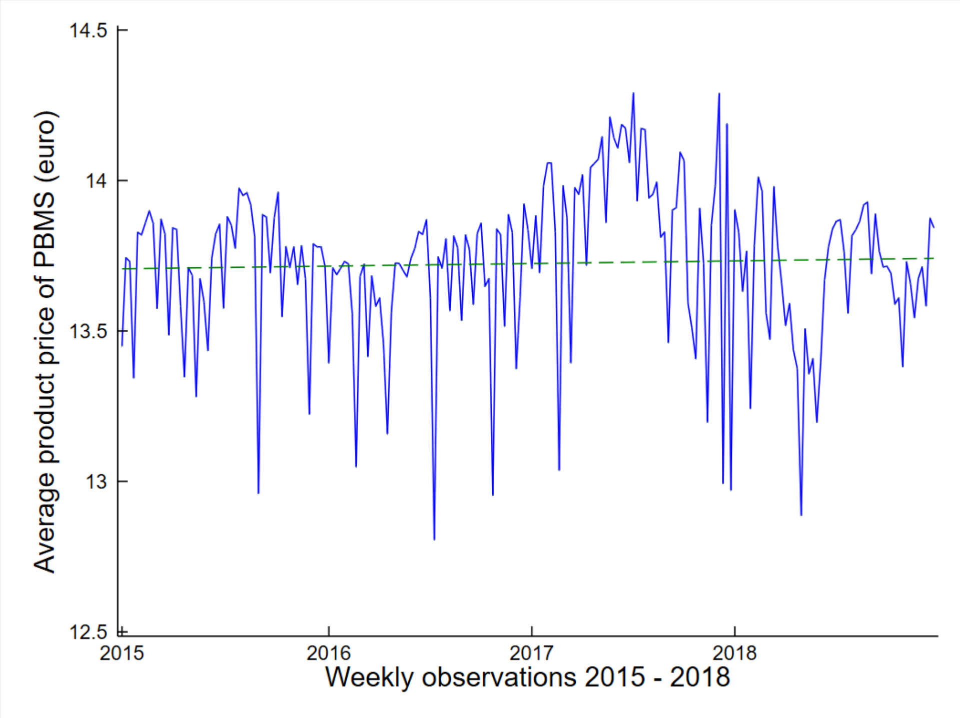

Figure 5: Average product prices 2015-2018, adjusted for CPI (2015 = 100)

As for the cross-price elasticities, we expect that people often substitute between animal-based product categories. We find this expectation confirmed for substitution between beef and pork, and between fish and pork. However, we find that many cross-price elasticities between animal-based products are negative, which indicates that they are complements rather than substitutes for each other. Similar findings have been seen in the study of 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 plant-based meat substitutes are price complements to beef, poultry, and fish, and price substitutes to pork. This is different from the general notion that plant-based meat substitutes are replacements of animal products. Still, it is consistent with the estimates of Zhao et al. (2023) which also find negative cross-price elasticities between the prices of beef, pork, and other meats, and the demand for PBMS. However, they find positive cross-price elasticities for chicken, turkey, and fish. Our estimates indicate that a 1% increase in beef, poultry or fish price will lead to 1.1%, 1.25%, or 0.75% decrease in the demand for plant-based meat substitutes respectively. Given that beef, poultry, and fish are also good sources of protein and score higher in animal welfare, it could be that consumers who value health and animal rights always consume these products together with PBMS. This is in line with the study of Dhar and Foltz (2005), which finds that organic milk and rBST-free milk are complementary goods, and these two products are both aimed at consumers who have more concerns about the environment and health.

4.2 Robustness checks

We perform a set of robustness checks to test if our results are sensitive to model selection, sample selection, alternative instruments, and the use of moving averages for market shares. Additionally, we also show a QAIDS model which only includes animal products. Results from the alternative models are shown in Appendix B - F. First, we show a standard AIDS model. Second, we estimate the same models using an alternative randomly selected subsample of 50% of the stores in the full sample. We find the estimates of the price elasticities given by Table C3 are very similar to the previous estimates. Third, given that the geographical distance we select for defining the neighboring stores will affect the number of observations we have in the demand model estimation, we test for average prices from supermarket stores within 8 km and 12 km instead of 10 km as robustness checks. Choosing a narrower definition of neighboring stores will result in a smaller sample size, but it also means that these stores are competing for more similar consumers and hence the prices they offer are more similar because consumers are more likely to do groceries within a certain distance. However, we could also choose a broader definition of neighboring stores given that from the supply side, the logistical costs of going for another 5 km are marginal compared to other costs. The benefit is that it will result in a larger sample size. As shown in Table D2 and Table D4, we find that overall our results are not very sensitive to the geographical distance we select to construct our instruments. Fourth, estimates from the model without using moving averages for market shares are given by Table E2. We have used moving averages for market shares to control potential hoarding behaviors, which means one would expect larger behavioral responses to prices without using moving averages. Indeed we find that these price elasticities are much more elastic than in our main results, which confirmed our hypothesis on hoarding behaviors in response to discounts. Finally, estimates from the model only including animal products are given by Table F2. We conduct this alternative demand system model because of the concern that the demand system may not perform well when some groups account for a small share of the total demand, which is the case of PBMS. We find that the own-price elasticities are very much in line with the main results, except for relatively more elastic own-price elasticities for beef and pork. The significant and positive cross-price elasticities between pork and other animal-based products further confirm that pork is a substitute for other animal-based products. This model seems to perform better estimating cross-price elasticities between animal-based products than the main model.

5 Discussions and conclusion

In this paper, we estimate price elasticities of beef, pork, poultry, fish, and PBMS using a unique store-level supermarket scanner dataset in the Netherlands. Although existing studies have provided estimations of price elasticities of major meat types and sometimes together with other food groups, to our knowledge, we are one of the first studies that specifically include a category of PBMS and hypothesize this food group as potential substitutes for animal-based proteins. Only Zhao et al. (2023) has estimated price elasticities between meat and PBMS products for the United States. The major limitation of their study as stated by the author is that they have aggregated state-level supermarket consumption data which does not allow for more detailed exploration between stores. In terms of methodology, they use a basic AIDS model without controlling for price endogeneity. Our estimates are based on a QUAIDS model with an instrumental variable approach to control for potential price endogeneity.

Our results provide new insights for policy-making in the domain of the protein transition. In the context of a Dutch case study, we show that a potential meat tax is probably more effective in reducing pork consumption, and less so in reducing beef or poultry consumption. An important observation is that price increases of beef, pork, and poultry (e.g. due to a tax on meat) are not likely to lead to substitution to PBMS.

In addition to these new insights, our other results are largely in line with earlier studies. Several meta-analyses present estimates of own-price elasticities of meat which suggest that these are rather inelastic, although the point estimates differ by methodology, data, country, and the food groups included in the estimations (Cornelsen et al., 2016). These results are not directly comparable to our study given that they do not include a separate group for

PBMS in the demand system estimation. Besides, results of this type of studies are always sensitive to local food culture, which highlights the importance of conducting country-specific studies. Our setting is in the Netherlands. Earlier studies in the Netherlands mostly rely on meta-analysis results from other countries (e.g., CE Delft, 2020). Nevertheless, most of our own-price elasticities for meat are in line with previous literature, for example, we also find that beef, poultry, and fish have inelastic own-price elasticities. We provide new evidence that the demand for pork and PBMS is price elastic in the Netherlands, and PBMS have a significant positive own-price elasticity.

Regarding cross-price elasticities, existing literature often suggests that meat or animal-based products in general are substitutes for each other. We confirmed this result for three combinations of product types in our data: beef and pork, poultry and pork, as well as fish and pork, although only significant results are found for fish and pork. Interestingly, we find that most of the animal-based products (beef, poultry, and fish) are complements for PBMS, and the demand for PBMS is very price-elastic, or close to price-elastic to the prices of these animal-based products. This confirms results by Zhao et al. (2023).

Our study has some limitations. First, we treat the products within each product category as homogenous products without any quality difference as implied by using category prices in the demand system. This assumption mostly holds for meat and fish products as the composition of higher-priced products and lower-priced products are more or less the same in different supermarket stores and over the observed years. However, the composition of PBMS products may vary over time and between stores due to the heterogeneity in demand. Because we do not control for the price increase due to quality changes of products in the PBMS category, we may face the issue of quality bias (Deaton, 1988; Cornelsen et al., 2016). This could be an important factor affecting both the own-price and cross-price elasticities of PBMS. Thus, future studies can further look into the within-store composition of PBMS products. Besides, changes in consumer preferences, or social norms are also not captured in our study. Future studies which have more data on household consumer preferences can help answer these questions. Nevertheless, we shed light on the first exploration of the demand response of PBMS to prices and how consumers substitute between animal-based products and plant-based products.

References

Allied Market Research (2019). Meat substitute market by product (tofu-based, tempeh-based, tvp-based, seitan-based, quorn-based, and others), source (soy-based, wheat-based, myco-protein, and others), category (frozen, refrigerated, and shelf stable): Global opportunity analysis and industry forecast, 2019–2026. Technical Report.

Andreyeva, T., Long, M. W., and Brownell, K. D. (2010). The impact of food prices on consumption: a systematic review of research on the price elasticity of demand for food. *American journal of public health*, 100(2):216–222.

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

Asgar, M., Fazilah, A., Huda, N., Bhat, R., and Karim, A. (2010). Nonmeat protein alternatives as meat extenders and meat analogs. *Comprehensive Reviews in Food Science and Food Safety*, 9(5):513–529.

Banks, J., Blundell, R., and Lewbel, A. (1997). Quadratic engel curves and consumer demand. *Review of Economics and Statistics*, 79(4):527–539.

Berry, S., Levinsohn, J., and Pakes, A. (1995). Automobile prices in market equilibrium. *Econometrica*, pages 841–890.

Berry, S. T. (1994). Estimating discrete-choice models of product differentiation. *RAND Journal of Economics*, pages 242–262.

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.

Bonnet, C., Bouamra-Mechemache, Z., Réquillart, V., and Treich, N. (2020). Regulating meat consumption to improve health, the environment and animal welfare. *Food Policy*, 97:101847.

Bronnmann, J. (2016). The german whitefish market: An application of the la/aids model using retail-scanner-data. *Aquaculture Economics & Management*, 20(4):330–341.

Caillavet, F., Fadhuile, A., and Nichèle, V. (2016). Taxing animal-based foods for sustainability: environmental, nutritional and social perspectives in france. *European Review of Agricultural Economics*, 43(4):537–560.

Capps Jr, O. (1989). Utilizing scanner data to estimate retail demand functions for meat products. *American journal of agricultural Economics*, 71(3):750–760.

Caputo, V. and Lusk, J. L. (2022). The basket-based choice experiment: a method for food demand policy analysis. *Food Policy*, 109:102252.

Carlsson, F. et al. (2011). Non-market valuation: stated preference methods. *The Oxford handbook of the economics of food consumption and policy*, 181:214.

CE Delft (2020). A sustainability charge on meat. *Report*.

Chintagunta, P. K. (2001). Endogeneity and heterogeneity in a probit demand model: Estimation using aggregate data. *Marketing Science*, 20(4):442–456.

Christensen, L. R., Jorgenson, D. W., and Lau, L. J. (1975). Transcendental logarithmic utility functions. *American Economic Review*, 65(3):367–383.

Cornelsen, L., Mazzocchi, M., Green, R., Dangour, A. D., and Smith, R. D. (2016). Estimating the relationship between food prices and food consumption—methods matter. *Applied Economic Perspectives and Policy*, 38(3):546–561.

Cox, T. L. and Wohlgenant, M. K. (1986). Prices and quality effects in cross-sectional demand analysis. *American journal of agricultural economics*, 68(4):908–919.

Crippa, M., Solazzo, E., Guizzardi, D., Monforti-Ferrario, F., Tubiello, F., and Leip, A. (2021). Food systems are responsible for a third of global anthropogenic ghg emissions. *Nature Food*, 2(3):198–209.

De Boer, J. and Aiking, H. (2019). Strategies towards healthy and sustainable protein consumption: A transition framework at the levels of diets, dishes, and dish ingredients. *Food Quality and Preference*, 73:171–181.

Deaton, A. (1988). Quality, quantity, and spatial variation of price. *The American economic review*, pages 418–430.

Deaton, A. and Muellbauer, J. (1980a). An almost ideal demand system. *American Economic Review*, 70(3):312–326.

Deaton, A. and Muellbauer, J. (1980b). *Economics and consumer behavior*. Cambridge university press.

Dhar, T. and Foltz, J. D. (2005). Milk by any other name... consumer benefits from labeled milk. *American Journal of Agricultural Economics*, 87(1):214–228.

Dong, D., Davis, C. G., and Stewart, H. (2015). The quantity and variety of households' meat purchases: A censored demand system approach. *Agricultural Economics*, 46(1):99–112.

Einav, L., Leibtag, E., and Nevo, A. (2010). Recording discrepancies in nielsen homescan data: Are they present and do they matter? *QME*, 8(2):207–239.

Espinosa, R. and Treich, N. (2024). Animal welfare as a public good. *Ecological Economics*, 216:108025.

EU (2018). Commission reports on development of plant proteins in the eu. Technical report, European Commission.

Foodservice Instituut (2019). *Foodservice passeert de grens van €20 miljard*. Foodservice Instituut.

Funke, F., Mattauch, L., Bijgaart, I. v. d., Godfray, H. C. J., Hepburn, C., Klenert, D., Springmann, M., and Treich, N. (2022). Toward optimal meat pricing: is it time to tax meat consumption? *Review of Environmental Economics and Policy*, 16(2):219–240.

Gallet, C. A. (2010a). The income elasticity of meat: a meta-analysis. *Australian Journal of Agricultural and Resource Economics*, 54(4):477–490.

Gallet, C. A. (2010b). Meat meets meta: a quantitative review of the price elasticity of meat. *American Journal of Agricultural Economics*, 92(1):258–272.

Gillingham, K. T., van Benthem, A. A., Weber, S., Saafi, M. A., and He, X. (2023). Has consumer acceptance of electric vehicles been increasing? evidence from microdata on every new vehicle sale in the united states. In *AEA Papers and Proceedings*, volume 113, pages 329–335. American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203.

Godfray, H. C. J., Aveyard, P., Garnett, T., Hall, J. W., Key, T. J., Lorimer, J., Pierrehumbert, R. T., Scarborough, P., Springmann, M., and Jebb, S. A. (2018). Meat consumption, health, and the environment. *Science*, 361(6399):eaam5324.

Hausman, J. A., Pakes, A., and Rosston, G. L. (1997). Valuing the effect of regulation on new services in telecommunications. *Brookings Papers on Economic Activity. Microeconomics*, 1997:1–54.

Health Council of the Netherlands (2023). A healthy protein transition. Technical Report 2023/19, Health Council of the Netherlands, The Hague.

Hestermann, N., Le Yaouanq, Y., and Treich, N. (2020). An economic model of the meat paradox. *European Economic Review*, 129:103569.

Holmes, T. and Adamowicz, W. (2003). Attribute-based methods. in 'a primer on nonmarket valuation'.(eds p. champ, kj boyle and tc brown.) pp. 171–219.

Huang, D., Rojas, C., and Bass, F. (2008). What happens when demand is estimated with a misspecified model? *Journal of Industrial Economics*, 56(4):809–839.

Jarka, C., Tinggaard, S. G., and Tomas, Z. (2018). A global meat tax: from big data to a double dividend. *Agricultural Economics*, 64(6):256–264.

Jones, E., Akbay, C., Roe, B., and Chern, W. S. (2003). Analyses of consumers' dietary behavior: An application of the aids model to supermarket scanner data. *Agribusiness: An International Journal*, 19(2):203–221.

Katare, B., Wang, H. H., Lawing, J., Hao, N., Park, T., and Wetzstein, M. (2020). Toward optimal meat consumption. *American Journal of Agricultural Economics*, 102(2):662–680.

Lecocq, S. and Robin, J.-M. (2015). Estimating almost-ideal demand systems with endogenous regressors. *Stata Journal*, 15(2):554–573.

Lensing, C. and Purcell, W. D. (2006). Impact of mandatory price reporting requirements on level, variability, and elasticity parameter estimations for retail beef prices. *Applied Economic Perspectives and Policy*, 28(2):229–239.

Lewbel, A. and Pendakur, K. (2009). Tricks with hicks: The easi demand system. *American Economic Review*, 99(3):827–63.

Lindström, H. (2022). The swedish consumer market for organic and conventional milk: A demand system analysis. *Agribusiness*, 38(3):505–532.

Louviere, J. J., Hensher, D. A., and Swait, J. D. (2000). *Stated choice methods: analysis and applications*. Cambridge university press.

Lusk, J. L. and Norwood, F. B. (2011). Animal welfare economics. *Applied Economic Perspectives and Policy*, 33(4):463–483.

Lusk, J. L. and Tonsor, G. T. (2016). How meat demand elasticities vary with price, income, and product category. *Applied Economic Perspectives and Policy*, 38(4):673–711.

Mbow, C., Rosenzweig, C., Barioni, L., Benton, T., Herrero, M., Krishnapillai, M., Liwenga, E., Pradhan, P., Rivera-Ferre, M., Sapkota, T., Tubiello, F., and Xu, Y. (2019). *Food Security*.

McFadden, D. (1974). Conditional logit analysis of qualitative choice behavior. In Zarembka, P., editor, *Frontiers in Econometrics*. Academic Press, New York.

Meyer, S., Yu, X., and Abler, D. G. (2011). Comparison of several demand systems. Working Paper.

Neill, C. L. and Lahne, J. (2022). Matching reality: A basket and expenditure based choice experiment with sensory preferences. *Journal of choice modelling*, 44:100369.

Nevo, A. (2003). New products, quality changes, and welfare measures computed from estimated demand systems. *Review of Economics and Statistics*, 85(2):266–275.

Norat, T., Bingham, S., Ferrari, P., Slimani, N., Jenab, M., Mazuir, M., Overvad, K., Olsen, A., Tjønneland, A., Clavel, F., et al. (2005). Meat, fish, and colorectal cancer risk: the european prospective investigation into cancer and nutrition. *Journal of the National Cancer Institute*, 97(12):906–916.

Nordgren, A. (2012). Ethical issues in mitigation of climate change: The option of reduced meat production and consumption. *Journal of Agricultural and Environmental Ethics*, 25(4):563–584.

Purcell, J. C. and Raunikar, R. (1971). Price elasticities from panel data: meat, poultry, and fish. *American Journal of Agricultural Economics*, 53(2):216–221.

Rickertsen, K. (1996). Structural change and the demand for meat and fish in norway. *European review of agricultural economics*, 23(3):316–330.

Rohrmann, S., Overvad, K., Bueno-de Mesquita, H. B., Jakobsen, M. U., Egeberg, R., Tjønneland, A., Nailler, L., Boutron-Ruault, M.-C., Clavel-Chapelon, F., Krogh, V., et al. (2013). Meat consumption and mortality-results from the european prospective investigation into cancer and nutrition. *BMC medicine*, 11(1):63.

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

Säll, S. (2018). Environmental food taxes and inequalities: Simulation of a meat tax in sweden. *Food Policy*, 74:147–153.

Säll, S. and Gren, M. (2015). Effects of an environmental tax on meat and dairy consumption in sweden. *Food Policy*, 55:41–53.

Smed, S., Jensen, J. D., and Denver, S. (2007). Socio-economic characteristics and the effect of taxation as a health policy instrument. *Food Policy*, 32(5-6):624–639.

Taylor, M. R. and Tonsor, G. T. (2013). Revealed demand for country-of-origin labeling of meat in the united states. *Journal of Agricultural and Resource Economics*, pages 235–247.

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

Tonsor, G. T., Lusk, J. L., and Schroeder, T. C. (2023). Market potential of new plant-based protein alternatives: Insights from four us consumer experiments. *Applied Economic Perspectives and Policy*, 45(1):164–181.

Tziva, M., Negro, S., Kalfagianni, A., and Hekkert, M. (2020). Understanding the protein transition: The rise of plant-based meat substitutes. *Environmental Innovation and Societal Transitions*, 35:217–231.

Van Loo, E. J., Caputo, V., and Lusk, J. L. (2020). Consumer preferences for farm-raised meat, lab-grown meat, and plant-based meat alternatives: Does information or brand matter? *Food Policy*, 95:101931.

Van Rossum, C., Buurma-Rethans, E., Vennemann, F., Beukers, M., Brants, H., De Boer, E., and Ocké, M. (2016). The diet of the dutch: Results of the first two years of the dutch national food consumption survey 2012-2016. *RIVM letter report 2016-0082*.

Wolk, A. (2017). Potential health hazards of eating red meat. *Journal of Internal Medicine*, 281(2):106–122.

Zhao, S., Wang, L., Hu, W., and Zheng, Y. (2023). Meet the meatless: Demand for new generation plant-based meat alternatives. *Applied Economic Perspectives and Policy*, 45(1):4–21.

Zhen, C., Taylor, J. L., Muth, M. K., and Leibtag, E. (2009). Understanding differences in self-reported expenditures between household scanner data and diary survey data: a comparison of homescan and consumer expenditure survey. *Applied Economic Perspectives and Policy*, 31(3):470–492.

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 in Table 1. Table A1 shows the price distributions of beef, pork, poultry, fish and PBMS, respectively, which is also very similar to the subsample, as shown in Figure 2. Figure A2-A3 show the trends of average prices and market shares of beef, pork, poultry, fish and PBMS, which is again very similar to Figure 2-3.

Table A1: Full Sample: Descriptive Statistics on Average Prices and Budget Shares

	Mean	SD	Min	Max
Beef price (euro)	11.64	2.37	6.67	16.63
Pork price (euro)	7.81	0.57	6.40	9.79
Poultry price (euro)	8.20	0.63	6.56	10.04
Fish price (euro)	13.37	1.53	9.35	17.93
PBMS price (euro)	12.43	0.94	8.12	14.64
Beef share	0.20	0.07	0.08	0.40
Pork share	0.22	0.06	0.08	0.37
Poultry share	0.37	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	132654			

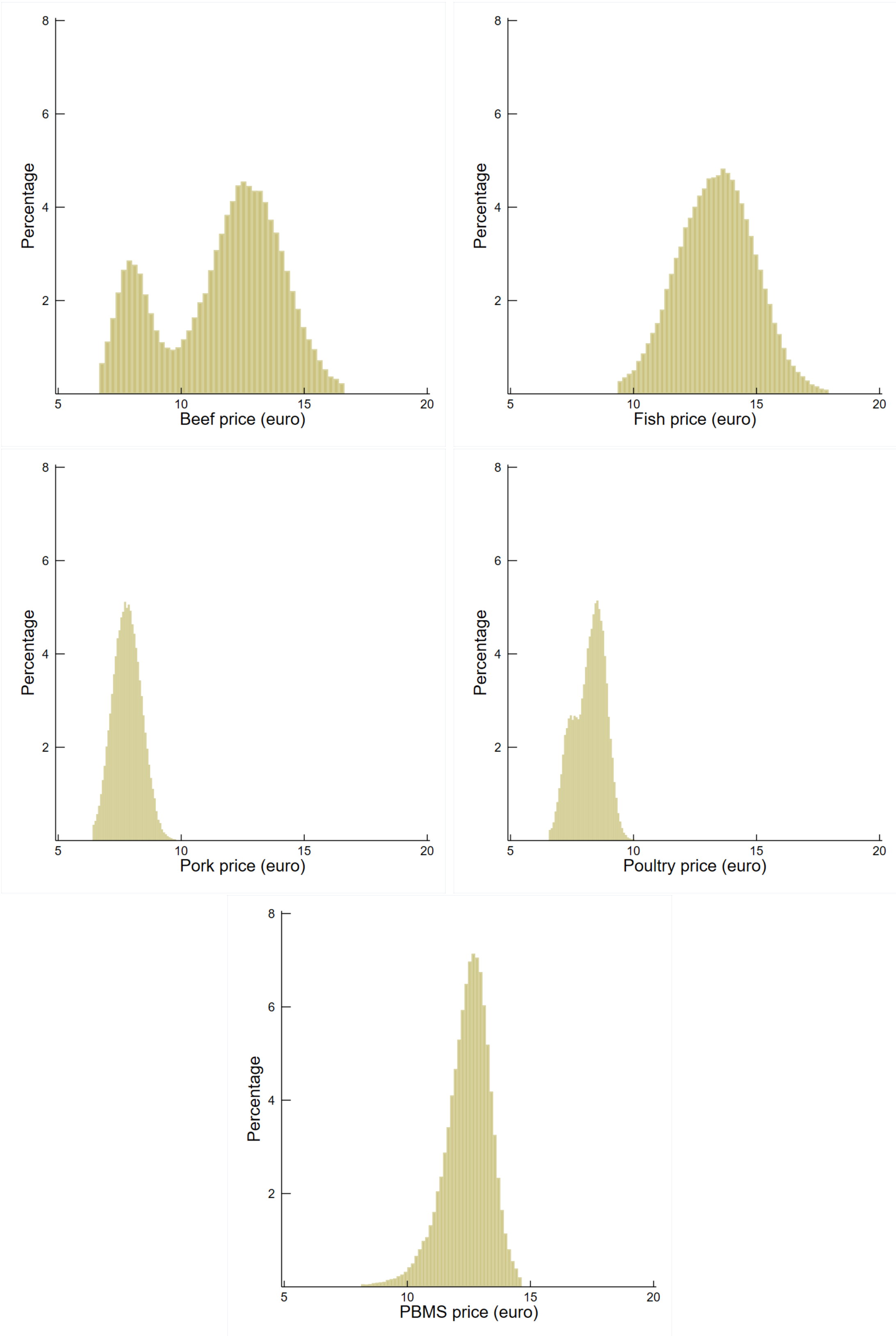

Figure A1: Full Sample: Histograms of Price Distribution, by Category of Products

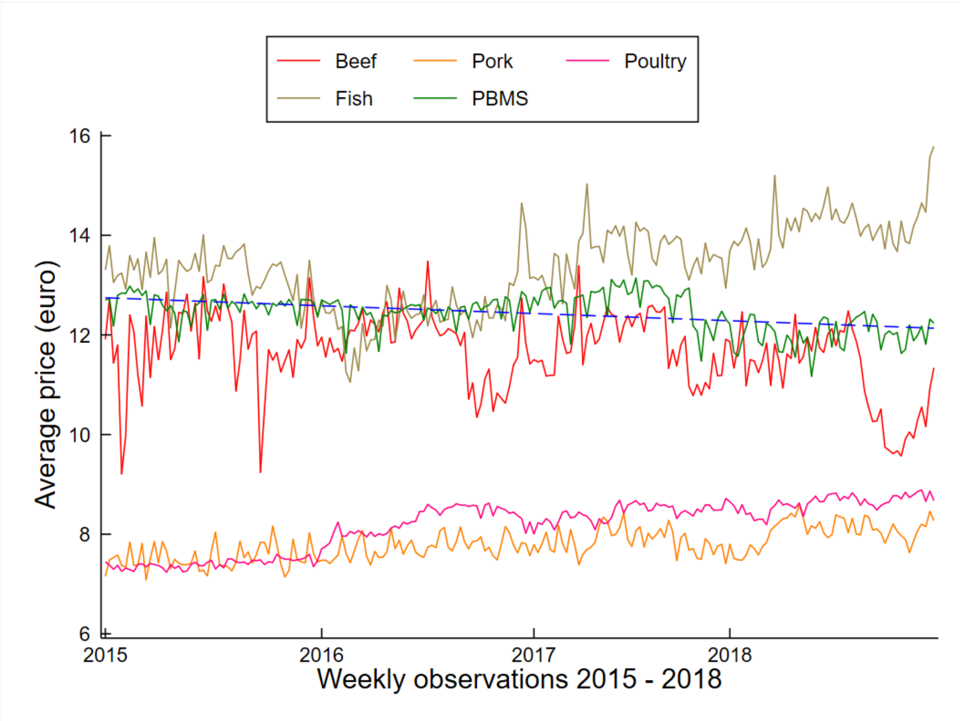

Figure A2: Full Sample: Average Prices 2015-2018, adjusted for CPI (2015 = 100)

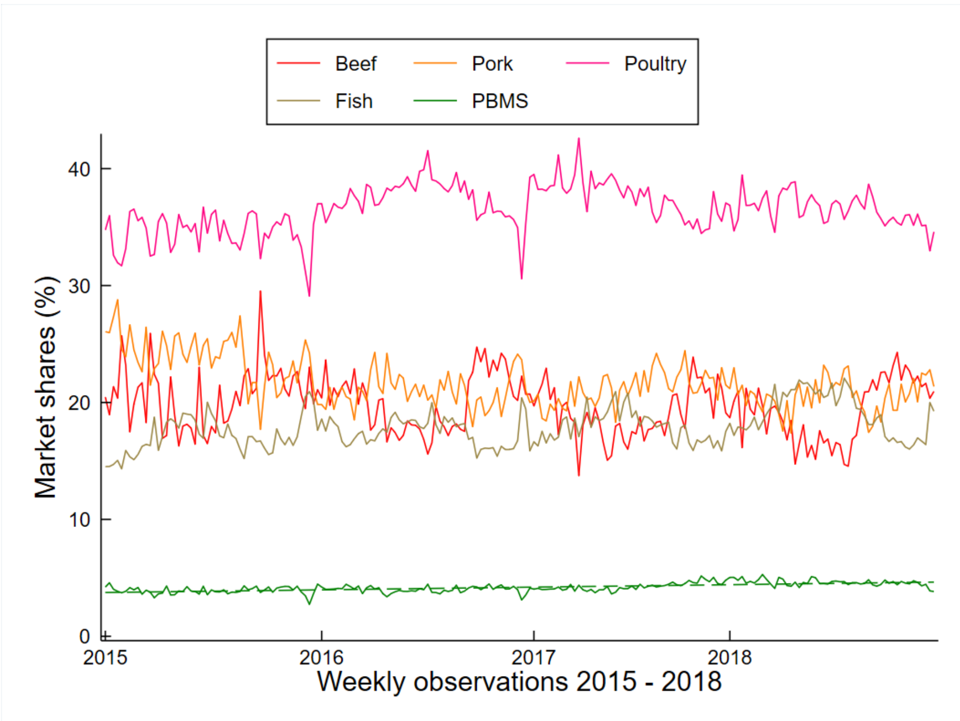

Figure A3: Full Sample: Market Shares (%) 2015-2018

B Robustness check on using the standard AIDS model

In this robustness check, we conduct a standard AIDS model estimation instead of its quadratic version. Model regression results are shown in Table B1, while the uncompensated own- and cross-price elasticities are shown in Table B2. Compared to the main results, the magnitudes of the coefficients for total consumption and many other coefficients in the first three regressions are slightly smaller. However, the price elasticities are very similar to the main results.

Table B1: AIDS Model Regression Results

	Beef share	Pork share	Poultry share	Fish share	PBMS share
Beef price (ln)	0.087***	0.047	-0.006	-0.080***	-0.049***
	(0.027)	(0.025)	(0.022)	(0.019)	(0.010)
Pork price (ln)	0.047	-0.218***	0.050	0.091**	0.030
	(0.043)	(0.040)	(0.035)	(0.031)	(0.016)
Poultry price (ln)	-0.006	0.050	0.004	0.006	-0.054**
	(0.047)	(0.043)	(0.038)	(0.034)	(0.018)
Fish price (ln)	-0.080***	0.091***	0.006	0.016	-0.033***
	(0.017)	(0.015)	(0.013)	(0.012)	(0.006)
PBMS price (ln)	-0.049	0.030	-0.054	-0.033	0.105***
	(0.041)	(0.038)	(0.033)	(0.029)	(0.015)
Total consumption (ln)	0.032***	0.025***	-0.026***	-0.024***	-0.007***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
Observations	55439				

Note: Standard errors in parenthesis.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B2: Uncompensated Own- and Cross-price Elasticities, AIDS Model

	Beef price	Pork price	Poultry price	Fish price	PBMS price
Share of beef	-0.604***	0.197	-0.084	-0.421***	-0.247
	(0.129)	(0.215)	(0.229)	(0.081)	(0.200)
Share of pork	0.197	-2.057***	0.196	0.409***	0.138
	(0.117)	(0.191)	(0.204)	(0.072)	(0.180)
Share of poultry	-0.000	0.155	-0.964***	0.029	-0.147
	(0.059)	(0.098)	(0.105)	(0.037)	(0.092)
Share of fish	-0.402***	0.518**	0.075	-0.892***	-0.173
	(0.102)	(0.168)	(0.180)	(0.064)	(0.158)
Share of PBMS	-1.137***	0.767	-1.239**	-0.764***	1.546***
	(0.237)	(0.392)	(0.418)	(0.148)	(0.367)

Note: Standard errors in parenthesis.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

C Robustness check on alternative subsample

In this robustness check, we run the same QAIDS model on a alternative subsample of 50% of the stores in the total sample. Descriptive statistics on average prices and budget shares are shown in Table C1, which are very similar to the summary statistics of the subsample that is used for the main results. Model regression results are shown in Table C2, while the uncompensated own- and cross-price elasticities are shown in Table C3. Both regression results and price elasticities are very similar to the main results, which suggests that our results are robust to the choice of sampling.

Table C1: Descriptive Statistics on Average Prices and Budget Shares, Alternative Subsample

	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	53875			

Table C2: QAIDS Model Regression Results, Alternative Subsample

	Beef share	Pork share	Poultry share	Fish share	PBMS share
Beef price (ln)	0.066**	0.063***	-0.016	-0.077***	-0.037***
	(0.020)	(0.019)	(0.017)	(0.015)	(0.007)
Pork price (ln)	0.063*	-0.180***	0.033	0.093***	-0.009
	(0.031)	(0.029)	(0.025)	(0.023)	(0.010)
Poultry price (ln)	-0.016	0.033	0.030	-0.020	-0.027
	(0.041)	(0.039)	(0.034)	(0.031)	(0.014)
Fish price (ln)	-0.077***	0.093***	-0.020*	0.024**	-0.020***
	(0.012)	(0.011)	(0.010)	(0.009)	(0.004)
PBMS price (ln)	-0.037	-0.009	-0.027	-0.020	0.093***
	(0.034)	(0.032)	(0.028)	(0.025)	(0.012)
Total consumption (ln)	0.046***	0.037***	-0.057***	-0.017***	-0.009***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
Squared total consumption (ln)	0.012***	0.008***	-0.024***	0.005***	-0.001***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Observations	53875				

Note: Standard errors in parenthesis.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table C3: Uncompensated Own- and Cross-price Elasticities, Alternative Subsample

	Beef price	Pork price	Poultry price	Fish price	PBMS price
Share of beef	-0.709***	0.276	-0.126	-0.407***	-0.186
	(0.097)	(0.153)	(0.201)	(0.057)	(0.167)
Share of pork	0.274**	-1.897***	0.115	0.426***	-0.047
	(0.091)	(0.140)	(0.185)	(0.052)	(0.154)
Share of poultry	-0.025	0.108	-0.893***	-0.044	-0.073
	(0.045)	(0.071)	(0.093)	(0.026)	(0.078)
Share of fish	-0.392***	0.535***	-0.067	-0.846***	-0.103
	(0.081)	(0.125)	(0.165)	(0.047)	(0.137)
Share of PBMS	-0.824***	-0.167	-0.585	-0.439***	1.202***
	(0.160)	(0.250)	(0.328)	(0.093)	(0.272)

Note: Standard errors in parenthesis.

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

D Robustness check on the choice of distance in IV

In this robustness check, we run the same QAIDS model using alternative IVs to check if the results are sensitive to the choice of distance to nearby stores. Table D1 and Table D2 show the model regression results and the uncompensated own- and cross-price elasticities when the price IVs are constructed by using the average prices from nearby stores within 8 km. Results show that the own-price elasticities for meat (beef, pork, and poultry) are slightly more elastic than in the main study, while PBMS own-price elasticity becomes less elastic. Own-price elasticity of fish remains the same. Table D3 and Table D4 show the model regression results and the uncompensated own- and cross-price elasticities when the price IVs are constructed by using the average prices from nearby stores within 12 km. The results are very similar to the main results. Note that the change in the number of observations is due to the lack of instruments in some stores which do not have stores from other chains within 8 km, and more available instruments in some stores which have stores from other chains within 12 km.

Table D1: QAIDS Model Regression Results, Alternative IV - Average Prices from Nearby Stores within 8 km

	Beef share	Pork share	Poultry share	Fish share	PBMS share
Beef price (ln)	0.075**	0.053*	0.004	-0.088***	-0.043***
	(0.026)	(0.026)	(0.022)	(0.020)	(0.009)
Pork price (ln)	0.053	-0.244***	0.061	0.100**	0.029
	(0.045)	(0.043)	(0.037)	(0.033)	(0.016)
Poultry price (ln)	0.004	0.061	-0.008	-0.002	-0.056**
	(0.050)	(0.047)	(0.040)	(0.037)	(0.018)
Fish price (ln)	-0.088***	0.100***	-0.002	0.016	-0.026***
	(0.017)	(0.016)	(0.014)	(0.013)	(0.006)
PBMS price (ln)	-0.043	0.029	-0.056	-0.026	0.096***
	(0.040)	(0.039)	(0.033)	(0.030)	(0.014)
Total consumption (ln)	0.049***	0.038***	-0.053***	-0.024***	-0.010***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.001)
Squared total consumption (ln)	0.009***	0.007***	-0.016***	0.001	-0.001***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Observations	49854				

Note: Standard errors in parenthesis.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table D2: Uncompensated Own- and Cross-price Elasticities, Alternative IV - Average Prices from Nearby Stores within 8 km

	Beef price	Pork price	Poultry price	Fish price	PBMS price
Share of beef	-0.671***	0.219	-0.035	-0.468***	-0.220
	(0.128)	(0.227)	(0.244)	(0.082)	(0.199)
Share of pork	0.220	-2.198***	0.251	0.458***	0.135
	(0.121)	(0.210)	(0.225)	(0.077)	(0.186)
Share of poultry	0.033	0.191	-0.995***	0.007	-0.152
	(0.059)	(0.103)	(0.111)	(0.037)	(0.091)
Share of fish	-0.443***	0.570**	0.033	-0.891***	-0.133
	(0.104)	(0.182)	(0.195)	(0.066)	(0.161)
Share of PBMS	-0.980***	0.735	-1.262**	-0.577***	1.275***
	(0.221)	(0.388)	(0.416)	(0.141)	(0.341)

Note: Standard errors in parenthesis.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table D3: QAIDS Model Regression Results, Alternative IV - Average Prices from Nearby Stores within 12 km

	Beef share	Pork share	Poultry share	Fish share	PBMS share
Beef price (ln)	0.089***	0.047*	-0.018	-0.068***	-0.050***
	(0.025)	(0.023)	(0.021)	(0.018)	(0.010)
Pork price (ln)	0.047	-0.207***	0.054	0.083**	0.023
	(0.040)	(0.037)	(0.033)	(0.028)	(0.015)
Poultry price (ln)	-0.018	0.054	0.015	-0.004	-0.048**
	(0.045)	(0.041)	(0.037)	(0.032)	(0.017)
Fish price (ln)	-0.068***	0.083***	-0.004	0.023*	-0.034***
	(0.016)	(0.015)	(0.013)	(0.011)	(0.006)
PBMS price (ln)	-0.050	0.023	-0.048	-0.034	0.109***
	(0.041)	(0.038)	(0.033)	(0.029)	(0.015)
Total consumption (ln)	0.044***	0.036***	-0.050***	-0.021***	-0.010***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
Squared total consumption (ln)	0.008***	0.007***	-0.014***	0.001	-0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Observations	59169				

Note: Standard errors in parenthesis.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table D4: Uncompensated Own- and Cross-price Elasticities, Alternative IV - Average Prices from Nearby Stores within 12 km

	Beef price	Pork price	Poultry price	Fish price	PBMS price
Share of beef	-0.592***	0.196	-0.142	-0.368***	-0.257
	(0.123)	(0.201)	(0.223)	(0.080)	(0.202)
Share of pork	0.193	-2.009***	0.216	0.371***	0.105
	(0.110)	(0.175)	(0.195)	(0.070)	(0.179)
Share of poultry	-0.030	0.170	-0.934***	0.003	-0.129
	(0.056)	(0.090)	(0.100)	(0.036)	(0.091)
Share of fish	-0.342***	0.478**	0.021	-0.856***	-0.179
	(0.095)	(0.154)	(0.170)	(0.062)	(0.156)
Share of PBMS	-1.160***	0.591	-1.084**	-0.780***	1.596***
	(0.225)	(0.363)	(0.402)	(0.146)	(0.367)

Note: Standard errors in parenthesis.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

E Robustness check on without moving average of market shares

In this robustness check, we run the same QAIDS model without using moving average of market shares. Table E1 and Table E2 show the model regression results and the uncompensated own- and cross-price elasticities. Overall, the price elasticities are much more elastic than in the main study, which is within our expectation. Thus, using the moving average helps control hoarding behavior.

Table E1: QAIDS Model Regression Results, without Moving Average of Market Shares

	Beef share	Pork share	Poultry share	Fish share	PBMS share
Beef price (ln)	0.074*	0.074*	-0.002	-0.076***	-0.069***
	(0.032)	(0.031)	(0.026)	(0.023)	(0.014)
Pork price (ln)	0.074	-0.272***	0.024	0.097**	0.078***
	(0.052)	(0.050)	(0.042)	(0.037)	(0.023)
Poultry price (ln)	-0.002	0.024	0.080	0.000	-0.102***
	(0.056)	(0.054)	(0.046)	(0.040)	(0.025)
Fish price (ln)	-0.076***	0.097***	0.000	0.029*	-0.050***
	(0.020)	(0.019)	(0.016)	(0.014)	(0.009)
PBMS price (ln)	-0.069	0.078	-0.102**	-0.050	0.143***
	(0.049)	(0.047)	(0.040)	(0.034)	(0.021)
Total consumption (ln)	0.062***	0.048***	-0.073***	-0.022***	-0.014***
	(0.003)	(0.003)	(0.003)	(0.002)	(0.001)
Squared total consumption (ln)	0.012***	0.007***	-0.019***	0.002*	-0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Observations	55439				

Note: Standard errors in parenthesis.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table E2: Uncompensated Own- and Cross-price Elasticities, without Moving Average of Market Shares

	Beef price	Pork price	Poultry price	Fish price	PBMS price
Share of beef	-0.690***	0.310	-0.084	-0.419***	-0.351
	(0.155)	(0.260)	(0.277)	(0.098)	(0.241)
Share of pork	0.306*	-2.340***	0.055	0.428***	0.365
	(0.147)	(0.240)	(0.256)	(0.091)	(0.227)
Share of poultry	0.027	0.099	-0.736***	0.023	-0.278*
	(0.070)	(0.116)	(0.124)	(0.044)	(0.109)
Share of fish	-0.381**	0.555**	0.045	-0.818***	-0.266
	(0.121)	(0.200)	(0.213)	(0.076)	(0.188)
Share of PBMS	-1.586***	1.936***	-2.356***	-1.148***	2.440***
	(0.332)	(0.551)	(0.586)	(0.208)	(0.514)

Note: Standard errors in parenthesis.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

F Robustness check on a demand system with only animal products

In this robustness check, we run an alternative QAIDS model without PBMS. Table E1 and Table E2 show the model regression results and the uncompensated own- and cross-price elasticities estimated from a QAIDS demand system with only animal products. The own-price elasticities for poultry and fish are very similar to the main results, however, beef and pork become much more price elastic in this model. The major differences are shown in cross-price elasticities. The cross-price elasticities for pork and beef become very significant instead of insignificant, and the magnitudes are bigger than in the main results. This evidence supports that consumers treat beef and pork as substitutes. Likewise, we find similar changes in the cross-price elasticities for pork and poultry.

Table F1: QAIDS Model Regression Results, a Demand System with Only Animal Products

	Beef share	Pork share	Poultry share	Fish share
Beef price (ln)	0.043**	0.128***	-0.065***	-0.106***
	(0.013)	(0.015)	(0.011)	(0.010)
Pork price (ln)	0.128***	-0.365***	0.109***	0.128***
	(0.028)	(0.029)	(0.023)	(0.021)
Poultry price (ln)	-0.065*	0.109***	-0.006	-0.038
	(0.028)	(0.030)	(0.023)	(0.021)
Fish price (ln)	-0.106***	0.128***	-0.038***	0.016
	(0.013)	(0.014)	(0.011)	(0.010)
Total consumption (ln)	0.065***	0.051***	-0.088***	-0.028***
	(0.002)	(0.003)	(0.002)	(0.002)
Squared total consumption (ln)	0.013***	0.007***	-0.022***	0.002
	(0.001)	(0.001)	(0.001)	(0.001)
Observations	55439			

Note: Standard errors in parenthesis.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table F2: Uncompensated Own- and Cross-price Elasticities, a Demand System with only Animal Products

	Beef price	Pork price	Poultry price	Fish price
Share of beef	-0.852***	0.556***	-0.383**	-0.546***
	(0.064)	(0.133)	(0.135)	(0.062)
Share of pork	0.538***	-2.715***	0.435**	0.549***
	(0.067)	(0.134)	(0.137)	(0.064)
Share of poultry	-0.132***	0.328***	-0.967***	-0.073*
	(0.029)	(0.061)	(0.062)	(0.029)
Share of fish	-0.509***	0.698***	-0.143	-0.889***
	(0.054)	(0.109)	(0.112)	(0.052)

Note: Standard errors in parenthesis.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.