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Price Elasticities of Meat, Fish and Seafood: A Meta-Analysis

Bachelor's thesis

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Declaration of Authorship

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During the preparation of this thesis, the author used OpenAI's ChatGPT to assist in developing the R-code, creating tables in LATEX, and refining the writing style. After using this tool, the author reviewed and edited the content as necessary and takes full responsibility for the content of the publication.

Prague, July 30, 2024

Kateřina Kozlíková

Abstract

This meta-analysis investigates consumer responsiveness to price changes by analyzing 459 own-price elasticity estimates from 56 studies, focusing on Marshallian and Hicksian elasticity categories across meat, fish, and seafood. We address the problem of publication bias using both linear and recently developed nonlinear methods, uncovering a slight negative bias in the Marshallian meat category, while estimates for Hicksian meat elasticities and for fish and seafood remain unchanged. Additionally, we apply Bayesian Model Averaging and Frequentist Model Averaging techniques to identify significant factors influencing price elasticity estimates. Our findings reveal regional differences and variations across different estimation approaches. Specifically, for Hicksian meat elasticities, we find evidence that the price elasticity of demand for beef is more elastic compared to other meat types. For fish and seafood, we detect disparities between high and low-income households.

JEL Classification	D12, Q11, Q18, I12
Keywords	meta-analysis, elasticity, price elasticity, food, meat, fish, seafood, prices, heterogeneity, cross-country, publication bias, consumer sensitivity
Title	Price Elasticities of Meat, Fish and Seafood: A Meta-Analysis

Abstrakt

Tato meta-analýza zkoumá reakce spotřebitelů na změny cen analyzováním 459 odhadů vlastní cenové elasticity z 56 studií, zaměřených na Marshalliánské a Hicksiánské kategorie napříč masem, rybami a mořskými plody. Zaměřujeme se na problém publikačního zkreslení, kde pomocí lineárních i nedávno vyvinutých nelineárních metod, odhalujeme mírné negativní zkreslení v kategorii Marshalliánské elasticity masa, přičemž pro Hicksiánské elasticity masa a pro ryby a mořské plody zůstávají odhady nezměněné. Dále používáme techniky Bayesovského průměrování modelů a Frekventistického průměrování modelů k identifikaci významných faktorů ovlivňujících odhady cenové elasticity. Naše zjištění odhalují regionální rozdíly a variace napříč různými přístupy k odhadu elasticity. Konkrétně u Hicksiánské elasticity masa nacházíme důkazy, že cenová poptávka po hovězím masu je pružnější ve srovnání s ostatními druhy masa. Pro ryby a mořské plody zjišťujeme rozdíly mezi domácnostmi s vysokými a nízkými příjmy.

Klasifikace JEL	D12, Q11, Q18, I12
Klíčová slova	metaanalýza, elasticita, cenová elasticita, potraviny, maso, ryby, mořské plody, ceny, heterogenita, mezi zeměmi, publikační zkreslení, citlivost spotřebitelů
Název práce	Cenové Elasticity Masa, Ryb a Mořských Plodů: Meta-Analýza

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Acronyms

AIDS Almost Ideal Demand System

BE Between-study Effects

BMA Bayesian Model Averaging

EDLP Every Day Low Prices

EK Endogenous Kink

FE Fixed Effects

FAT Funnel Asymmetry Test

GLM Generalized Linear Model

HL High-Low Pricing

LA/AIDS Linear Approximate Almost Ideal Demand System

LES Linear Expenditure System

MLE Maximum Likelihood Estimation

MSE Mean Squared Error

OLS Ordinary Least Squares

PET Precision Effect Test

QUAIDS Quadratic Almost Ideal Demand System

SKU Stock-Keeping Unit

SUR Seemingly Unrelated Regression

WAAP Weighted Average of Adequately Powered

WLS Weighted Least Squares

Chapter 1

Introduction

How do consumers respond to changes in the prices of meat, fish, and seafood? This response can be measured by economists through the concept of price elasticity of demand. Understanding price elasticity is crucial for assessing the impact of fiscal policies aimed at influencing the consumption of these foods. While some studies focus on the potential health risks of excessive meat consumption, it is equally important to consider the nutritional benefits and consumer preferences that drive demand for meat, fish, and seafood.

Meat, fish, and seafood provide essential nutrients and play a significant role in many diets around the world. For example, lean meats are a valuable source of high-quality protein, vitamins, and minerals that are vital for maintaining health (Lennerz *et al.* 2021). Fish and seafood are particularly rich in omega-3 fatty acids, which have been linked to numerous health benefits, including improved heart health and cognitive function (Guasch-Ferré & Willett 2021). Additionally, certain dietary approaches such as the ketogenic diet, which includes high-fat and moderate-protein foods like meat, have shown neuroprotective and disease-modifying effects (Gasior *et al.* 2006). Understanding the price elasticity of demand for these food items can help policymakers design balanced fiscal policies that promote healthy dietary choices without discouraging the consumption of beneficial nutrients.

However, excessive consumption of red and processed meats has been linked to various health issues, including cardiovascular diseases and certain cancers (Domingo & Nadal 2017). To address these public health concerns, some countries are implementing taxes on meat products to discourage excessive consumption. Similarly, policies aimed at reducing the intake of high-mercury seafood can help mitigate health risks associated with overconsumption of these products (Andreyeva *et al.* 2010).

From an environmental perspective, the livestock industry is a major contributor to greenhouse gas emissions, deforestation, and water consumption. Overfishing and destructive fishing practices also lead to significant ecological damage by depleting marine biodiversity and disrupting ecosystems (Tveterås *et al.* 2012). Understanding price elasticities can guide the development of environmental policies that promote sustainable consumption patterns and mitigate these impacts.

Specific policy initiatives are being discussed in various regions. Denmark, for instance, proposed a significant measure in February 2024: a tax on livestock carbon dioxide emissions set to take effect from 2030. This move aims to address environmental concerns and is poised to be the world's first CO2 tax targeting farms. Denmark, a major pork and dairy exporter, hopes this initiative will set an example and encourage other nations to implement similar measures.

This study aims to understand how consumers respond to changes in the prices of meat, fish, and seafood. This research question necessitates a comprehensive investigation; however, after identifying previous meta-analyses on this topic, we found that they do not consider publication bias, overlook endogeneity bias, and only one of them provides a ceteris-paribus analysis while neglecting model uncertainty.

To explore this, we employ meta-regression analysis using the newest meta-analytical methods. Our dataset comprises 459 estimates from 56 studies, providing a comprehensive overview of the price elasticity of demand for these food categories. We particularly focus on identifying and addressing publication bias and the heterogeneity in the estimates. Publication selection bias occurs when certain results are more likely to be reported than others. Typically, preference is given to statistically significant results or parameter values that align with well-established theories. This can lead to a distortion of the overall body of literature and an inflated mean estimate of price elasticity (Stanley 2005). Addressing this bias is crucial as policymakers rely on published studies to inform their decisions, and biased studies can lead to misinformed policies. To identify publication bias, we will use methods such as the test of funnel asymmetry proposed by Stanley (2005) and more advanced methods like weighted averaging and p-uniform* estimation. These methods help correct for biases and provide a more accurate estimate of price elasticity. Our results showed that Marshallian meat is negatively biased due to selective reporting and that fish and seafood, surprisingly, do not suffer from this bias.

To understand the variations in estimated elasticities, we examine the influence of study design and employ model averaging techniques. This process involves coding variables that capture different aspects of study design, including country-level factors, definitions of demand, and methods of price measurement. Our analysis revealed that using the QUAIDS model consistently produces more elastic estimates across all categories. Additionally, regional variations in the results highlight significant geographical differences in price elasticities. By using both Bayesian and Frequentist model averaging approaches, we aim to address multicollinearity and account for model uncertainty.

The study is structured as follows: Chapter 2 explores the background of the topic and literature review. Chapter 3 focuses on the process of obtaining our data set. Chapter 4 explores publication bias identification and includes results for both the linear and non-linear methods. Chapter 5 explains the influence on our findings using BMA and FMA averaging techniques. Lastly, Chapter 6 discusses how price elasticities are utilized in practice, both from a macroeconomic and microeconomic perspective, which we discussed in collaboration with Yieldigo, company focused on pricing strategies.

Chapter 2

Price elasticity and literature review

2.1 Estimating price elasticity

Price elasticity of demand quantifies how changes in the price of a good affect the quantity demanded by consumers. It is a crucial metric for understanding consumer behavior, especially in the food sector where price fluctuations are common. Estimating price elasticity involves analyzing historical data on prices and quantities sold, using econometric models to adjust for factors like income effects.

The own-price elasticity of demand (η_{ii}) can be calculated as:

$$\eta_{ii} = \frac{\delta \ln X_i(y, p)}{\delta p_i} \tag{2.1}$$

Where η_{ii} denotes the elasticity, X_i is the demand for input i, y is the output, p is the vector of factor prices and p_i is the price for input i.

The estimation of price elasticity typically employs econometric models that can handle the complex relationship between price changes and demand. Beyond basic econometric approaches, the estimation of price elasticity in the food sector has benefited significantly from the development of sophisticated models like the Almost Ideal Demand System AIDS and its quadratic extension, the Quadratic Almost Ideal Demand System QUAIDS. The AIDS model, introduced by Deaton & Muellbauer (1980), has been widely used over the past two decades and provides a comprehensive framework for estimating demand systems. It is expressed through a budget share equation:

$$w_i = \alpha_i + \sum_j \gamma_{ij} \ln(p_j) + \beta_i \ln\left(\frac{X}{P}\right) \tag{2.2}$$

Here, w_i is the budget share of the ith good, p_j is the price of jth good, X is total expenditure, and P is a price index defined as:

$$\ln(P) = \alpha_0 + \sum_k \alpha_k \ln(p_k) + \frac{1}{2}\sum_j \sum_k \gamma_{kj} \ln(p_k) \ln(p_j) \tag{2.3}$$

The price index from 2.2 causes equation 2.3 to become nonlinear, leading to additional empirical problems. Stone (1954)'s Price Index (P^*) was used for P in many investigations in order to prevent nonlinear approximation. Using the Stone Price Index, Blanciforti & Green (1983) expressed it as LA/AIDS (linear approximate AIDS). Because the factor of proportionality of P to P^* is incorporated within the intercept, the LA/AIDS model allows for the estimation of the parameters of the AIDS model with extremely collinear prices (Green & Alston 1990). The Stone Price Index (P^*) is expressed as:

$$\ln(P^*) = \sum_k w_k \ln(p_k) \tag{2.4}$$

Nonetheless, many studies of household demand analysis tend to favor the quadratic form of the AIDS model (QUAIDS) proposed by Banks *et al.* (1997). Certain consumer preferences are quadratic in contrast to the linear form of the AIDS, according to Banks *et al.* (1997); for this reason, the QUAIDS specification is more appropriate, particularly when examining household demand.

The second most commonly used demand system among our sample of studies is the Translog (Transcendental Logarithmic) system, introduced by Christensen *et al.* (1975). It offers a flexible approach for modeling consumer behavior without restrictive assumptions on substitutability between goods. It uses a second-order Taylor series approximation to represent the utility function, allowing for the analysis of both own-price and cross-price elasticities. The model is expressed as follows:

$$\ln x_i = \alpha_i + \sum_j \beta_{ij} \ln(p_j) + \gamma_i \ln(m) + \frac{1}{2}\sum_j \sum_k \gamma_{ijk} \ln(p_j) \ln(p_k) \tag{2.5}$$

Here, x_i is the quantity of good i, p_j is the price of good j, and m is total expenditure. This model's ability to capture nonlinear price relationships is advantageous but also brings about estimation challenges due to its complexity and the high dimensionality of parameters, particularly when dealing with many goods. According to Blackorby *et al.* (1978), handling these estimation challenges requires robust econometric techniques and often substantial computational resources to ensure precision in the elasticities derived.

About 62% of the studies in our sample utilize one of these sophisticated models, demonstrating their widespread acceptance.

In addition to the models discussed, there are also other types of econometric models used in the rest of the studies. Single-equation demand systems also hold significant value. Notably, the Linear Expenditure System (LES) by Stone (1954) and the Rotterdam model by Theil (1965) provide focused insights into basic consumption patterns and the effects of substitution, respectively. These simpler models are especially useful in scenarios focused on specific commodity groups or where complex multi-equation systems are untenable due to data constraints.

Overall, there are numerous approaches to modeling the demand for goods. For detailed methodologies, applications, and estimations utilizing these models, the aforementioned articles provide comprehensive insights.

2.2 Contribution

Price elasticities, especially within the food sector, are crucial for guiding policymakers and businesses by offering insights into consumer behavior in response to price changes. These elasticities help predict how variations in prices can significantly influence consumer demand and spending habits, which is essential for formulating effective pricing strategies, as well as for designing and implementing policies related to taxes and subsidies. Understanding price elasticity allows for the efficient management of food supply and demand, ensuring food security, and tackling issues related to nutrition and public health.

For policymakers, analyzing the price elasticity of meat, fish, and seafood is invaluable. For instance, by understanding the elasticity of meat, policymakers can introduce taxes to reduce its consumption due to health concerns. The study by Springmann *et al.* (2018) supports the implementation of health-motivated taxes on red and processed meat to mitigate associated health risks. Similarly, understanding the elasticity of fish and seafood can aid in promoting sustainable fishing practices and ensuring the longevity of aquatic resources.

From the perspective of businesses, particularly those in the food industry, price elasticities are essential for setting optimal prices. By understanding how consumers respond to price changes, companies can strategically adjust their pricing levels to maximize profits while maintaining demand. The study by Mhurchu *et al.* (2010) demonstrates that price discounts, combined with tailored nutrition education, significantly influence supermarket purchases, indicating how strategic pricing can drive consumer behavior. Additionally, Huangfu *et al.* (2024) found that financial incentives and subsidies on healthy foods effectively increase their purchase and consumption, underscoring the impact of pricing strategies on dietary choices.

Moreover, price elasticity data is vital for agriculture and environmental planning. Farmers and producers can align their production strategies with market demands and price sensitivity, promoting more sustainable practices such as reducing meat production or increasing the availability of sustainable fish and seafood options. Poore & Nemecek (2018) highlight that the food system is responsible for approximately 26% of global anthropogenic greenhouse gases, with animal production alone contributing to about 56-58% of food-related greenhouse gas emissions and utilizing 83% of farmland, despite providing a much smaller proportion of global caloric and protein, emphasizing the need for sustainable agricultural practices.

On an international scale, comprehending the price elasticity of food commodities is crucial for framing trade policies and food aid programs. It enables the anticipation of how global price fluctuations might affect food security, assisting countries in crafting trade agreements that support local agriculture while ensuring that food remains accessible to all segments of the population. Understanding price elasticity in this context helps balance the goals of promoting domestic agricultural sectors and maintaining global food security amidst changing market dynamics. The study by Green *et al.* (2013) provides evidence that global food price changes have a more pronounced effect on food consumption in lower-income countries and among poorer households within countries. This underscores the importance of considering price elasticity when developing international trade and food aid strategies to ensure food affordability and security globally.

Sievert *et al.* (2021) show that public acceptance of the afore-mentioned policies varies, necessitating targeted and culturally sensitive approaches. Therefore, the focus of this study on publication bias and heterogeneity is essential. Addressing biases not only supports the formulation of effective and equitable policies but also strengthens their acceptance and implementation by accurately reflecting consumer behavior and market realities. Thus, by grounding our analysis in unbiased and comprehensive data, we enhance the potential for successful environmental and economic outcomes, fostering a sustainable future for the global food system.

2.2.1 Previous meta-analyses and their limitations

In the exploration of consumer responses to changes in food prices, we have identified five published meta-analyses that deal with the own-price food elasticities, those of Andreyeva *et al.* (2010), Cornelsen *et al.* (2015), Green *et al.* (2013), Chen *et al.* (2016), and the most recent one by Bouyssou *et al.* (2024). Additionally, studies by Gallet (2009) and Gallet (2010) that focus strictly on meat and fish were also examined. However, a critical evaluation of these meta-analyses uncovers common methodological shortcomings and analytical constraints, particularly the lack of comprehensive treatment for publication and endogeneity biases.

Gallet (2010) observes a common trend toward reporting more substantial elasticity values in meat studies. Gallet (2010) attempts to quantify this bias by categorizing studies based on the prestige of the publishing journal, implying a systematic review of publication sources. However, the study does not employ any statistical methods and tools for detecting publication bias in meta-analyses. The lack of these methodologies means that while Gallet (2010) acknowledges the bias, no quantitative correction is applied to adjust the reported elasticities. Andreyeva *et al.* (2010) also notes a tendency in the literature to emphasize results that depict significant consumer responsiveness, potentially skewing policy and market understanding.

The study by Cornelsen *et al.* (2015) provides average elasticity figures but does not effectively address endogeneity. It lacks the use of econometric techniques to isolate the impact of price from other correlated variables, potentially leading to biased estimates. Green *et al.* (2013) similarly reports elasticity estimates without adequately accounting for endogeneity, omitting any advanced econometric correction that would ensure the purity of the price impact measured.

Chen *et al.* (2016) stands out for attempting to control for extraneous variables more systematically. Chen employs a more refined methodological approach, likely using fixed or random effects models to adjust for observed heterogeneity across studies. However, the study does not specify whether techniques such as controlling for unobserved heterogeneity, which are crucial for a true ceteris paribus condition that would ensure the reported elasticities reflect only the impact of price changes.

The most recent study by Bouyssou *et al.* (2024) offers the latest insights into food price elasticities, but also does not address the unique challenges of publication and endogeneity biases in meat elasticity studies.

These reviews collectively indicate that while some attempts have been made to recognize methodological issues such as publication and endogeneity biases, comprehensive and robust statistical techniques to effectively correct these biases are lacking. This study aims to address these gaps by utilizing advanced statistical methods, including numerous methods to correct for publication bias. This approach not only enhances the accuracy of the elasticity estimates but also ensures that the insights provided are reliable and applicable for policymakers and industry stakeholders focused on the meat market.

Chapter 3

Data

3.1 Data collection

Data collection is a crucial part of every meta-analysis, requiring careful and thorough gathering of information. Following the guidelines provided by Irsova *et al.* (2023), we started our data collection by setting up a search query in Google Scholar. We targeted keywords directly related to price elasticities of food demand. s a search query we, therefore, used "*food and price elasticity*," "*price elasticity*," "*demand elasticity*," "*food demand*," "*price elasticities*". This search query resulted in 187,000 results and we went through the first 500 results, ensuring a broad yet relevant pool of studies for potential inclusion.

Next, we restricted on the most recent studies, specifically those published from 2019 onwards, and checked the first 100 results. We also looked at the studies included in prevous meta-analyses to find those that reported food-related price elasticity estimates.

Due to the large number of food categories and the practical limits on data collection, we decided to focus our study on meat, fish and seafood. These categories were chosen because they have different market dynamics and are important for understanding how sensitive consumers are to price changes due to their significant relevance in current discussions on taxation and sustainability. This focus helped us keep our research manageable and detailed. The criteria for including studies in our dataset were:

1. Studies must provide an own-price elasticity estimate for meat, fish or seafood. We categorized these estimates into several sub-categories:

    - *Meat not specified* (when the type of meat was not clearly specified in the study), *Beef*, *Pork*, *Poultry*, *Fish* and *Seafood*.

2. Because of the nature of our methodology, the estimate in the study must be presented with the standard error or t-statistic. The relationship between the estimates and their standard errors forms the basis of our publication bias detection methods.

3. The study needs to be written in English.

We ended up with 56 studies that provided a total of 459 price elasticity estimates. You can find a detailed list of these studies in the Appendix A. Breaking down the estimates by category, we have total of 307 estimates for meat and 152 for fish and seafood. Due to the small number of seafood-specific estimates, we decided to combine fish and seafood into one larger category for analysis. This decision allowed us to work with a larger set of data and perform a more thorough analysis.

We also collected an additional 44 variables related to various aspects influencing price elasticity. These variables play a crucial role in understanding the heterogeneity among the studies we analyzed. We will discuss these variables in depth in Chapter 5, where we discuss heterogeneity and explore how different factors impact the estimates.

3.2 Marshallian vs Hicksian elasticity

Next, we distinguish between Marshallian and Hicksian demand elasticities, which are central to our analysis framework. We have compiled 292 estimates of Marshallian elasticities and 164 estimates for Hicksian elasticities. The differentiation is crucial because each estimation method is derived from different economic theories introduced by influential economists Marshall (1890) and Hicks (1963).

Marshall (1890) developed the uncompensated elasticity concept, also known as Marshallian elasticity, which measures the total response of quantity demanded to a change in price, incorporating both substitution effect and the income effect. For instance, if the price of meat increases, consumers might buy less meat not only because it is more expensive (substitution effect) but also because they now have less money to spend on other good (income effect). The Marshallian elasticity is calculated as:

$$\epsilon_{\text{Marshallian}} = \frac{\partial Q}{\partial P} \times \frac{P}{Q} \tag{3.1}$$

where $\partial Q/\partial P$ is the partial derivative of quantity demanded with respect to price, P is the price, and Q is the quantity demanded. The quantity demanded, Q, is typically derived from demand functions where:

$$Q = f(P, I) \tag{3.2}$$

Here, P is the price, and I represents income. The function f indicates how quantity demanded varies with price and income.

Hicks (1963) introduced the concept of compensated, or Hicksian, elasticity, refining the analysis by adjusting for income changes to isolate the substitution effect. In this context, if price of meat increases, consumers are given additional money to offset the price increase. If they still choose to buy less meat, this reflects solely the substitution effect - shifting away from meat due to its higher price compared to other goods, regardless of their unchanged purchasing power. The Hicksian elasticity is calculated as:

$$\epsilon_{\text{Hicksian}} = \frac{\partial Q^c}{\partial P} \times \frac{P}{Q} \tag{3.3}$$

where $\partial Q^c/\partial P$ is the partial derivative of the compensated demand with respect to price, P is the price, and Q^c is the compensated quantity demanded. To derive Q^c, the following adjustment is made:

$$Q^c = f(P, I^c) \tag{3.4}$$

where I^c is the adjusted income that maintains the consumer's utility at its original level despite the change in price. This adjustment is crucial for calculating Q^c and involves using an expenditure function to find I^c that keeps the utility constant at different price levels:

$$I^c = e(P, u) \tag{3.5}$$

Here, $e(P, u)$ is the expenditure function that calculates the minimum expenditure necessary to achieve a certain utility level u at the new price P. This function provides the compensated income I^c required for utility constancy.

3.3 Data overview

The Marshallian elasticities, as summarized in Table 3.1, indicate high price sensitivity for both meat and fish & seafood, with mean elasticities of -0.95 and -0.87, respectively. Figure 3.1 illustrates the distributions of these estimates, showing a clear left skew for meat, with significant concentration around -1 and tail extending towards more negative values. This skewness indicates a higher frequency of more elastic estimates, suggesting variability due to factors like market type or specific meat products. The distribution for fish & seafood, marked in red, shows a similar left skew but with a more pronounced peak just less elastic than -1 and a narrower spead, which denotes a more uniform price sensitivity across studies.

For the Hicksian elasticities detailed in Table 3.2, the mean values are -0.68 for meat and -0.80 for fish & seafood, highlighting a generally less elastic response when income effects are removed. The histogram in Figure 3.2 depicts a broader range for meat, including a noticable left skew with many observations clustering close to zero.

Significantly, the use of a 1% winsorization was considered essential because of the variability in our data set. Winsorization is a method used to manage outliers by minimizing their degree of extremeness. This approach is preferable to removing outliers entirely, especially when there are few estimates available. Failing to address outliers could skew the outcomes of the analysis.

Table 3.1: Summary of Marshallian elasticities

	Observations	Mean	Median	SD	Min	Max
Meat	202	-0.95	-0.84	0.72	-4.23	-0.11
Fish and seafood	90	-0.87	-0.73	0.53	-2.97	-0.17

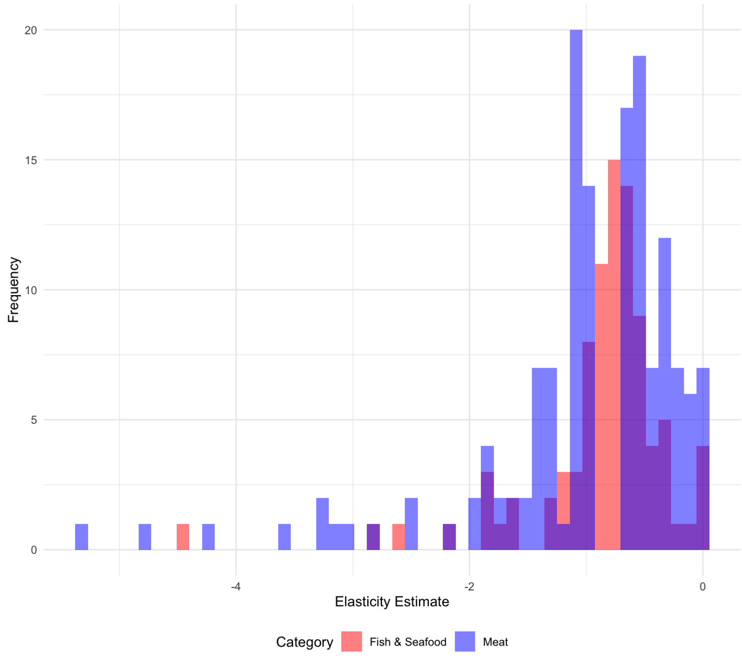
Note: This table displays the summary statistics of the Marshallian price elasticities for meat, fish & seafood, where SD stands for Standard Deviation.

Table 3.2: Summary of Hicksian elasticities

	Observations	Mean	Median	SD	Min	Max
Meat	104	-0.68	-0.62	0.48	-3.10	-0.08
Fish and seafood	62	-0.80	-0.61	0.59	-3.27	-0.20

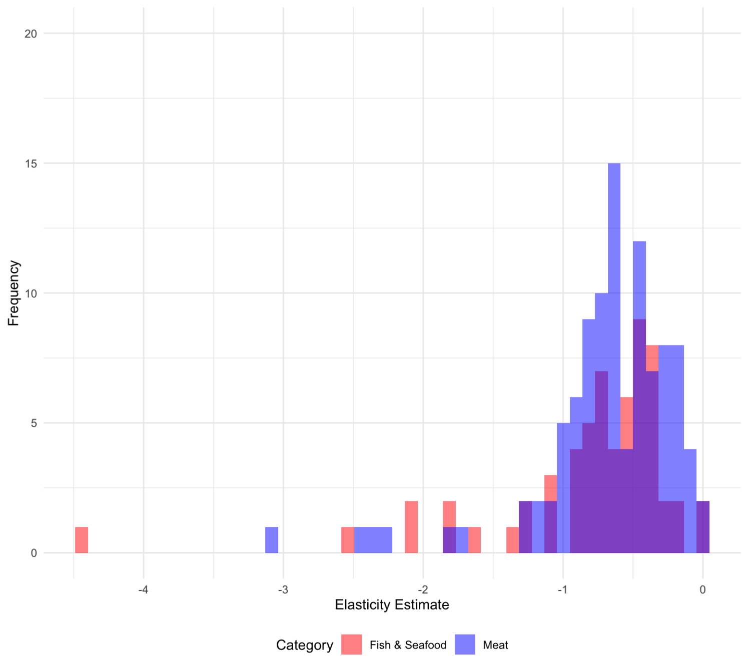
Note: This table displays the summary statistics of the Hicksian price elasticities for meat, fish & seafood, where SD stands for Standard Deviation.

Figure 3.1: Distribution by effect magnitude - Marshallian elasticities



Note: The histogram illustrates the distribution of Marshallian elasticity estimates (non-winsorized) we gathered, categorizing meat (blue) and fish and seafood (red) into two distinct groups.

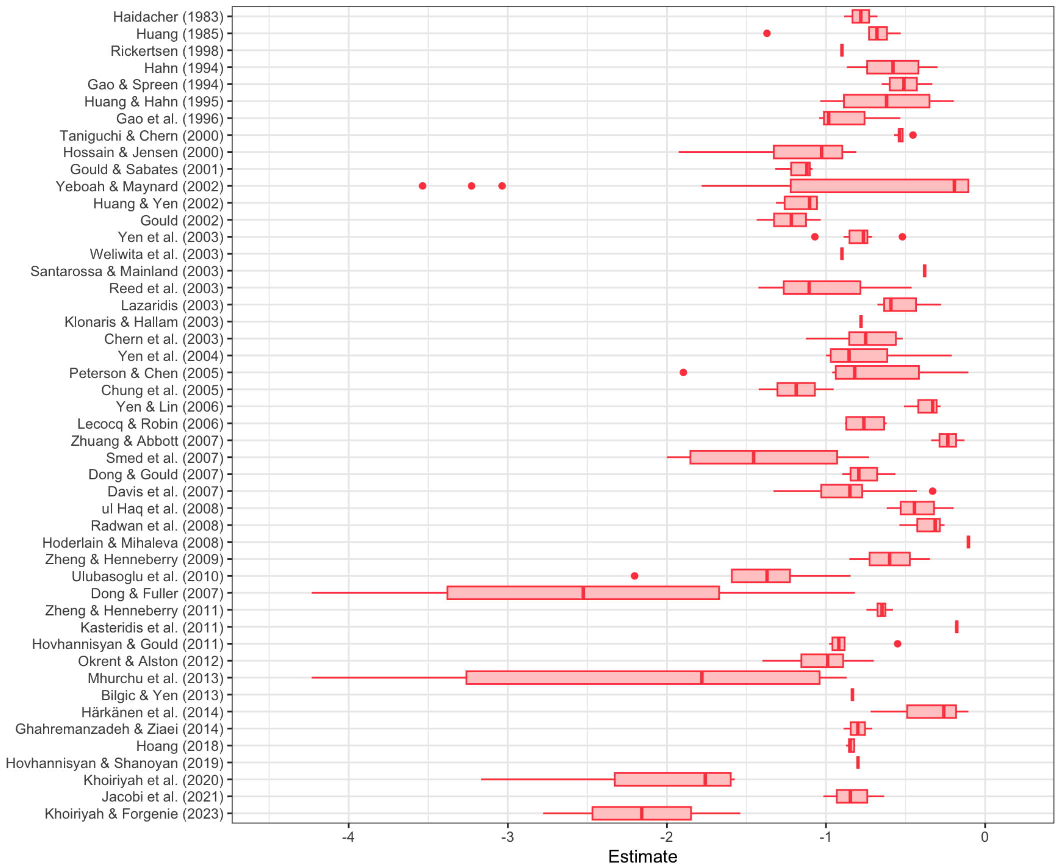
Figure 3.2: Distribution by effect magnitude - Hicksian elasticities



Note: The histogram illustrates the distribution of Hicksian elasticity estimates (non-winsorized) we gathered, categorizing meat (blue) and fish & seafood (red) into two distinct groups.

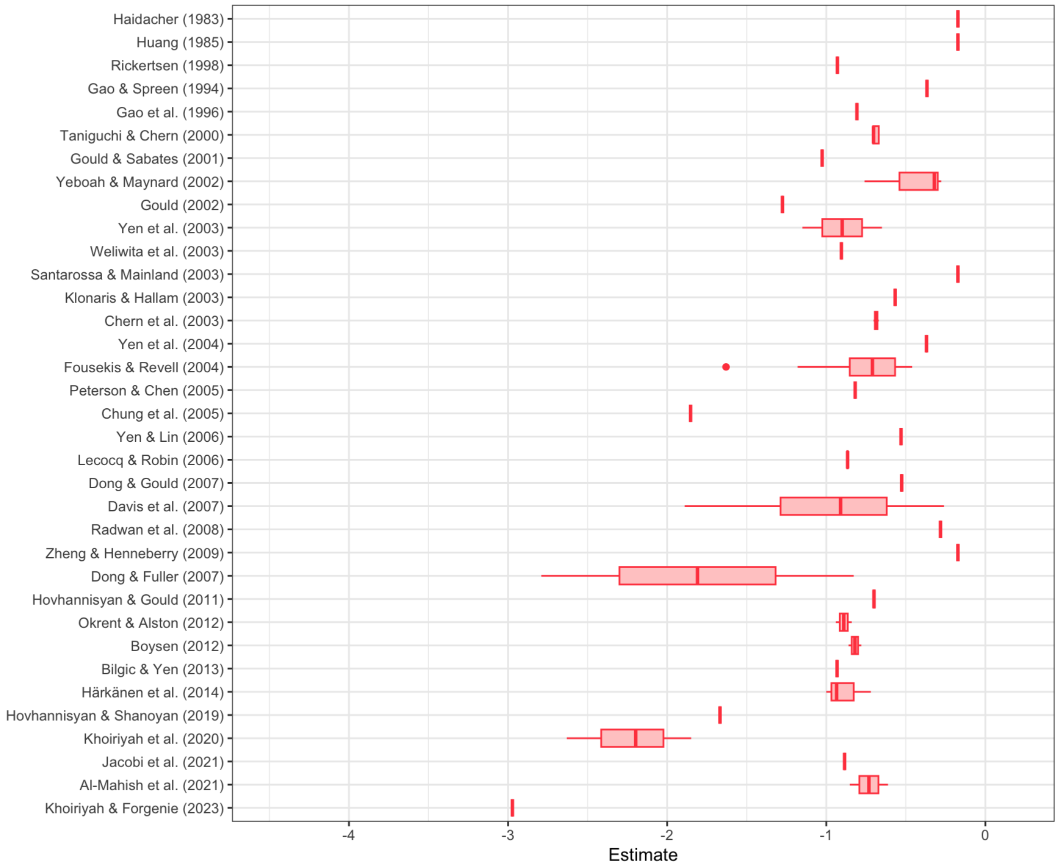
Our analysis spans a comprehensive dataset covering 40 years of research, from 1983 to 2023. The historical span begins with study by Haidacher (1983) and extends to recent contribution by Khoiriyah *et al.* (2023). Figures 3.3 and 3.4 visually represent the variation in Marshallian elasticity estimates for meat and fish & seafood, arranged chronologically. The dataset features both journal articles and working papers, with a mean number of 5 elasticity estimates per study. Mean number is influenced by extensive studies like the one by Fousekis & Revell (2004) or Davis *et al.* (2007). In the boxplot, studies such as Dong & Fuller (2010) and Ni Mhurchu *et al.* (2013) demonstrate some of the highest variation in elasticity estimates. These studies show a wide range of values from near-zero to extremely negative estimates, reflecting significant discrepancies in consumer responsiveness within their respective datasets.

Figure 3.3: Boxplot of the Marshallian elasticity across studies - meat



Note: The figure display a boxplot of Marshallian elasticity estimates for meat from individual studies. Each box indicates the interquartile range with a median line inside. Whiskers extend from the top and bottom of the box to cover most of the data, and outliers are depicted as dots.

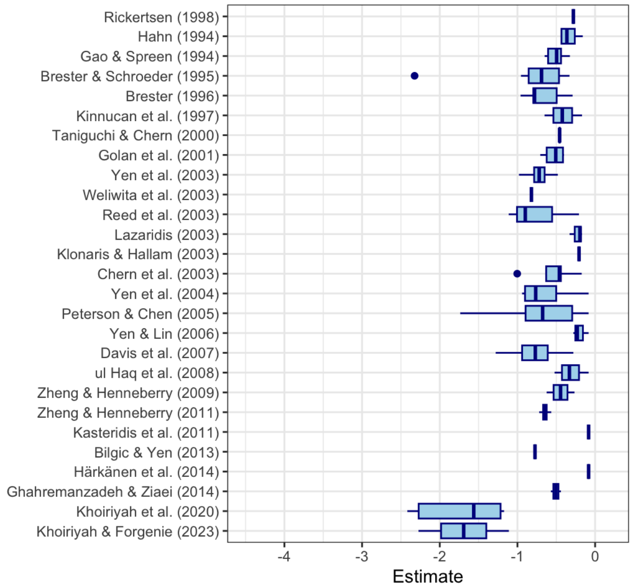
Figure 3.4: Boxplot of the Marshallian elasticity across studies - fish & seafood



Note: The figure display a boxplot of Marshallian elasticity estimates for fish & seafood from individual studies. Each box indicates the interquartile range with a median line inside. Whiskers extend from the top and bottom of the box to cover most of the data, and outliers are depicted as dots.

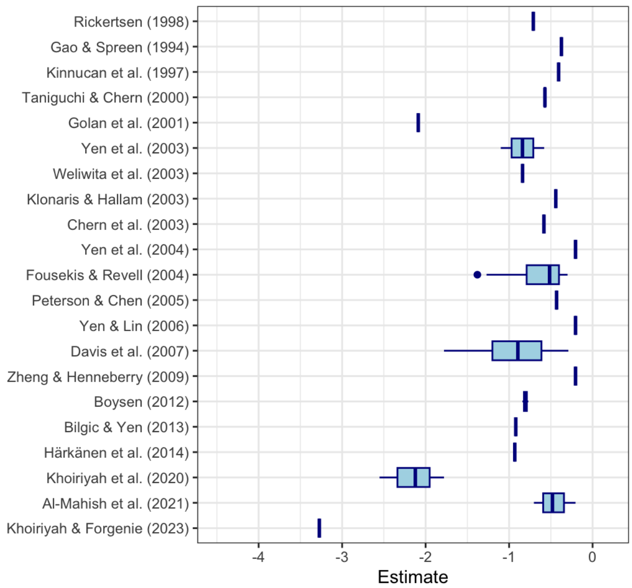
Boxplots for Hicksian elasticity estimates can be seen on Figures 3.5 and 3.6. For both meat and fish & seafood, the Hicksian elasticity distributions are notably less spread, with fewer outliers, suggesting a more stable range of elasticity estimates across studies. The mean number of estimates per study is 5, the same as observed for Marshallian elasticities, but there is a narrower variability observed.

Figure 3.5: Boxplot of the Hicksian elasticity across studies - meat



Note: The figure display a boxplot of Hicksian elasticity estimates for meat from individual studies. Each box indicates the interquartile range with a median line inside. Whiskers extend from the top and bottom of the box to cover most of the data, and outliers are depicted as dots.

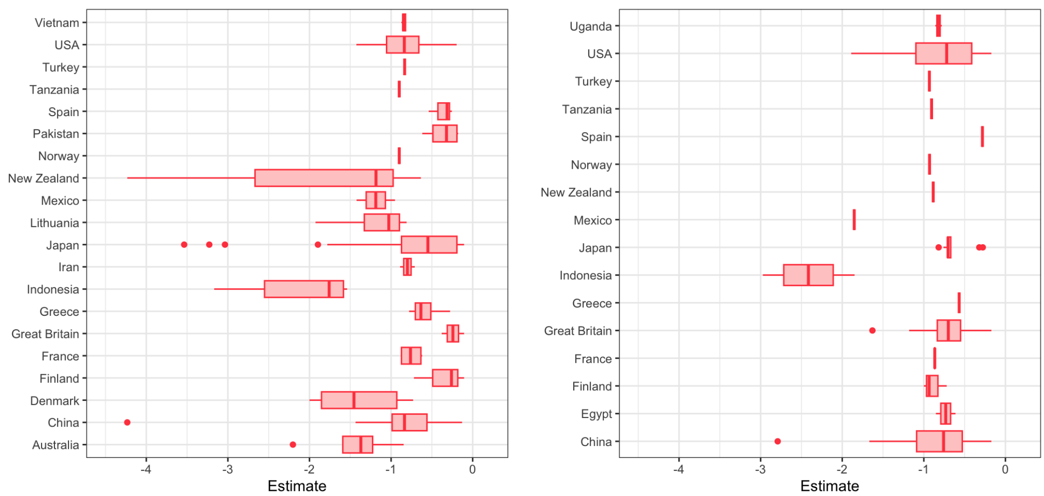
Figure 3.6: Boxplot of the Hicksian elasticity across studies - fish & seafood



Note: The figure display a boxplot of Hicksian elasticity estimates for fish & seafood from individual studies. Each box indicates the interquartile range with a median line inside. Whiskers extend from the top and bottom of the box to cover most of the data, and outliers are depicted as dots.

Next, we analyzed elasticity estimates more closely, focusing on specific countries and how their boxplot data for meat and fish & seafood reflect unique consumer price sensitivities. Marshallian elasticity estimates are depicted on Figure 3.7. New Zealand displays the widest range of elasticity estimates for meat, including some extreme values. This could be reflective of diverse market conditions or consumer preferences within the country. Japan, Indonesia and Denmark also show considerable variability in their elasticity estimates for meat. The median values for these countries fall between -1.5 and -0.5. Indonesia stands out as a special case for fish & seafood, displaying much more negative elasticity values compared to other countries, with a median around -2.5. This indicates an exceptionally high sensitivity to price changes, possibly due to the cultural and economic importance of fish & seafood in Indonesia, offering many possible substitutes.

Figure 3.7: Boxplots of the Marshallian elasticity across countries

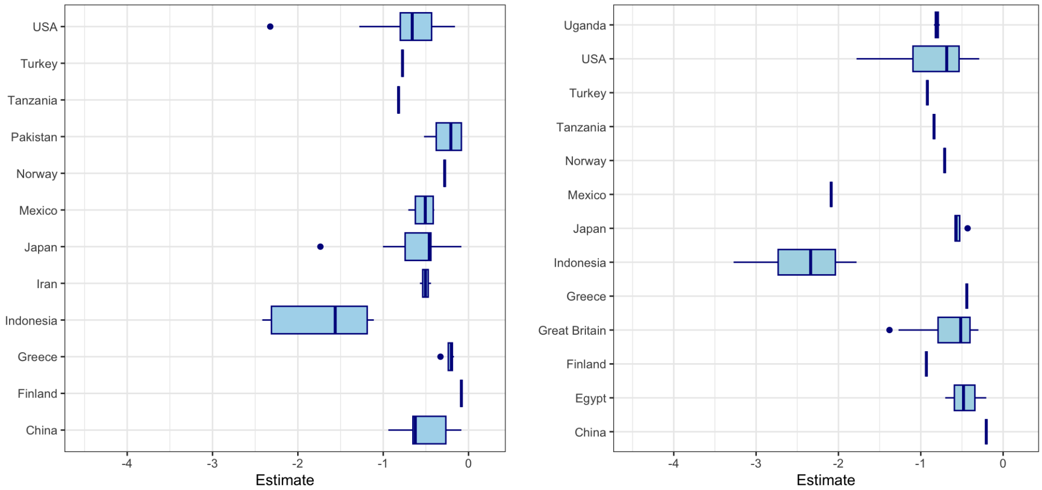


a) Meat b) Fish and seafood

Note: These figures display boxplots of Marshallian elasticity estimates for meat and fish & seafood from individual studies. Each box indicates the interquartile range with a median line inside. Whiskers extend from the top and bottom of the box to cover most of the data, and outliers are depicted as dots.

Hicksian elasticity estimates across countries are presented in Figure 3.8. Indonesia stands out again with significantly more negative values for both meat and fish & seafood compared to other countries. Compared to the Marshallian estimates, Hicksian figures generally show a less dramatic spread and fewer outliers, suggesting a more direct and uniform response to price changes.

Figure 3.8: Boxplots of the Hicksian elasticity across countries



a) Meat b) Fish and seafood

Note: These figures display boxplots of Hicksian elasticity estimates for meat and fish & seafood from individual studies. Each box indicates the interquartile range with a median line inside. Whiskers extend from the top and bottom of the box to cover most of the data, and outliers are depicted as dots.

Chapter 4

Publication bias

Publication selection bias represents a situation in which some results are more likely to be reported than others (Stanley 2005). Typically, preference is given to statistically significant results or parameter values that align with well-established theories. The Law of Demand is possibly the strongest economic theory of all: with an increase in prices, demand falls. Food of most sorts is considered an ordinary good, deeming the price elasticity to be negative. Thus, if a researcher gets a positive estimate, they may choose not to write a study based on such results, or to adjust (intentionally or not) their methodology or dataset in order to produce the intuitive outcome. Even if such adjustment might be easily defendable on the level of a single study (possibly the error was due to a misspecified model, small sample, or noise in data), if done systematically the whole literature gets distorted and the overall mean is biased (in our example towards larger negative values). Ioannidis *et al.* (2017) show, for example, that the mean estimate reported in economics is exaggerated twofold because of this bias.

4.1 Testing for publication bias

To identify the publication bias meta-researchers usually employ a funnel plot of Egger *et al.* (1997). Given that this test is only visual, Stanley (2005) proposed a formal analogy called the test of funnel asymmetry. The basic idea of the test is that in the absence of publication bias, there should be no systematic relation or correlation between the estimate and its standard error. Given that researchers of the primary studies implicitly assume that the ratio of the estimates to their standard errors has a t-distribution (they so report t-statistics), it indeed makes sense that estimates and standard errors should be statistically independent. When published studies preferentially report estimates with a specific sign or statistical significance, the estimates should then be correlated with standard errors. The trouble with the funnel asymmetry test is, nevertheless, twofold: first, it assumes that the relationship between the estimate and the standard error is linear (but there could be jumps at the conventional critical values of statistical significance) and second, it assumes that the standard error is exogenous to the estimate (but there could be reverse causality, omitted variable bias, and even measurement error, as described in Havranek *et al.* (2022)). We use the weighted average of adequately powered by Ioannidis *et al.* (2017), the stem-based method by Furukawa (2019), the selection model by Andrews & Kasy (2019), and the endogenous kink by Bom & Rachinger (2019) that do drop the linearity assumption, and p-uniform* estimation based on the p-values reported for the effects by van Aert & van Assen (2021) that drops the exogeneity assumption.

4.1.1 Funnel plot

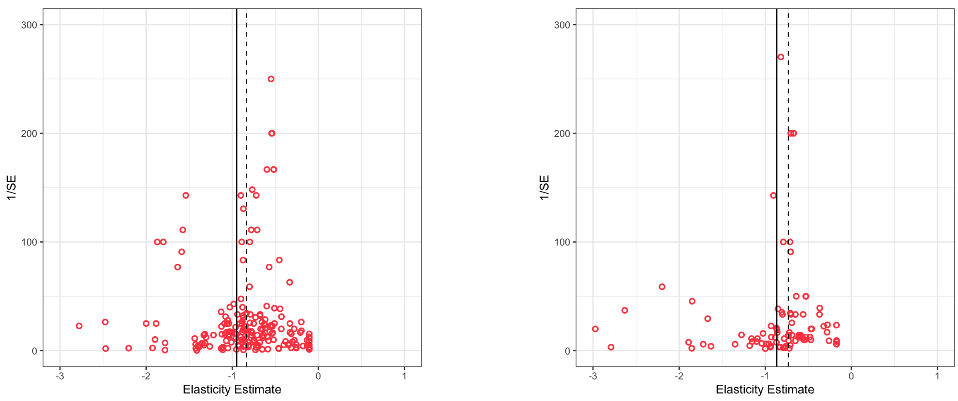
When assessing publication bias in price elasticities for meat and aquatic products, we use the funnel plot of Egger *et al.* (1997) as our investigative tool. This graphical device, meant to reveal publication bias, is plotted by placing the elasticity estimates against their precision, as denoted by the inverse of the standard error (Egger *et al.* 1997). Estimates with the smallest errors are near the top of the funnel and are grouped closely together. As the errors get bigger, the estimates spread out more, making the shape of an upside-down funnel that is narrow at the top and wide at the bottom. If there is no bias in reporting, the funnel should look symmetrical on both sides, meaning that all estimates, no matter how imprecise, have an equal chance of being reported Havranek *et al.* (2015). In contrast, a biased funnel plot may appear asymmetrical or skewed, often lacking studies on one side of the effect size axis, which could indicate a type I bias, where estimates that do not align with prevailing theory are less likely to be published. Alternatively, it may also demonstrate a type II bias, characterized by an underreporting of insignificant estimates, regardless of their direction.

Figure 4.1 reveals a funnel plots of Marshallian elasticity estimates for meat and fish and seafood. It is important to note that the funnel plots exclude a few estimates with extremely high precision. These were omitted to maintain clarity and readability of the graphs, as their inclusion could disproportionately affect the visual distribution of data. The graphs are visibly asymmetrical with a clustering of estimates displaying substantial heterogeneity at more precise levels. Notably, there are no estimates crossing into positive elasticity territory for either category; instead, all estimates veer towards the negative, indicating a potential stronger tendency to report or publish findings that are consistent with the anticipated negative relationship between price and demand for these products.

In Figure 4.2, the funnel plots for Hicksian elasticity estimates for meat and fish and seafood are presented. Despite a smaller body of research, the less densely populated plots exhibit a similar asymmetry to their Marshallian counterparts, with an absence of positive elasticity estimates that might imply a publication bias.

The asymmetry in the funnel plots for both meat and aquatic products suggests a potential publication bias, but this is not conclusive. To provide a more definitive assessment, we will utilize additional statistical techniques within this chapter that move beyond the visual interpretation offered by funnel plots.

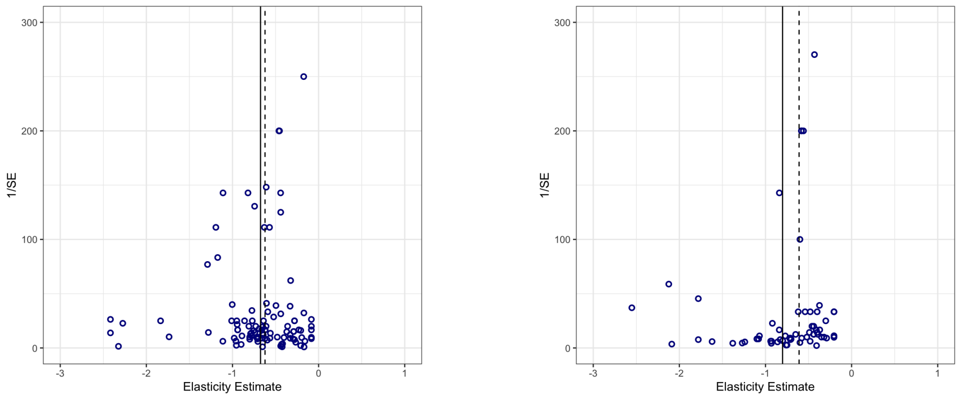
Figure 4.1: Funnel plots: Marshallian elasticities



a) Meat b) Fish and seafood

Note: The figures are funnel plots for Marshallian elasticity estimates only. Highly precise estimates are excluded for clarity but included in deeper analysis. Figure (a) describes meat, figure (b) fish and seafood. The mean and median are shown by solid and dashed black lines, respectively. SE stands for standard error.

Figure 4.2: Funnel plots: Hicksian elasticities



a) Meat b) Fish and seafood

Note: The figures are funnel plots for Hicksian elasticity estimates only. Highly precise estimates are excluded for clarity but included in deeper analysis. Figure (a) describes meat, figure (b) fish and seafood. The mean and median are shown by solid and dashed black lines, respectively. SE stands for standard error.

4.1.2 Linear tests for detecting publication bias

To explore potential selective reporting in our study further, we apply the Funnel Asymmetry Test (FAT) and the Precision Effect Test (PET), sophisticated methods that examine the relationships between study estimates and their standard errors via regression (Stanley 2005). Literature suggests that in an unbiased research environment, the effect estimates should scatter randomly around the central estimate of effect size (Card & Krueger 1995). However, if a bias exists - due to preferences for statistically significant or theoretically aligned results - these estimates will likely correlate with their standard errors.

The following equation is estimated, to perform the regression analysis:

$$Y_{ij} = \beta_0 + \beta_1 \times SE\left(Y_{ij}\right) + \epsilon_{ij} \tag{4.1}$$

Here, Y_{ij} is the i-th effect size estimate from j-th study and $SE(Y_{ij})$ is its standard error . The intercept β_0, represents the "true effect," which is the effect size adjusted to remove any influence from publication bias. β_1 measures the size and direction of the bias, and ϵ_{ij} is the error term (Stanley 2005).

Table 4.1 details the outcomes from a variety of analyses conducted according to Equation 4.1, shaped by methodologies recommended by experts like Stanley (2008) or Stanley & Doucouliagos (2015). Unless noted otherwise, we apply clustered standard errors at the study level and assume that the standard error variable is exogenous. We begin with Ordinary Least Squares (OLS) as our baseline method and then continue with implementing study-level fixed effects (FE) and between-study effects (BE) to control for unobserved heterogeneity within and across the studies, respectively.

Additionally, we use two forms of Weighted Least Squares (WLS). The first method weights estimates by the inverse of their standard errors, adressing heteroscedasticity, as suggested by Ioannidis *et al.* (2017). The second method assigns weights based on the inverse of the number of estimates each study contributes, ensuring all studies equally influence the results.

Results of the linear tests are summarized in Table 4.1. For Marshallian elasticities of meat, the analysis indicates statistically significant and negative publication bias across almost all methods. The mean elasticity, after accounting for this bias, is estimated to be about -0.8. This is less negative than the observed mean of -0.95 presented in Table 3.1, implying that the actual mean is skewed by negative publication bias. Despite the presence of the negative bias in Marshallian meat, its impact appears to be rather minor, as it doesn't dramatically increase the mean several times over. However, the impact remains significant.

The only method that shows inconsistent but significant results is the WLS weighted by precision method. The reason for this inconsistency is likely due to one or two large studies that report very high precision. This high precision skews the results, leading to significant findings that differ from other methods.

Surprisingly, since only two out of our five methods identified a statistically significant mean estimate, we conclude that there is no significant publication bias detected for Hicksian meat and both categories of fish & seafood. The absence of publication bias in fish and seafood studies might be due to factors such as lower research intensity or differing market dynamics. However, these potential reasons are not definitive and would require further investigation.

Table 4.1: Linear tests for detecting publication bias

	OLS	**FE**	**BE**	**Precision**	**Study**
			Marshallian elasticities		
Meat					
Publication bias	-0.484**	-0.590***	-0.623	-16.095***	-0.661*
(SE)	(0.160)	(0.083)	(0.326)	(3.603)	(0.283)
Mean beyond bias	-0.835***	-0.810***	-0.783***	-0.263*	-0.777***
(Constant)	(0.042)	(0.043)	(0.090)	(0.118)	(0.050)
Observations	202	202	202	202	202
Fish & Seafood					
Publication bias	-0.881	-1.347*	-1.121	-2.254	-1.121
(SE)	(0.525)	(0.594)	(0.929)	(1.476)	(0.726)
Mean beyond bias	-0.772***	-0.722***	-0.774***	-0.738***	-0.774***
(Constant)	(0.076)	(0.073)	(0.135)	(0.030)	(0.117)
Observations	90	90	90	90	90
			Hicksian elasticities		
Meat					
Publication bias	0.032	-1.894***	0.318	-16.437***	0.159
(SE)	(0.311)	(0.448)	(0.406)	(3.124)	(0.193)
Mean beyond bias	-0.678***	-0.458***	-0.626***	-0.157*	-0.607***
(Constant)	(0.055)	(0.061)	(0.091)	(0.067)	(0.065)
Observations	102	102	102	102	102
Fish & Seafood					
Publication bias	-0.618	-1.964**	-0.267	-4.820*	-0.360
(SE)	(0.794)	(0.607)	(1.574)	(2.243)	(1.313)
Mean beyond bias	-0.736***	-0.593***	-0.832**	-0.558***	-0.823***
(Constant)	(0.126)	(0.075)	(0.229)	(0.058)	(0.203)
Observations	62	62	62	62	62

Note: The table presents the results from estimating Equation 4.1 using different methods: OLS (Ordinary Least Squares), FE (Fixed Effects), BE (Between Effects), and RE (Random Effects). Precision refers to weighting the estimates by the inverse of their standard error, while Study refers to weighting by the inverse of the number of observations per study. Standard errors, clustered at the study level, are included in parentheses. Statistical significance is indicated by *, **, and *** for the 10%, 5%, and 1% levels, respectively.

4.1.3 Non-linear tests for detecting publication bias

Although traditional linear methods are a solid baseline for detecting publication bias, they can have limitations with accuracy. These methods assume a linear relationship between effect size estimates and their standard errors, and that these variables are uncorrelated in the absence of publication bias. However, these assumptions often do not hold true, resulting in imprecise estimates of publication bias. Notably, the FAT-PET test tends to underestimate the "true underlying effect" when it is other than zero (Bom & Rachinger 2019).

To address these limitations, we employ several advanced methods that relax these assumptions. Results can be seen in Table 4.2.

We begin with the Weighted Average of Adequately Powered (WAAP) method as proposed by Ioannidis *et al.* (2017). This approach addresses publication bias by selecting only those effect size estimates that have sufficient statistical power, discarding those with disproportionately large standard errors. The WAAP method uses the weighted least squares technique only for estimates that are "adequately powered," meaning that when the estimated effect is divided by 2.8, it remains larger than its standard error. This ensures the estimates can accurately detect true effects.

Next, we apply the Selection model introduced by Andrews & Kasy (2019). This model accounts for the likelihood of an estimate being published based on its statistical significance. By adjusting for this so-called "conditional publication probability", it ensures that underrepresented estimates are given appropriate weight.

Another method is the Stem-based method by Furukawa (2019) which focuses on the most precise estimates from the funnel plot, referred to as the "stem". By minimizing the Mean Squared Error (MSE) through a balance of bias and variance, it offers a robust estimate of the true effect by including only the most precise studies.

Furthermore, we employ the Endogenous Kink (EK) meta-regression model introduced by Bom & Rachinger (2019). This method identifies a threshold in the standard error below which publication bias is unlikely. Having identified this kink, Bom & Rachinger (2019) suggest fitting a piecewise linear regression of the estimates on to the data, capturing the underlying effect size.

The results of these methods are displayed in Table 4.2. Overall, the results are consistent with the linear tests described above. However, the only significant method that shows inconsistency with the others is the kink method.

When no kink is found, the endogenous kink model defaults to a WLS FAT-PET weighted by precision. This occurs because the kink is defined as where the lower confidence bound of the bias-corrected mean meets the significance line. If no intersection is found, the endogenous kink results match the Precision method, making the explanation the same as for the WLS weighted by precision method in Section 4.1.2 .

Table 4.2: Non-linear tests for detecting publication bias

	WAAP	**Selection**	**Stem**	**Kink**
		Marshallian elasticities		
Meat				
Mean beyond bias	-0.841***	-0.861***	-0.318	-0.263***
(Constant)	(0.037)	(0.03)	(0.266)	(0.025)
Observations	202	202	202	202
Fish & Seafood				
Mean beyond bias	-0.832***	-0.854***	-0.867***	-0.738***
(Constant)	(0.056)	(0.056)	(0.085)	(0.030)
Observations	90	90	90	90
		Hicksian elasticities		
Meat				
Mean beyond bias	-0.677***	-0.674***	-0.149	-0.157***
(Constant)	(0.049)	(0.044)	(0.198)	(0.024)
Observations	102	102	102	102
Fish & Seafood				
Mean beyond bias	-0.788***	-0.797***	-0.524**	-0.558***
(Constant)	(0.076)	(0.075)	(0.202)	(0.045)
Observations	62	62	62	62

Note: WAAP (Weighted Average of Adequately Powered), Selection (Selection Model), Stem (Stem-Based Method), and Kink (Endogenous Kink Model). Standard errors are included in parentheses. Statistical significance is indicated by *, **, and *** for the 10%, 5%, and 1% levels, respectively.

4.1.4 Relaxing the endogeneity assumption

Lastly, we employ the p-uniform* test developed by van Aert & van Assen (2021). P-uniform*, compared to the other methods we use, does not assume the endogeneity assumption. This method is an enhancement of their earlier p-uniform approach, which operates on the principle that p-values should follow a uniform distribution around the mean in the absence of bias. The p-uniform* method improves upon its predecessor by incorporating statistically insignificant estimates into the analysis. This inclusion addresses certain limitations of the original p-uniform method, such as a reduction in efficiency, thereby providing a more robust and comprehensive estimation.

Results of this method are displayed in Table 4.3 and are consistent with results of the other above-mentioned methods. For Hicksian fish and seafood, the p-uniform* method did not converge, lacking an upper bound. This method typically requires a larger number of studies and performs better when publication bias is present but not extreme. Some assumptions of the p-uniform* method were likely violated, causing the maximum-likelihood process to converge incorrectly. Hence, we do not include this result as it cannot be calculated for our sample.

Table 4.3: p-uniform* test for detecting publication bias

	p-uniform*
Marshallian elasticities	
Meat	
Mean beyond bias (Constant)	-0.812***
	(0.084)
Observations	202
Fish & Seafood	
Mean beyond bias (Constant)	-0.708*
	(0.229)
Observations	90
Hicksian elasticities	
Meat	
Mean beyond bias (Constant)	-0.607**
	(0.118)
Observations	102
Fish & Seafood	
Mean beyond bias (Constant)	N/A
Observations	62

Note: Standard errors are included in parentheses. Statistical significance is indicated by *, **, and *** for the 10%, 5%, and 1% levels, respectively.

Chapter 5

Heteregeneity

This chapter investigates the heterogeneity in price elasticities of meat, fish and seafood, focusing on the critical role of contextual factors. Gallet (2010) highlights that variables like the type of product, market conditions, and geographic regions significantly influence price responsiveness, underscoring the critical role of context in economic analyses.

We have selected a comprehensive set of variables that cover effect characteristics, methodological approaches, and the specifics of the study design. This selection is guided by insights from previous research, which suggests that both observable and unobservable factors may influence the outcomes. 44 variables are categorized to cover different dimensions. We divided our variables into 7 categories: *Type of product*, *Demand type*, *Form of demand system*, *Estimation method*, *Data characteristics*, *Geographical origin* and *Publication characteristics.* This categorization helps us understand the potential drivers behind the observed variability in price elasticities across different studies and markets. All of them are listed in Table 5.1.

To ensure the robustness of our analysis, we apply both Bayesian and frequentist model averaging methods. These approaches help us address model uncertainty, allowing for a more nuanced interpretation of results.

5.1 Variable overview

Type of product We have organized the price elasticity estimates by product type to analyze market dynamics specific to each category. The dataset includes a total of 306 observations for meat products. Within this group, beef is the most prominent category, holding a significant share of the observations, followed closely by poultry and pork. Additionally, a significant number of observations were categorized under a general category where the specific type was not identified in the studies.

For aquatic products, our dataset details 20 observations for seafood and 132 for fish, totalling 152 observations. This breakdown helps us recognize differences between these two types, altough the smaller number of seafood-specific observations led us to combine fish and seafood into a single category for analysis.

Demand type In our study, we distinguish between unconditional and conditional demand, as well as Marshallian and Hicksian elasticities, although the latter distinctions are discussed in detail in Section 3.2.

Conditional demand depends specifically on expenditures and prices tied to a selected group of products. On the other hand, unconditional demand spans broader market dynamics, incorporating prices of all goods and encompassing total income or total expenditures. Rickertsen (1998) underlines the significance of differentiating these demand types, noting that unconditional elasticities, derived from models that include all goods, often show greater variability and are more indicative of general market sensitivities. He emphasizes that these elasticities are usually more relevant for policy purposes, as they reflect the full spectrum of market interactions and economic influences. Similarly, Klonaris & Hallam (2003) demonstrate in their study the importance of considering both conditional and unconditional elasticities. They use correction formulas to adjust conditional elasticities to better represent the broader economic impacts, highlighting significant differences that can arise between these measures.

Next, we also distinguish between Marshallian elasticity, which measure the total response to price changes including both substitution and income effects, and Hicksian elasticity, which isolate the substitution effect by adjusting for income changes. However, due to reasons discussed in Chapter 3, we analyze these two categories separately.

Form of demand system We have created a set of dummy variables to categorize the functional form of demand used in the studies. We have categories for the Almost Ideal Demand System (AIDS), Linear Approximate Almost Ideal Demand System (LA/AIDS), Quadratic Almost Ideal Demand System (QUAIDS) and Transcendental Logarithmic model (Translog). Additionally, models that were not so highly represented and do not fit into these more common categories are grouped under "Other type". For detailed examples of studies employing each system and foundational papers providing theoretical context, please refer to Section 2.1. Andreyeva *et al.* (2010) emphasizes that different econometric models, each with its own assumptions and specifications, can yield varied elasticity estimates. This highlights the importance of categorizing these in our analysis to assess how significantly these differences might impact our results.

Estimation method Cornelsen *et al.* (2015) demonstrated that the estimation methods significantly influence the estimated values of price elasticities. Following their insights, we included in our database a set of dummy variables that indentifies the estimation method used in the primary studies, adopting the same classification as Cornelsen *et al.* (2015). These dummies categorize the methods into four groups: Seemingly Unrelated Regression (SUR), Ordinary Least Squares (OLS), Maximum Likelihood Estimation (MLE), and other less common methods grouped under "Other method".

Data characteristics Next, we evaluate the various characteristics of the datasets used in primary studies. This category covers the largest number of variables. In the initial set, we consider three main types of data: time-series, cross-sectional, and panel data. Time-series data involve observations over a period of time, allowing us to capture trends and temporal dependencies. These datasets are particularly useful for analyzing long-term trends and shifts in consumer behavior. For example, studies utilizing time-series data can effectively identify cyclical patterns and seasonal effects in consumer demand (Deaton & Muellbauer 1980). Cross-sectional data, on the other hand, provide a snapshot at a single point in time across different subjects. This type of data is beneficial for capturing variations across different groups or regions at a specific time, offering insights into consumer behavior diversity (Greene 2012). Panel data combine elements of both time-series and cross-sectional data, following the same subjects over multiple time periods.

We also consider the frequency of data collection, creating four categories ranging from high-frequency data (e.g., daily or weekly) to annual data. High-frequency data are quite rare in our dataset. Notably, Smed *et al.* (2007) is the only study in our dataset that collected data on a weekly basis.

Next set of variables is the type of data source. We include categories for

Scanner data, Survey data and "Other data types". Scanner data are collected through product code scanners at points of sale and are useful for linking quantities directly to prices, offering precise insight into consumer purchasing behavior and immediate price responses. However, Scanner data have limitations. For example, Feenstra & Shapiro (2007) discuss the challenges of using Scanner data for economic statistics, noting that it often fails to capture transactions outside conventional retail settings. Survey data, collected from households or individuals via questionnaires and interviews, can capture broader consumption patterns and preferences. It can also provide insights into informal purchases that scanner data might miss. Despite their advantages, survey data might not be representative of national-level consumption and may not accurately reflect aggregate-level effects crucial for broader economic analysis (Chen *et al.* 2016). Other data variable includes other sources such as administrative records, experimental data or databases from governmental or international organizations. For example, Klonaris & Hallam (2003) used time series data from the National Accounts of Greece.

Chen *et al.* (2016) highlights the importance of distinguishing between urban and rural areas, noting that these regions differ in myriad ways, including income levels, availability of goods, and consumer preferences. Thus, we use variables to categorize data into urban and rural datasets. Variations based on income levels are also considered, distinguishing between low-income and high-income households. Following the approach of Andreyeva *et al.* (2010), in cases where studies provided demand parameter estimates for both low-income consumers and all consumers, we included estimates for both groups to capture the full spectrum of consumer behavior. Another variable considered in this category, although not very common in our dataset, is Imported which identifies products that were imported from some other country.

We also include variables for the number of years the data covers and the mid-year of the data collection period. Klonaris & Hallam (2003) utilized the longest time period in our dataset, spanning 36 years, while other studies, such as Jacobi *et al.* (2021), only use data from one single year. The mid-year variable represents the average year of the data collection period.

Geographical origin The geographical scope of the data is another important characteristic. We distinguish between studies conducted in different regions, including North America, Asia, Europe, Australia and New Zealand, Africa, and Latin America. Each region has unique economic, cultural, and market conditions that can significantly influence consumer behavior and price elasticity estimates. Cross-country heterogeneity is an important factor to consider because differences in income levels, market structure, availability of substitutes, and cultural preferences can lead to variations in how consumers respond to price changes. According to Green *et al.* (2013), low-income countries tend to have higher price elasticities for all foods compared to high-income countries, because food represents a larger share of total income in these countries.

Publication characteristics We also consider the publication characteristics of the studies included in our analysis. Specifically, we distinguish between papers published in journals, presented at conferences, and working papers. This classification helps account for the different levels of peer review and dissemination associated with each type of publication. In addition to publication type, we include variable for the number of citations per year since the paper's publication.

Table 5.1: Summary statistics and descriptions for each of the study characteristics

Variable	Description	Mean for MC (M/H)	Mean for FSC (M/H)
Estimate	The own-price elasticity of demand (Dependent variable)	-0.95/-0.67	-0.87/-0.80
Standard Error	The standard error or the elasticity estimate	0.23/0.11	0.11/0.11
Product type			
Meat not specified	= 1 if the estimate refers to meat category but does not specify its type (Reference group for MC)	0.26/0.25	-
Poultry	= 1 if the estimate refers to poultry meat category	0.26/0.28	-
Pork	= 1 if the estimate refers to pork meat category	0.20/0.18	-
Beef	= 1 if the estimate refers to beef meat category	0.28/0.28	-
Fish	= 1 if the estimate refers to fish category (Reference group for FSC)	-	0.84/0.90
Seafood	= 1 if the estimate refers to seafood category	-	0.16/0.10
Demand type			
Unconditional	= 1 if the demand function is unconditional	0.22/0.25	0.28/0.32
Estimation			
AIDS	= 1 if the demand model is Almost Ideal Demand System (Reference category)	0.09/0.06	0.38/0.52
LA/AIDS	= 1 if the demand model is Linear Approximate Almost Ideal Demand System	0.17/0.16	0.08/0.08
QUAIDS	= 1 if the demand model is Quadratic Linear Approximate Almost Ideal Demand System	0.10/0.11	0.11/0.11
Translog	= 1 if the demand model is Translog demand system	0.20/0.27	0.18/0.23
Other system	= 1 if the demand model is neither of the above	0.40/0.42	0.26/0.10
SUR	= 1 if Seemingly Unrelated Regression or its variant is used as estimation method (Reference category)	0.24/0.38	0.42/0.60
Maximum Likelihood	= 1 if Maximum likelihood or its variant is used as estimation method	0.32/0.15	0.23/0.11
OLS	= 1 if Ordinary least squares is used as estimation method	0.02/0.02	0.06/0.03
Other method	= 1 if estimation method is neither of the above	0.43/0.47	0.31/0.29
Data Characteristics			

Continued on next page

Table 5.1: Summary statistics and descriptions for each of the study characteristics (continued)

Variable	**Description**	**Mean for MC (M/H)**	**Mean for FSC (M/H)**
Time-series	= 1 if the data used is time-series (Reference group)	0.29/0.31	0.48/0.53
Cross-sectional	= 1 if the data used is cross-sectional	0.51/0.56	0.37/0.31
Panel	= 1 if the data used is panel	0.20/0.13	0.16/0.16
High Frequency	= 1 if the data are more frequent than monthly	0.03/0.00	0.00/0.00
Monthly	= 1 if the data has monthly frequency (Reference group)	0.32/0.25	0.56/0.65
Quarterly	= 1 if the data has quarterly frequency	0.07/0.06	0.03/0.02
Annually	= 1 if the data as annual frequency	0.17/0.17	0.17/0.10
One-time	= 1 if the data was collected at one specific point in time	0.41/0.52	0.22/0.21
Number of years	The number of year the data covers	5.46/7.68	7.30/7.42
Mid-year	The mean year of the data collection period	1998/1996	1998/1999
Urban	= 1 if the data includes urban population only (Reference category)	0.20/0.19	0.16/0.08
Rural	= 1 if the data includes rural population only	0.04/0.03	0.03/0.03
Low-income household	= 1 if the data includes low-income households only (Reference category)	0.10/0.09	0.09/0.08
High-income household	= 1 if the data includes high-income households only	0.10/0.08	0.09/0.08
Imported	= 1 if the data includes imported food products	0.04/0.10	0.00/0.00
Survey data	= 1 if the data is survey data (Reference category)	0.81/0.72	0.54/0.39
Scanner data	= 1 if the data is scanner data	0.10/0.13	0.40/0.58
Other data	= 1 if the data is neither survey nor scanner	0.09/0.16	0.06/0.03
Geographical Origin			
North America	= 1 if the data is from North America (Reference group)	0.30/0.49	0.20/0.23
Asia	= 1 if the data is from Asia	0.47/0.40	0.31/0.19
Latin America	= 1 if the data is from Latin America	0.01/0.04	0.01/0.02
Europe	= 1 if the data is from Europe	0.14/0.06	0.40/0.47
Australia	= 1 if the data is from Australia or New Zealand	0.08/0.00	0.01/0.00
Africa	= 1 if the data is from Africa	0.01/0.01	0.07/0.10
Publication Characteristics			
Published	= 1 if the study was published in a journal (Reference group)	0.68/0.80	0.70/0.76
Working	= 1 if the study is a working paper	0.06/0.05	0.07/0.05
Conference	= 1 if the study is a conference paper	0.26/0.15	0.23/0.19
Citations per year	Number of citations per year (collected from Google Scholar in April 2024)	4.07/4.96	2.69/2.91

Note: MC = meat category group, FSC = fish & seafood category group, both groups are further divided between Marshallian (M) and Hicksian (H) type of elasticities.

5.2 Model averaging techniques

In the analysis of heterogeneity, we will employ both Bayesian and Frequentist model averaging approaches as described in Steel (2020). This decision stems from the need to address model uncertainty and avoid pitfalls associated with traditional regression methods, such as overspecification bias and multicollinearity.

Bayesian Model Averaging (BMA) is a sophisticated statistical method that accounts for model uncertainty by averaging over multiple candidate models. The core idea of BMA is to compute a weighted average of the models, where the weights are the posterior probabilities of each model. Each model is assigned a Posterior Model Probability (PMP), which reflects the likelihood that the model is the correct one given the data. This probability is calculated using Bayes' theorem, which integrates the likelihood of the data under the model with the prior probability of the model. The PMP provides a measure of the model's performance and serves as a weight in the overall averaging process.

To determine the significance of individual variables across different models, we calculate the Posterior Inclusion Probability (PIP). The PIP for a variable is the sum of the PMPs of all models that include that variable, providing a measure of the variable's overall importance. A PIP value can range from 0 to 1, with higher values indicating stronger evidence for the variable's inclusion in the model. According to Kass & Raftery (1995), the strength of evidence can be categorized as follows:

- **Weak evidence:** PIP ranges from 0.50 to 0.75
- **Positive evidence:** PIP ranges from 0.75 to 0.95
- **Strong evidence:** PIP ranges from 0.95 to 0.99
- **Decisive evidence:** PIP exceeds 0.99

This classification is also adopted by other researchers, such as Havranek *et al.* (2015), to interpret the robustness and relevance of the variables.

For our analysis, we will use the dilution prior, as suggested by George (2010). The dilution prior is particularly effective in handling multicollinearity, a common issue in datasets with numerous explanatory variables. The dilution prior works by multiplying the model probabilities with the determinant of the correlation matrix of the independent variables. This approach assigns larger weights to models where the variables are less correlated, as the determinant of the correlation matrix will be closer to one. Conversely, in the presence of high correlation, the determinant will be smaller, resulting in reduced weights for those models. This mechanism ensures that models with less multicollinearity are favored.

In addition to BMA, we will use Frequentist Model Averaging (FMA) as a robustness check. FMA offers a different perspective on handling model uncertainty by combining predictions from various models based on weights derived from frequentist metrics such as information criteria. By employing both BMA and FMA, we can compare the results and gain a deeper understanding of the robustness and reliability of our findings.

Before moving to the actual procedure, we will investigate the correlations between our variables and their Variance Inflation Factors (VIFs). Understanding the correlation matrix and VIFs is crucial to ensure that multicollinearity does not undermine our analysis.

VIF quantifies how much the variance of a regression coefficient is inflated due to multicollinearity. In other words, it measures how much the variance of an estimated regression coefficient increases if your predictors are correlated. Mathematically, the VIF for a given predictor is calculated as:

$$\mathrm{VIF}_j = \frac{1}{1 - R_j^2} \tag{5.1}$$

where R_j^2 is the coefficient of determination of the regression of the j-th predictor on all the other predictors.

- **VIF = 1:** Indicates no correlation between the j-th predictor and the remaining predictors, suggesting no multicollinearity.
- **1 < VIF < 5:** Suggests moderate correlation that typically doesn't pose serious problems.
- **VIF > 5:** Indicates high correlation, suggesting a potential multicollinearity problem.
- **VIF > 10:** Often considered as a threshold indicating serious multicollinearity issues, where the j-th predictor is highly correlated with other predictors, leading to inflated standard errors and unreliable estimates.

To ensure the robustness of our models, we first remove the reference group variables and variables with means less than 0.03. Next, we examine the correlation between variables, as seen in the Appendix B. Based on these correlations, we remove certain variables to address multicollinearity. Finally, we calculate the Variance Inflation Factors (VIFs) and remove variables with VIFs higher than 10 to further mitigate multicollinearity affecting our analysis by inflating standard errors and producing unreliable estimates. The resulting VIFs for the included variables can be seen in Table B.1. We conduct this procedure separately for four categories:

- **1)** Marshallian meat category
- **2)** Marshallian fish & seafood category
- **3)** Hicksian meat category
- **4)** Hicksian fish & seafood category

5.3 Results

In this section, we delve into the results of our analysis. For each category, the results are visually represented using Bayesian Model Averaging (BMA) graphs and numerically presented in tables in Section 5.3.5.

The BMA graphs display the outcomes of Bayesian model averaging, specifically with the uniform g-prior and the dilution prior. The variables are listed in descending order of their posterior inclusion probability (PIP), with columns representing individual models sorted by their posterior model probabilities from left to right. In these figures, blue cells indicate positive effects, red cells indicate negative effects, and white cells show that the variable was not included in the model. The horizontal axis displays the cumulative posterior model probabilities for the partial correlation coefficient, providing a comprehensive view of the variable's impact across different models.

Additionally, in the Appendix B, you can find a figure for each category presenting the Bayesian model averaging variables plotted against their posterior inclusion probabilities (PIP). This figure includes a variety of priors: the uniform g-prior (UIP), the dilution prior (Dilut), the uniform model prior (Uniform), the benchmark g-prior (BRIC), the random model prior (Random), and the Hannan-Quinn criterion (HQ). By comparing these priors, we can see that our results are robust and consistent across different model specifications.

5.3.1 Marshallian meat category results

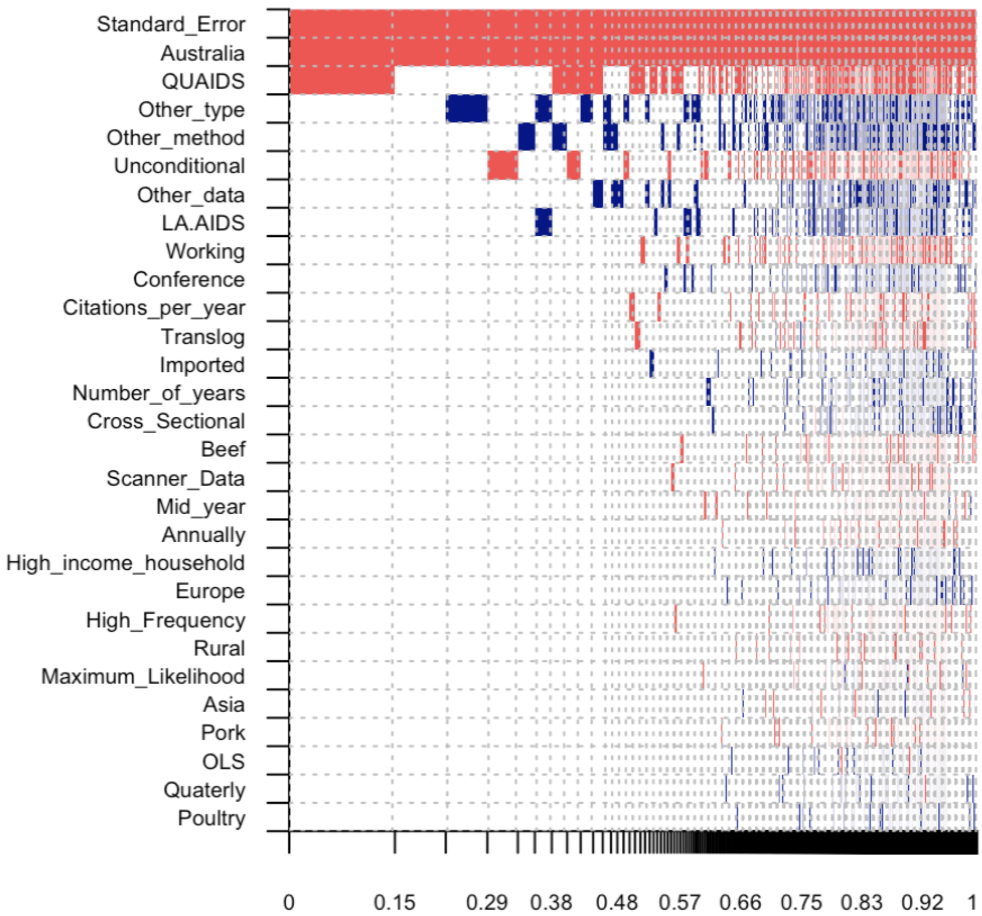
For the analysis of the Marshallian meat category, we omitted the *Africa* and *Latin America* variables due to their low means. These variables did not provide significant explanatory power, as their mean values were less than 0.03, rendering their inclusion in the analysis statistically insignificant. Additionally, we had to omit the *One-time* and *Panel Data* variables because of their high VIF values, indicating a high degree of multicollinearity.

The results, as illustrated graphically in Figure 5.1 and numerically in Table 5.2, indicate that there are two variables with PIP > 0.5. The variable for *Australia* has the PIP of 0.998, indicating a substantial regional effect on Marshallian meat demand. This means that for studies incorporating Australian data, the estimated demand for meat tends to show greater sensitivity to price changes, as reflected by more negative elasticity values. This finding is reinforced by a significant p-value of 0.007 in the Frequentist Model Averaging (FMA) results, underscoring the robustness of this observation.

Interestingly, a study by Gallet (2010) found that among other regions, the demand for meat is significantly less elastic in Australia. Also the fact that Australia is one of the top countries globally in meat consumption per capita suggests that people might not be that sensitive to price changes, as meat is often a staple part of their diet (OECD 2023). However, only 8% of our Marshallian meat observations were obtained from Australia, therefore our results here should be treated with caution.

Notably, the *Standard Error* variable has a PIP of 1.0. The findings from Chapter 4, which identified a negative publication bias and a less elastic true mean effect, remain robust even after accounting for all other variables. This suggests that the observed bias is likely attributable to the methodological approaches employed in the studies. This could include aspects such as data collection methods, or specific analytical techniques favored in the literature. This bias skews results towards more negative elasticity values by overrepresenting studies with smaller standard errors and significant results.

Figure 5.1: BMA results for Marshallian meat category



Note: The figure displays the results of Bayesian model averaging with the uniform g-prior (Eicher *et al.* 2011) and the dilution prior (George 2010). Variables are listed in rows, ordered by their descending posterior inclusion probability (PIP). The columns represent individual models, sorted by their posterior model probabilities from left to right. Blue cells indicate positive effects, red cells indicate negative effects, and white cells show that the variable was not included in the model. The response variable is the partial correlation coefficient, displayed on the horizontal axis as cumulative posterior model probabilities. Refer to Table 5.2 for detailed numerical results and Table 5.1 for variable descriptions.

5.3.2 Marshallian fish & seafood category results

In our heterogeneity analysis of the Marshallian fish & seafood category, several variables were excluded to ensure the robustness and accuracy of our results. Specifically, we removed *High Frequency*, *Imported*, *Australia*, and *Latin America* due to their low means, indicating limited representation in the dataset. Additionally, to avoid multicollinearity, we excluded several other variables with high Variance Inflation Factors (VIFs). For a detailed overview of the variables that were ultimately included, please refer to Table B.1.

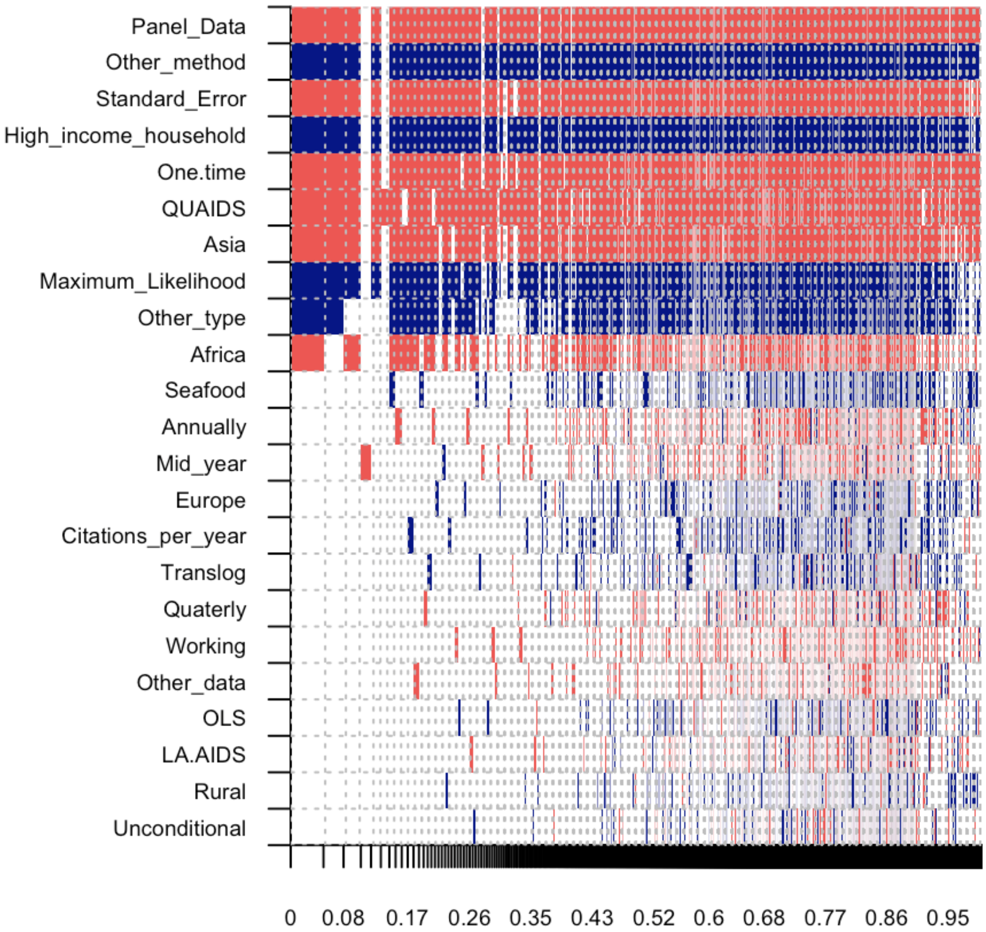
For this category, the *Standard Error* has a PIP of 0.898. Publication bias occurs after accounting for all other variables. This again suggests that the observed bias is likely attributable to the methodological approaches employed in the studies.

Among the variables related to the estimation method, there are five significant ones. Notably, the *QUAIDS* demand system shows a negative effect when used for elasticity estimation, indicating that estimates calculated using this demand system are more elastic. In contrast, the *Maximum Likelihood* method demonstrates a positive effect on the elasticity estimate when used, suggesting that models specified by this method yield less elastic estimates. Additionally, the *Other Method* and *Other type* variables, which cover various demand systems and estimation methods, also have a positive effect on elasticity, indicating that these approaches also result in less elastic estimates.

Furthermore, looking at the data characteristics, we observe three significant variables. *Panel Data*, with the highest PIP of 0.937, shows a negative impact on the elasticity estimate, indicating that studies using panel data typically report more elastic estimates compared to *Time-series*. Estimates derived from data collected at a single point in time, rather than on a recurring monthly basis, also tend to be more elastic, as evidenced by the *One-time* variable, which has a high PIP and a negative effect. Moreover, *high-income households* are less responsive to price changes compared to low-income ones when buying fish & seafood, a finding consistent with the results of Green *et al.* (2013).

Lastly, *Asia* is a significant variable in our model with a negative effect, indicating that estimates from Asia are more elastic compared to the baseline North America. Notably, China accounts for almost half of our fish and seafood estimates from Asia. Indeed, the meat market in China has expanded significantly since the 1970s, when it was limited to a few traditional products; today, there is a wide variety of both fresh and processed products available (Zhou *et al.* 2012). A wider range of choices leads to greater substitution possibilities, and hence to more price-elastic demands.

Figure 5.2: BMA results for Marshallian fish & seafood category

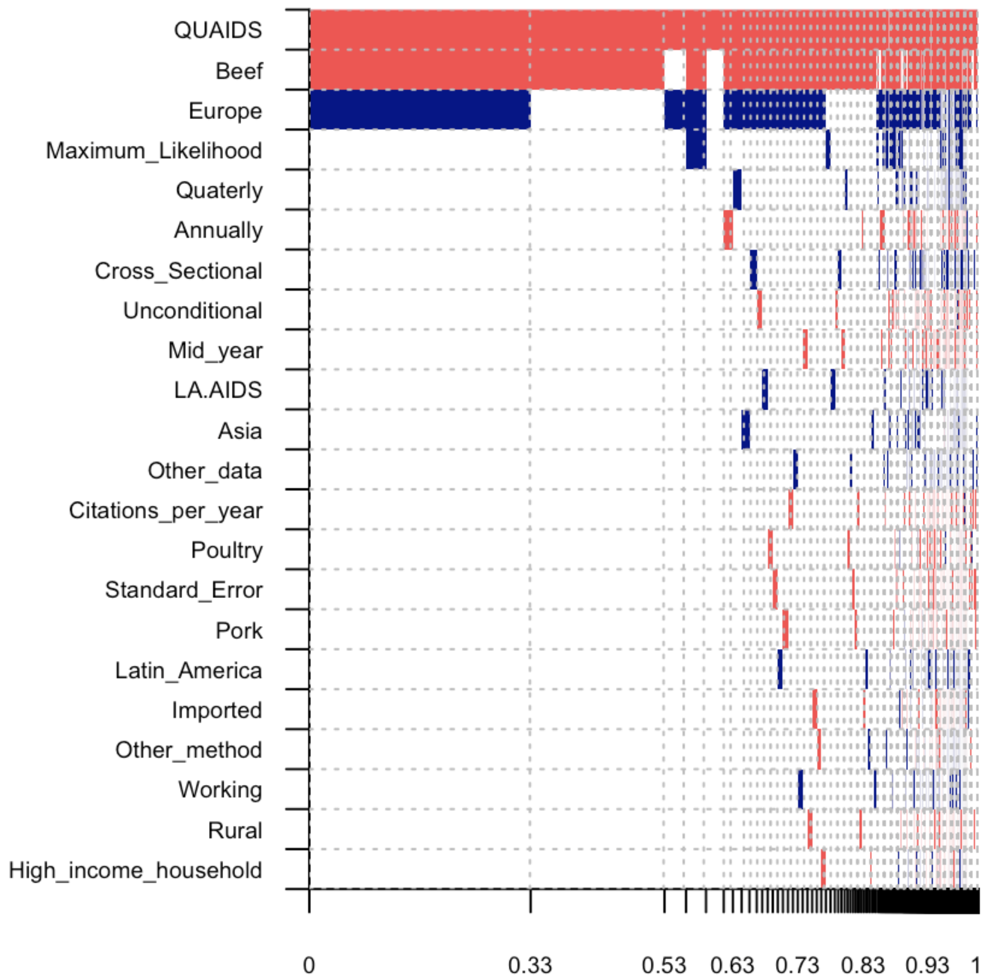


Note: The figure displays the results of Bayesian model averaging with the uniform g-prior (Eicher *et al.* 2011) and the dilution prior (George 2010). Variables are listed in rows, ordered by their descending posterior inclusion probability (PIP). The columns represent individual models, sorted by their posterior model probabilities from left to right. Blue cells indicate positive effects, red cells indicate negative effects, and white cells show that the variable was not included in the model. The response variable is the partial correlation coefficient, displayed on the horizontal axis as cumulative posterior model probabilities. Refer to Table 5.3 for detailed numerical results and Table 5.1 for variable descriptions.

5.3.3 Hicksian meat category results

Moving to the Hicksian meat category, we omitted four variables with very low means: *OLS*, *High-Frequency*, *Australia*, and *Africa*, as well as a few others with high VIFs, similar to the previous categories. This category is unique in that it is the only one where publication bias was not detected after controlling for all variables. *Beef* emerges as the first variable with a very high PIP of 0.908 and a negative effect, suggesting that the price elasticity of demand for beef is more elastic compared to the baseline group of unspecified meat types. This finding is consistent with Gallet (2010), who also found that beef prices are significantly more elastic than those of other meat groups. Additionally, similar to the Marshallian fish and seafood category, the *QUAIDS* demand system yields more elastic estimates. Lastly, *Europe* is a significant variable, indicating that meat prices in Europe tend to be less elastic compared to the baseline North America. This suggests that European consumers are less responsive to price changes in meat, which could be attributed to regional preferences.

Figure 5.3: BMA results for Hicksian meat category



Note: The figure displays the results of Bayesian model averaging with the uniform g-prior (Eicher *et al.* 2011) and the dilution prior (George 2010). Variables are listed in rows, ordered by their descending posterior inclusion probability (PIP). The columns represent individual models, sorted by their posterior model probabilities from left to right. Blue cells indicate positive effects, red cells indicate negative effects, and white cells show that the variable was not included in the model. The response variable is the partial correlation coefficient, displayed on the horizontal axis as cumulative posterior model probabilities. Refer to Table 5.4 for detailed numerical results and Table 5.1 for variable descriptions.

5.3.4 Hicksian fish & seafood category results

For the Hicksian fish and seafood category, significant multicollinearity was detected in the data, necessitating the omission of several variables with high VIFs. Details about which variables were omitted can be found in Table B.1 in Appendix B. From the remaining variables displayed in Table 5.5, more than half exhibit a strong Posterior Inclusion Probability (PIP) close to 1.00, indicating their significance.

In this category, again, publication bias occurs after accounting for other variables, as evidenced by the *Standard Error* variable, which has a PIP of 0.995.

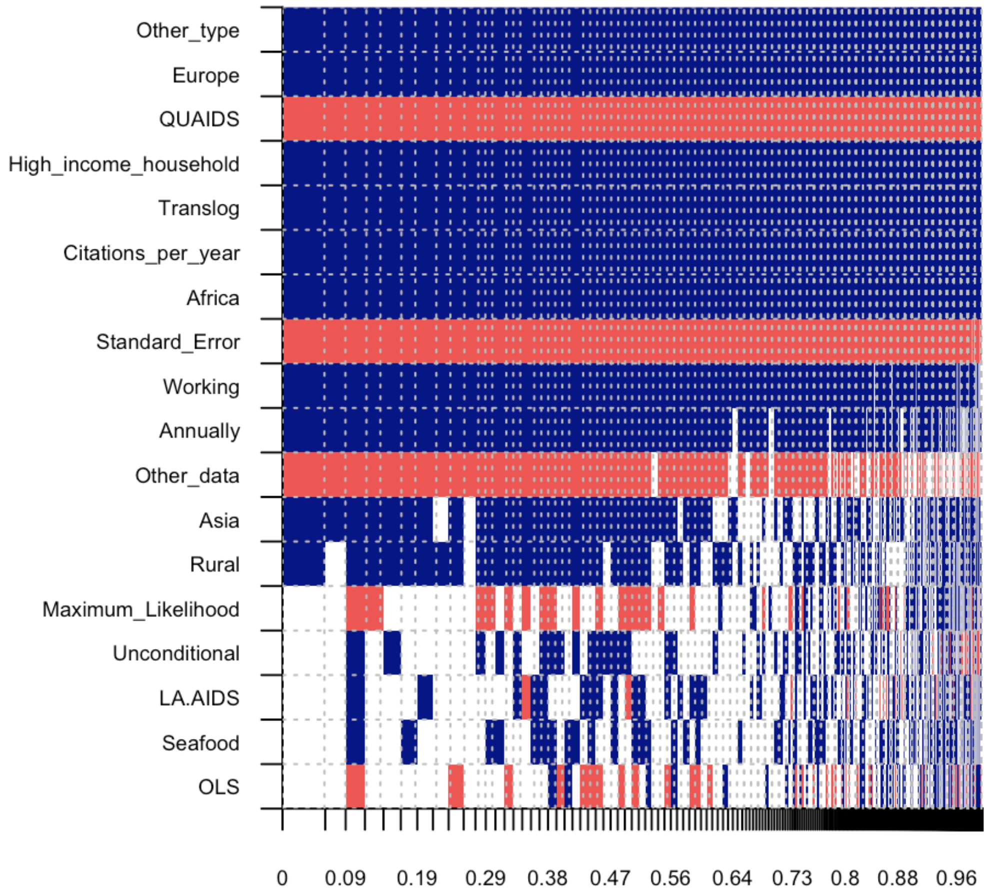
Among the estimation method variables, three are particularly significant. The *QUAIDS* variable is again significant with a negative effect. Conversely, the *Translog* variable has a positive effect, resulting in less elastic estimates compared to the baseline of AIDS. Similarly, the *Other type* variable, which includes less common demand systems, also has positive effect and produces less elastic estimates.

Regarding data characteristics, estimates derived from annually collected data appear to be less elastic, as indicated by the *Annually* variable with a PIP of 0.920. The *High-income households* variable also has a positive effect on the estimates, same as for the Marshallian category, aligning with the theory that higher-income households are less affected by price changes compared to other households.

Geographical origin is another important factor for Hicksian fish and seafood. Estimates from Europe and Africa are less elastic compared to the baseline of North America.

Finally, publication characteristics also play a significant role. Working papers tend to present less elastic estimates; however, with only three estimates obtained from working papers, this result should be interpreted with caution. The number of citations per year is also a significant factor, with higher citation counts correlating with less elastic estimates.

Figure 5.4: BMA results for Hicksian fish & seafood category



Note: The figure displays the results of Bayesian model averaging with the uniform g-prior (Eicher *et al.* 2011) and the dilution prior (George 2010). Variables are listed in rows, ordered by their descending posterior inclusion probability (PIP). The columns represent individual models, sorted by their posterior model probabilities from left to right. Blue cells indicate positive effects, red cells indicate negative effects, and white cells show that the variable was not included in the model. The response variable is the partial correlation coefficient, displayed on the horizontal axis as cumulative posterior model probabilities. Refer to Table 5.5 for detailed numerical results and Table 5.1 for variable descriptions.

5.3.5 Numerical results for all categories

Table 5.2: Model averaging numerical results for Marshallian meat category

	Bayesian model averaging			Frequentist model averaging		
	Post. mean	**Post. SD**	**PIP**	**Coef.**	**SE**	**p-value**
Intercept	-0.787	NA	**1.000**	-2.063	0.573	**0.000**
Standard Error	-0.490	0.081	**1.000**	-0.490	0.087	**0.000**
Product type						
Poultry	0.001	0.013	0.014	-0.048	0.122	0.696
Pork	-0.001	0.018	0.017	-0.111	0.158	0.482
Beef	-0.004	0.030	0.032	-0.244	0.167	0.144
Demand type						
Unconditional	-0.045	0.111	0.166	-0.087	0.127	0.495
Estimation						
LA/AIDS	0.044	0.134	0.118	0.255	0.252	0.312
QUAIDS	-0.218	0.251	0.479	-0.402	0.256	0.117
Translog	-0.008	0.051	0.044	0.120	0.267	0.654
Other type	0.077	0.136	0.280	0.347	0.251	0.168
Maximum Likelihood	-0.000	0.019	0.018	0.084	0.150	0.575
OLS	0.003	0.046	0.016	-0.338	0.443	0.445
Other method	0.049	0.107	0.201	0.230	0.151	0.128
Data characteristics						
Cross-Sectional	0.006	0.042	0.032	0.492	0.209	**0.019**
High frequency	-0.006	0.057	0.021	0.006	0.333	0.985
Quarterly	0.002	0.029	0.016	-0.018	0.120	0.884
Annually	-0.004	0.034	0.023	-0.440	0.232	0.058
Number of years	0.000	0.003	0.037	0.046	0.019	**0.014**
Mid-year	-0.000	0.001	0.024	0.012	0.010	0.246
Rural	-0.004	0.044	0.018	-0.059	0.186	0.752
High-income household	0.003	0.033	0.022	0.224	0.170	0.188
Imported	0.012	0.076	0.037	0.292	0.242	0.228
Scanner data	-0.006	0.047	0.030	-0.145	0.261	0.579
Other data	0.043	0.125	0.129	0.183	0.191	0.338
Geographical origin						
Asia	-0.000	0.017	0.017	0.014	0.109	0.898
Europe	0.003	0.029	0.022	0.303	0.217	0.162
Australia	-0.896	0.205	**0.998**	-0.840	0.311	**0.007**
Publication characteristics						
Working	-0.034	0.126	0.085	-0.354	0.236	0.133
Conference	0.011	0.051	0.055	0.492	0.252	0.051
Citations per year	-0.004	0.024	0.045	0.126	0.119	0.289

Note: Post. mean stands for Posterior Mean, Post. SD represents Posterior Standard Deviation, PIP denotes Posterior Inclusion Probability, Coef. refers to Coefficient, and SE indicates Standard Error. Variables with a PIP value above 0.5 or a p-value under 0.05 are highlighted, signifying a higher likelihood of inclusion. For a detailed explanation of the variables, refer to Table 5.1.

Table 5.3: Model averaging numerical results for Marshallian fish & seafood category

	Bayesian model averaging			**Frequentist model averaging**		
	Post. mean	**Post. SD**	**PIP**	**Coef.**	**SE**	**p-value**
Intercept	-0.589	NA	**1.000**	-0.364	0.267	0.173
Standard Error	-1.621	0.731	**0.898**	-2.038	0.480	**0.000**
Product type						
Seafood	0.036	0.095	0.193	0.118	0.139	0.397
Demand type						
Unconditional	0.000	0.029	0.084	0.000	0.022	**0.000**
Estimation						
LA/AIDS	-0.001	0.061	0.093	0.000	0.002	**0.000**
QUAIDS	-0.446	0.251	**0.861**	-0.328	0.185	0.076
Translog	0.020	0.099	0.136	0.068	0.188	0.717
Other type	0.184	0.179	**0.614**	0.351	0.188	0.062
Maximum Likelihood	0.367	0.246	**0.781**	0.586	0.198	**0.003**
OLS	0.010	0.098	0.107	0.087	0.234	0.711
Other method	0.529	0.210	**0.923**	0.655	0.166	**0.000**
Data characteristics						
Panel Data	-0.983	0.328	**0.937**	-1.057	0.248	**0.000**
Quarterly	-0.028	0.139	0.119	-0.338	0.365	0.354
Annually	-0.032	0.105	0.179	-0.185	0.176	0.294
One-time	-0.395	0.206	**0.871**	-0.558	0.173	**0.001**
Mid-year	-0.002	0.005	0.173	-0.003	0.007	0.665
Rural	0.006	0.075	0.088	0.000	0.044	**0.000**
High-income household	0.491	0.233	**0.885**	0.548	0.169	**0.001**
Other data	-0.014	0.077	0.109	-0.033	0.136	0.809
Geographical origin						
Asia	-0.384	0.223	**0.832**	-0.509	0.168	**0.002**
Europe	0.023	0.084	0.149	0.151	0.184	0.412
Africa	-0.226	0.279	0.482	-0.280	0.273	0.305
Publication characteristics						
Working	-0.018	0.085	0.117	-0.046	0.155	0.766
Citations per year	0.014	0.051	0.144	0.125	0.112	0.263

Note: Post. mean stands for Posterior Mean, Post. SD represents Posterior Standard Deviation, PIP denotes Posterior Inclusion Probability, Coef. refers to Coefficient, and SE indicates Standard Error. Variables with a PIP value above 0.5 or a p-value under 0.05 are highlighted, signifying a higher likelihood of inclusion. For a detailed explanation of the variables, refer to Table 5.1.

Table 5.4: Model averaging numerical results for Hicksian meat category

	Bayesian model averaging			Frequentist model averaging		
	Post. mean	**Post. SD**	**PIP**	**Coef.**	**SE**	**p-value**
Intercept	-0.534	NA	**1.000**	-0.364	0.267	0.173
Standard Error	-0.003	0.039	0.024	-0.225	0.283	0.427
Product type						
Poultry	-0.001	0.017	0.024	-0.001	0.086	0.987
Pork	-0.001	0.017	0.023	-0.011	0.101	0.910
Beef	-0.282	0.121	**0.908**	-0.245	0.118	**0.038**
Demand type						
Unconditional	-0.004	0.031	0.034	-0.157	0.165	0.341
Estimation						
LA/AIDS	0.003	0.028	0.032	0.076	0.169	0.654
QUAIDS	-0.728	0.136	**0.996**	-0.465	0.287	0.104
Maximum Likelihood	0.014	0.057	0.077	0.269	0.163	0.099
Other method	0.000	0.013	0.022	0.119	0.139	0.394
Data characteristics						
Cross-Sectional	0.003	0.024	0.035	0.033	0.143	0.818
Quarterly	0.009	0.057	0.043	0.509	0.329	0.122
Annually	-0.005	0.039	0.039	-0.102	0.206	0.619
Mid-year	-0.000	0.002	0.033	-0.015	0.011	0.171
Rural	-0.001	0.036	0.021	0.065	0.196	0.742
High-income household	-0.000	0.021	0.021	0.074	0.156	0.637
Imported	-0.001	0.022	0.022	-0.055	0.154	0.723
Other data	0.002	0.025	0.027	0.085	0.199	0.668
Geographical origin						
Asia	0.002	0.021	0.031	0.199	0.162	0.220
Europe	0.332	0.272	**0.659**	0.451	0.209	**0.031**
Latin America	0.002	0.032	0.023	0.120	0.217	0.581
Publication characteristics						
Working	0.001	0.028	0.022	-0.135	0.234	0.564
Citations per year	-0.001	0.011	0.025	-0.068	0.106	0.524

Note: Post. mean stands for Posterior Mean, Post. SD represents Posterior Standard Deviation, PIP denotes Posterior Inclusion Probability, Coef. refers to Coefficient, and SE indicates Standard Error. Variables with a PIP value above 0.5 or a p-value under 0.05 are highlighted, signifying a higher likelihood of inclusion. For a detailed explanation of the variables, refer to Table 5.1.

Table 5.5: Model averaging numerical results for Hicksian fish & seafood category

	Bayesian model averaging			Frequentist model averaging		
	Post. mean	**Post. SD**	**PIP**	**Coef.**	**SE**	**p-value**
Intercept	-2.326	NA	**1.000**	-2.428	0.253	**0.000**
Standard Error	-1.649	0.453	**0.995**	-1.623	0.447	**0.000**
Product type						
Seafood	0.022	0.082	0.349	0.019	0.084	0.824
Demand type						
Unconditional	0.018	0.056	0.365	0.036	0.079	0.652
Estimation						
LA/AIDS	0.027	0.133	0.354	0.010	0.100	0.923
QUAIDS	-1.018	0.177	**0.999**	-1.123	0.184	**0.000**
Translog	0.899	0.192	**0.999**	0.978	0.203	**0.000**
Other type	1.260	0.174	**1.000**	1.289	0.171	**0.000**
Maximum Likelihood	-0.007	0.148	0.386	-0.091	0.190	0.633
OLS	0.003	0.183	0.333	0.000	0.031	**0.000**
Data characteristics						
Annually	0.567	0.273	**0.920**	0.708	0.233	**0.002**
Rural	0.288	0.263	0.693	0.420	0.235	0.074
High-income household	0.786	0.152	**1.000**	0.800	0.162	**0.000**
Other data	-0.553	0.349	0.839	-0.715	0.294	**0.015**
Geographical origin						
Asia	0.237	0.208	0.727	0.346	0.200	0.083
Europe	1.444	0.195	**1.000**	1.521	0.201	**0.000**
Africa	1.162	0.289	**1.000**	1.221	0.295	**0.000**
Publication characteristics						
Working	0.703	0.228	**0.981**	0.728	0.218	**0.001**
Citations per year	0.420	0.086	**1.000**	0.435	0.089	**0.000**

Note: Post. mean stands for Posterior Mean, Post. SD represents Posterior Standard Deviation, PIP denotes Posterior Inclusion Probability, Coef. refers to Coefficient, and SE indicates Standard Error. Variables with a PIP value above 0.5 or a p-value under 0.05 are highlighted, signifying a higher likelihood of inclusion. For a detailed explanation of the variables, refer to Table 5.1.

Chapter 6

Elasticities in practice

In this chapter, we will explore the practical applications of price elasticities from two critical perspectives: macroeconomic and microeconomic. Price elasticity, a measure of the responsiveness of the quantity demanded or supplied to changes in price, is a fundamental concept in economics with significant implications for both policymakers and businesses.

From a macroeconomic standpoint, understanding price elasticities is essential for formulating effective economic policies and strategies. Governments and policymakers rely on elasticity measures to predict the impact of tax changes, subsidies, and price controls on the overall economy. For instance, environmental policies often rely on manipulating price elasticities to influence consumer behavior. For example, carbon taxes or meat taxes can be imposed to make high-emission products like beef more expensive, thereby reducing their consumption. Knowing the price elasticity of demand for various types of meat helps policymakers predict the effectiveness of these taxes. If the demand for beef is elastic, a small increase in price due to a tax could lead to a significant reduction in consumption, promoting environmental goals.

On the microeconomic front, price elasticity is a crucial tool for businesses in shaping their pricing strategies and market positioning. In this part, we explore the practical application of price elasticities in collaboration with Yieldigo, a renowned company in retail pricing software. Effective pricing is crucial for profitability and is influenced by factors such as competitor actions, supplier constraints, and customer expectations. Price elasticity is key to optimizing pricing strategies. However, its practical application is complex due to the interplay of various factors like cross-elasticities, consumer behavior, and market dynamics. Yieldigo's expertise helps bridge this gap by leveraging advanced data analysis and machine learning to incorporate price elasticities into dynamic pricing models. Our collaboration with Radim Dudek, founder of Yieldigo, provided valuable insights into how their software tackles the intricacies of real-time data analysis and optimal pricing. Yieldigo's approach integrates vast amounts of transactional data to accurately measure price elasticities and apply them effectively in pricing strategies.

We delve into how their platform overcomes traditional challenges in incorporating price elasticities into supermarket pricing. We explore their systematic approach to data alignment, cleaning, and modeling, showcasing how these processes enhance the accuracy and effectiveness of pricing decisions. By examining Yieldigo's innovative solutions, we aim to demonstrate how theoretical concepts of price elasticity are translated into practical applications that drive profitability and improve pricing strategies in the retail sector.

6.1 Macroeconomic perspective

Understanding the price elasticity of demand for meat is crucial for predicting the effectiveness of meat taxes. If the demand for meat is elastic, a small increase in price due to a tax could lead to a significant reduction in consumption. Conversely, if the demand is inelastic, higher taxes might be necessary to achieve the desired decrease in consumption.

The effectiveness of meat taxes in reducing consumption and achieving environmental goals depends significantly on the price elasticity of demand. Our findings indicate a negative publication bias in meat elasticities, where studies with higher elasticity estimates are more likely to be published than those with lower estimates. This bias can lead to an overestimation of the responsiveness of meat consumption to price changes, potentially influencing the design and expected outcomes of meat tax policies. If policymakers base their decisions on biased elasticity estimates, they may overestimate the effectiveness of meat taxes in reducing consumption and emissions. This could result in setting tax rates that are either too low to achieve the desired environmental impact or too high, causing undue economic strain on consumers, especially low-income households. To counteract this, it is crucial for policymakers to consider the potential for publication bias when reviewing elasticity estimates. Utilizing a range of elasticity values and conducting sensitivity analyses can provide a more balanced perspective on the likely outcomes of meat tax policies.

Revenue recycling is a critical component of meat tax policies to address their regressive nature. Policies that redistribute tax revenues to consumers, either through direct transfers or by reducing VAT on healthier food options like fruits and vegetables, can mitigate the adverse effects on low-income households. This approach not only promotes dietary shifts towards more sustainable food consumption patterns but also enhances the political feasibility of implementing such taxes. According to a report done by Ipsos, a reliable global market research and consulting firm, consumers in Germany, France, and the Netherlands, a majority of West Europeans support higher meat prices if the additional revenues are used for beneficial purposes (Ipsos 2023).

6.1.1 Meat tax in Denmark

Denmark has recently proposed a groundbreaking meat tax as part of its broader environmental policy to reduce greenhouse gas emissions and promote sustainable agriculture. This policy initiative, which involves imposing taxes on high-emission food products like meat, is designed to reduce meat consumption by making it more expensive and thus less attractive to consumers. The tax rates are set based on the carbon footprint of different types of meat, with higher taxes on beef and lamb due to their significantly higher emissions compared to pork and poultry.

Gallet (2010) found that the own-price elasticity for beef ranges from -0.27 to -0.80, while for chicken, it ranges from -0.27 to -0.65. In our heterogeneity part, we also found beef estimates more elastic compared to other meat categories. These variations imply that a tax on beef is likely to have a more substantial impact on reducing consumption compared to a similar tax on poultry. By leveraging these elasticity differences, the Danish government aims to achieve a substantial reduction in beef consumption, which is a major contributor to greenhouse gas emissions.

Säll (2018) analyzed the potential impact of meat tax in Sweden and showed that even modest taxes could lead to significant reductions in meat consumption if the demand is sufficiently elastic. This finding underscores the importance of accurately estimating price elasticities when designing tax policies. Even small changes in elasticity estimates can significantly affect the expected outcomes of such policies.

The Danish initiative aligns with the broader goals of the European Union's Farm to Fork Strategy, which is a central element of the European Green Deal. The Farm to Fork Strategy aims to make food systems fair, healthy, and environmentally-friendly. One of its key targets is to reduce the environmental and climate footprint of the EU food system, which includes a significant reduction in meat consumption due to its high environmental impact.

Looking ahead, the importance of policies aimed at reducing meat consumption is expected to grow as environmental concerns become more pressing. Globally, we can expect more countries to adopt similar measures. Behavioral changes among consumers will also drive this shift. Studies show that awareness of the environmental impact of meat consumption is growing, particularly among younger, environmentally-conscious individuals (Sanchez-Sabate & Sabaté 2019).

6.2 Microeconomic perspective

6.2.1 Current supermarket pricing practices

Supermarkets traditionally employ various pricing strategies to attract customers and drive sales. Two common approaches are so-called *Everyday low prices* (EDLP) and *High-low pricing* (HL). EDLP focuses on maintaining consistently low prices rather than fluctuating between high and low prices. This strategy is designed to build customer trust and loyalty by offering stable pricing, reducing the uncertainty and decision-making effort for shoppers (Hoch *et al.* 1994). Retailers using EDLP aim to streamline operations by minimizing the complexity associated with frequent price changes and promotions. According to Bell *et al.* (1999), this strategy also helps reduce advertising costs, as there is less need to promote periodic sales

HL pricing, on the other hand, involves setting higher regular prices with occasional significant discounts or sales events. This strategy aims to attract price-sensitive customers who are motivated by the savings offered during promotions. HL pricing can create a sense of urgency and excitement, driving short-term sales spikes. However, it also requires more complex inventory and promotional management, as retailers must carefully plan and execute sales events to avoid stockouts or overstock situations (Ellickson & Misra 2008).

Despite the benefits of these traditional pricing strategies, many supermarkets do not directly incorporate price elasticities into their pricing decisions for several reasons. Firstly, the complexity of real-time data analysis presents a significant challenge. Accurately determining the optimal price requires processing vast amounts of data from various sources, such as sales transactions, inventory levels, and competitive pricing. This data must be analyzed in real-time to adjust prices dynamically, which demands advanced technological infrastructure and significant computational power. Yieldigo highlights that the successful application of price elasticity in pricing strategies involves a robust data handling system capable of processing and analyzing this data efficiently (Yieldigo, 2024).

Secondly, accurately measuring price elasticities is inherently difficult. Price elasticity quantifies how changes in price affect demand, but this relationship can vary widely across different products, time periods, and customer segments. Factors such as brand loyalty, product necessity, and availability of substitutes can all influence elasticity, making it a complex variable to quantify reliably. Fischer *et al.* (2011) note that traditional models may not capture the dynamic nature of consumer behavior, further complicating elasticity measurements. Moreover, Fisher *et al.* (2018) suggest that machine learning algorithms can enhance the predictive accuracy of these models, providing more reliable inputs for pricing strategies.

Thirdly, the influence of other variables and market dynamics further complicates the direct use of price elasticities. Market conditions, seasonal variations, promotional activities, and competitive actions and other all interplay in ways that impact pricing decisions. For instance, a competitor's pricing move or a sudden change in consumer preferences can significantly alter the effectiveness of a price change based on elasticity alone. This interconnectedness of multiple factors requires a holistic approach to pricing that goes beyond simple elasticity calculations. Yieldigo's platform addresses these complexities by integrating a range of variables into their pricing models, ensuring a more comprehensive analysis (Yieldigo, 2024).

These challenges illustrate why many supermarkets might rely on more straightforward, traditional pricing strategies rather than directly applying price elasticities. However, advanced pricing tools like Yieldigo's software are designed to address these complexities, offering a way to integrate elasticities into pricing decisions effectively.

6.2.2 Yieldigo's approach and the pricing process overview

Yieldigo employs a comprehensive and systematic approach to pricing optimization, which involves several detailed steps to ensure accurate and effective price setting. The process begins with data alignment, a critical phase where various data sources such as transactions, promotions, inventory data, competitor prices, and even weather information are integrated. This step ensures that all relevant data is brought together in a consistent format.

Following data alignment, the next phase is data cleaning. In this step, the collected data is examined to identify and correct outliers, standardize data formats, and check for any errors. This rigorous cleaning process is essential to ensure the accuracy and reliability of the data used in the pricing models. Accurate data is crucial because any inconsistencies or errors could significantly impact the effectiveness of the pricing strategies. Once the data is cleaned, Yieldigo moves on to defining the pricing policy. This involves setting optimization objectives and determining various parameters such as basket types, zones, product families, and store formats. The pricing policy serves as a strategic framework that guides the overall pricing approach, ensuring that it aligns with the retailer's business goals and market conditions. Based on the established pricing policy, pricing specialists using the Yieldigo software set price ranges. This step involves considering multiple factors such as margin requirements, competitor pricing, zoning, brand positioning, and basket analysis. Setting appropriate price ranges is vital as it provides the boundaries within which the pricing can be adjusted, ensuring that prices remain competitive yet profitable.

After successful data alignment and cleaning they pre-model data using classification and clustering methods to group articles exhibiting the same patterns. Each method has its own model to find trends, seasonality, store popularity etc., but also correlations between them. Then, multilevel GLMs are applied to the outputs of pre-modelling. They use the multilevel Generalized Linear Models (GLMs) with a log-link function. This choice is driven by the fundamentally multiplicative nature of the effects being analyzed (e.g. the same promotion having a greater absolute impact on a bigger store, since its effect is not numerically additional, but rather scales with the store popularity). Effects included in the model calculation are: price elasticity & promo effects, cannibalization & cross-selling effects, influence of competitors, seasonal & weather-driven demand curves, holidays, day of week, day of month and store characteristics & popularity trends.

GLMs were introduced by Nelder & Wedderburn (1972) to unify various statistical models, including linear regression, logistic regression, and Poisson regression, under a single framework. GLMs extend traditional linear models to handle a broader range of data distributions and relationships between variables by introducing a link function that connects the linear predictor to the mean of the response variable. In the context of pricing optimization, GLMs are particularly useful for handling non-normal distributions and non-linear relationships, which are common in sales and pricing data. The log-link function is a crucial component, because it transforms the linear predictor, ensuring that the predicted values are always positive, which is essential for modeling sales and prices. Mathematically, the GLM with a log-link function can be expressed as:

$$\log(\mu) = X\beta \tag{6.1}$$

Where μ represents the expected value of the dependent variable (e.g., sales volume), X denotes the matrix of independent variables (e.g., price, promotions, store characteristics) and β represents the vector of coefficients to be estimated.

Yieldigo's GLMs are multilevel, meaning they account for the hierarchical structure of the data. In retail settings, data is often nested: sales data can be nested within stores, which are further nested within regions or time periods. A multilevel GLM can model these nested structures, providing more accurate and robust estimates. The multilevel structure can be expressed as:

$$\log(\mu_{ijk}) = \beta_0 + \beta_1 X_{ijk} + u_j + v_k \tag{6.2}$$

Where μ_{ijk} is the expected sales for product i in store j during time period k, X_{ijk} represents predictors for product i in store j during time period k, u_j is the random effect for store j, capturing store-specific deviations, and v_k is the random effect for time period k, capturing temporal deviations.

In addition to GLMs, Yieldigo employs Bayesian methods to enhance estimates for slow-moving stock-keeping units (SKUs) or items with limited data. Bayesian techniques offer a robust framework for incorporating prior information and updating these estimates as new data becomes available. This is particularly advantageous for products that do not have extensive sales histories, ensuring that pricing decisions for these items are as informed as possible. Bayesian methods also provide a probabilistic interpretation of the model parameters, which is useful for making decisions under uncertainty (Johnson & Kim 2017).

With the data models in place, Yieldigo then performs price optimization. This step involves adjusting prices to maximize revenue and profitability. The optimization process takes into account the effects from the models, product families, brand positions, and rounding rules. By carefully analyzing these factors, Yieldigo ensures that the prices set are optimal for achieving the best possible financial outcomes for the retailer. Once the optimized prices are determined, they are exported for implementation. The price export step involves setting limits on the number of price changes per store, scheduling the updates, and reviewing the process to ensure accuracy and consistency. This systematic approach ensures that the price changes are manageable and do not disrupt the retail operations.

The final phase of the process is the implementation of the price changes on the shelves. This step includes updating the price tags and ensuring that the changes are communicated effectively to consumers. Following the price updates, Yieldigo continuously monitors the impact of the changes on new purchases. This continuous feedback loop allows Yieldigo to adjust and refine pricing strategies based on real-time sales data and market responses, ensuring that the pricing remains effective and aligned with market conditions.

Chapter 7

Conclusion

This meta-analysis provides an extensive examination of consumer responses to price changes in meat, fish, and seafood. Utilizing advanced meta-regression techniques and a dataset comprising 459 estimates from 56 studies. We divided our dataset into 4 categories that we analyzed separately: Marshallian meat, Marshallian fish & seafood, Hicksian meat and Hicksian fish & seafood. Our research offers significant insights that can be useful for academic understanding, practical policy-making or creating pricing strategies.

The analysis identified negative publication bias in the literature regarding Marshallian meat elasticities, which results in an overestimation of consumer responsiveness to price changes. In contrast, estimates for Hicksian meat and both fish and seafood categories did not exhibit publication bias, indicating a more reliable depiction of consumer behavior in these categories. Moreover, the study highlights considerable heterogeneity in price elasticities across different countries and product categories. Factors such as geographic region, income levels, and market conditions influence price responsiveness.

To thoroughly analyze publication bias, we employed several methods. The funnel plot method of Egger *et al.* (1997) was utilized to visually inspect the symmetry of the distribution of estimates around the true effect size. An asymmetrical funnel plot suggests the presence of publication bias, as smaller studies reporting larger effect sizes are more likely to be published. In addition to the visual funnel plot, we applied the Funnel Asymmetry Test (FAT) and the Precision Effect Test (PET) (Stanley 2005). These tests examine the relationship between the effect sizes and their standard errors. The FAT-PET approach helps identify whether smaller studies with larger standard errors tend to report exaggerated effect sizes.

Moreover, we incorporated non-linear methods to further detect and correct for publication bias. These methods included the Weighted Average of Adequately Powered (WAAP) by Ioannidis *et al.* (2017), the Selection model by Andrews & Kasy (2019), the Stem-based method by Furukawa (2019), Endogenous kink (EK) model by Bom & Rachinger (2019) and the p-uniform* test by van Aert & van Assen (2021). These advanced techniques address limitations of linear methods by considering non-linear relationships and endogenous factors, providing a more comprehensive correction for publication bias.

To assess heterogeneity, we applied both Bayesian Model Averaging (BMA) and Frequentist Model Averaging (FMA) techniques. These approaches help account for model uncertainty by averaging over a set of possible models rather than relying on a single model specification. Our analysis revealed that in all categories except for Hicksian meat, the standard error had a very high Posterior Inclusion Probability (PIP), indicating the presence of publication bias even after accounting for all other variables. The persistent bias suggests that the bias is likely attributable to the methodological approaches (e.g., data collection methods) employed in the studies. Additionally, we found for all categories that using the QUAIDS model have a negative effect and yields more elastic estimates. Regional variations were also observed, highlighting geographical differences in the results.

From a policy perspective, understanding the true price elasticity of demand for food products is essential for designing effective fiscal policies. For example, Denmark's imposition of meat taxes aims to reduce consumption due to environmental and health concerns.

From a business perspective, understanding price elasticity is crucial for optimizing pricing strategies. Businesses should adopt data-driven approaches to pricing, utilizing elasticity estimates to make informed decisions. This can lead to better alignment with market demand and improved financial outcomes. By understanding how price changes affect consumer behavior, companies can strategically adjust their pricing levels to maximize profits while promoting sustainable consumption practices.

We discussed these two perspectives in more detail in Chapter 6 which was written in collaboration with Yieldigo, a company operating in the pricing sector.

Due to time constraints, this study did not explore the price elasticities of substitutes for meat, such as tofu and other vegetarian options. Future research could benefit from investigating these alternatives, particularly by considering cross-price elasticities. Understanding how the prices of meat substitutes influence the demand for meat and vice versa could also provide valuable insights for promoting healthier and more sustainable dietary choices.

Overall, this meta-analysis advances the understanding of price elasticities for meat, fish and seafood. By addressing publication bias and heterogeneity, the findings are robust and applicable across different contexts. The study underscores the importance of tailoring policies and business strategies to specific elasticity estimates, thereby promoting economic efficiency and sustainability in the global food system.

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Appendix A

List of studies used in the meta-analysis

Table A.1: Studies used in the meta-analysis

Al-Mahish et al. (2021)	Bilgic & Yen (2013)
Boysen (2012)	Brester (1996)
Brester & Schroeder (1995)	Chern et al. (2003)
Chung et al. (2005)	Davis et al. (2007)
Dong & Fuller (2007)	Dong & Gould (2007)
Fousekis & Revell (2004)	Gao & Spreen (1994)
Gao et al. (1996)	Ghahremanzadeh & Ziaei (2014)
Golan et al. (2001)	Gould (2002)
Gould & Sabates (2001)	Hahn (1994)
Haidacher (1983)	Hancock & Nieuwoudt (1986)
Härkänen et al. (2014)	Hoang (2018)
Hoderlain & Mihaleva (2008)	Hossain & Jensen (2000)
Hovhannisyan & Gould (2011)	Hovhannisyan & Shanoyan (2019)
Huang (1985)	Huang & Hahn (1995)
Huang & Yen (2002)	Jacobi et al. (2021)
Kasteridis et al. (2011)	Khoiriyah et al. (2020)
Khoiriyah & Forgenie (2023)	Kinnucan et al. (1997)
Klonaris & Hallam (2003)	Lazaridis (2003)
Lecocq & Robin (2006)	Mhurchu et al. (2013)
Okrent & Alston (2012)	Peterson & Chen (2005)
Radwan et al. (2008)	Reed et al. (2003)

Table A.1: Studies used in the meta-analysis (continued)

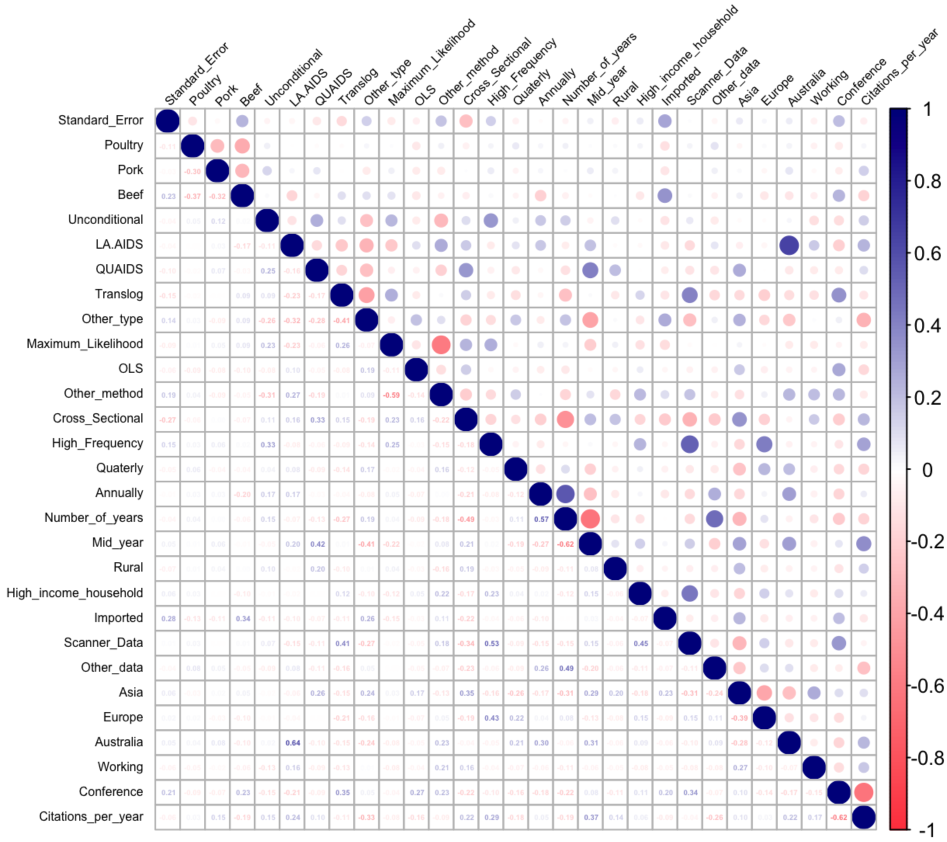
Rickertsen (1998)	Santarossa & Mainland (2003)
Smed et al. (2007)	Taniguchi & Chern (2000)
ul Haq et al. (2008)	Ulubasoglu et al. (2010)
Weliwita et al. (2003)	Yen et al. (2003)
Yen et al. (2004)	Yen & Lin (2006)
Yeboah & Maynard (2002)	Zheng & Henneberry (2009)
Zheng & Henneberry (2011)	Zhuang & Abbott (2007)

Appendix B

Heterogeneity

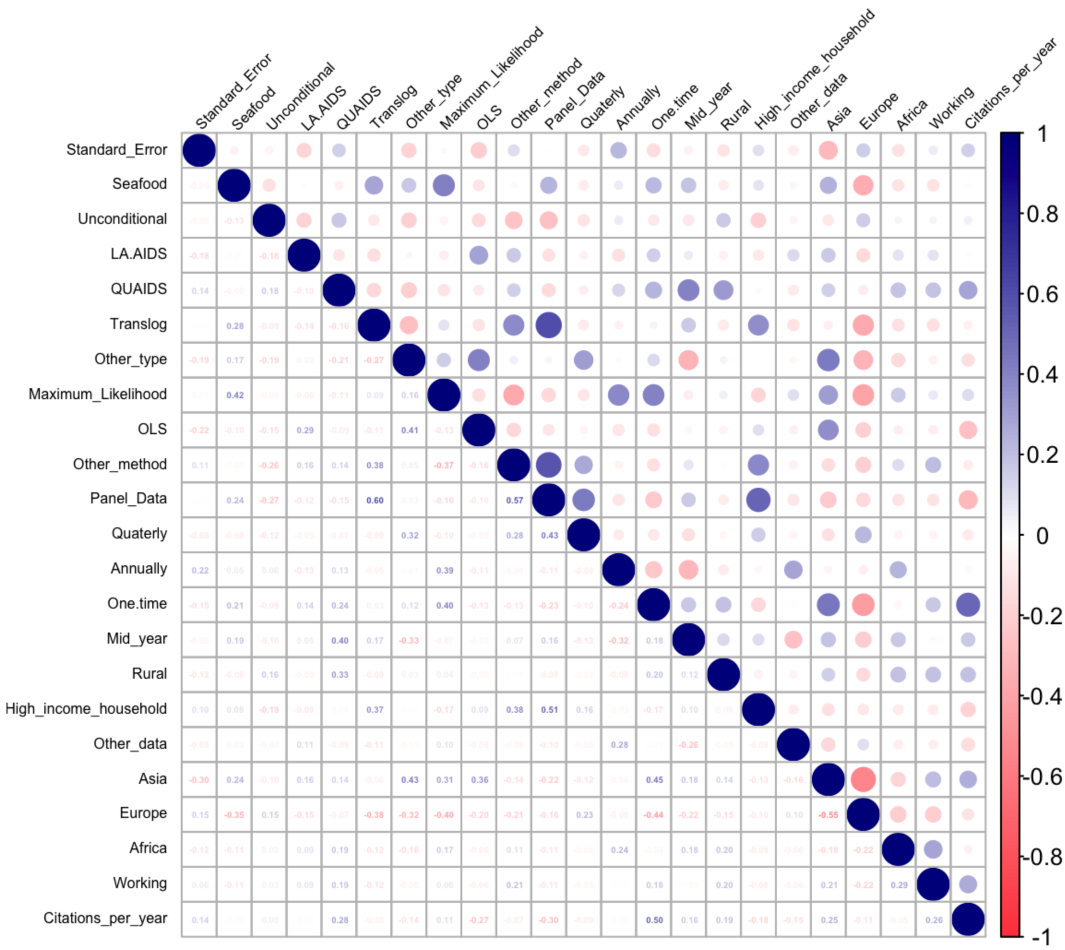
B.1 Correlation matrices

Figure B.1: Correlation matrix - Marshallian meat



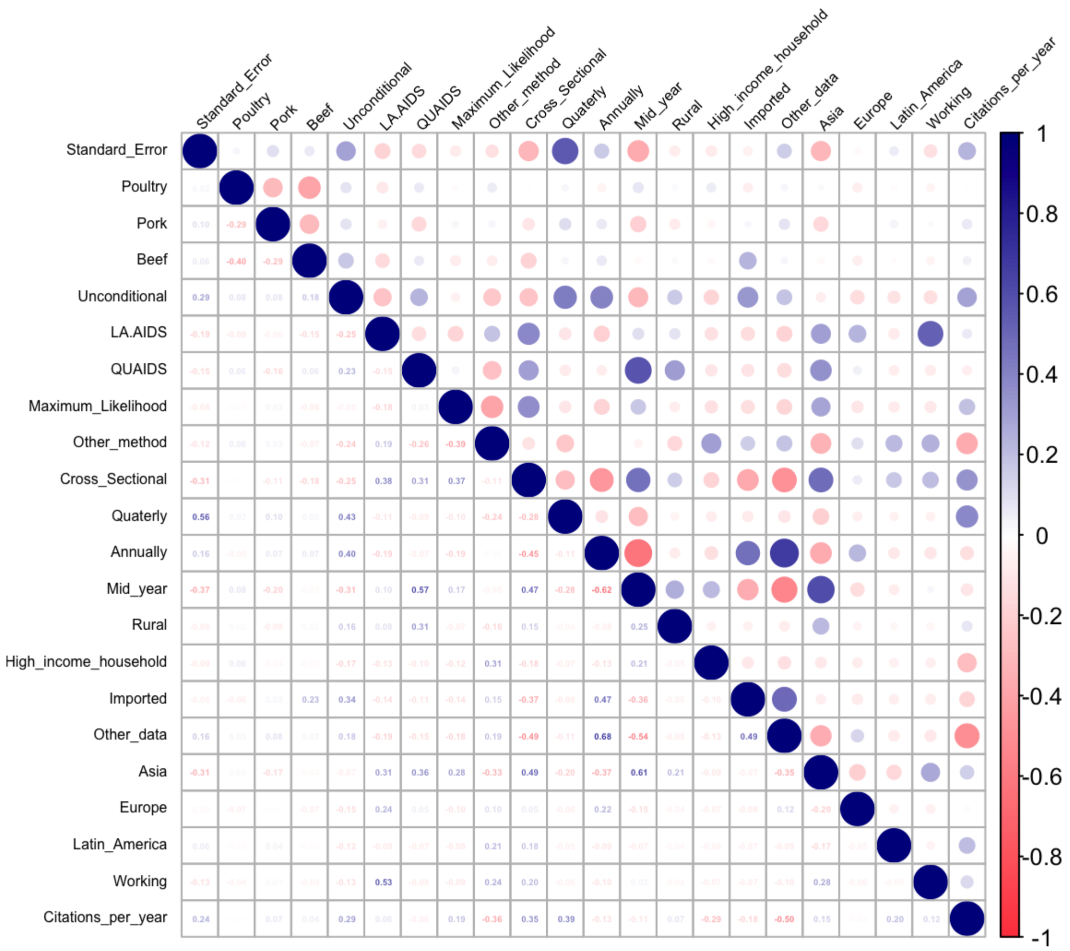
Note: The figure displays a correlation matrix with coefficients among different independent variables, which are described in Table 5.1.

Figure B.2: Correlation matrix - Marshallian fish & seafood



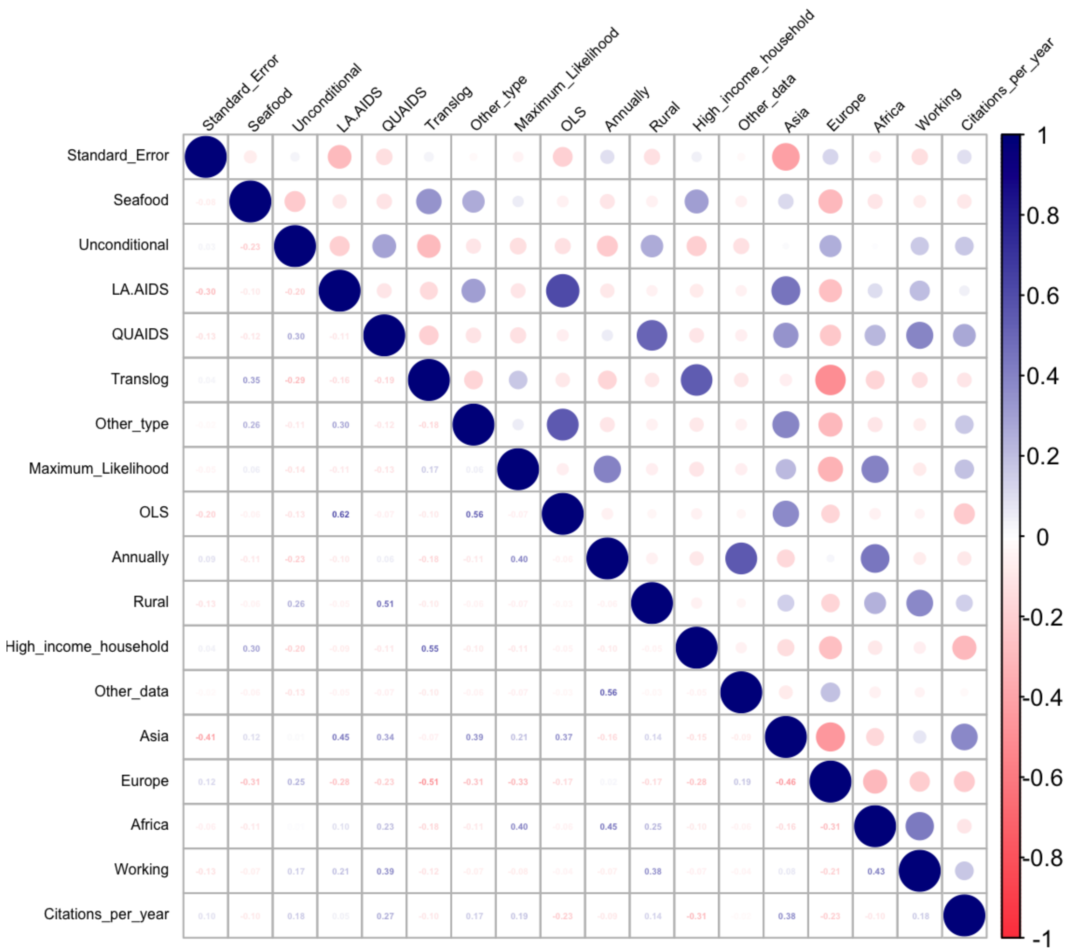
Note: The figure displays a correlation matrix with coefficients among different independent variables, which are described in Table 5.1.

Figure B.3: Correlation matrix - Hicksian meat



Note: The figure displays a correlation matrix with coefficients among different independent variables, which are described in Table 5.1.

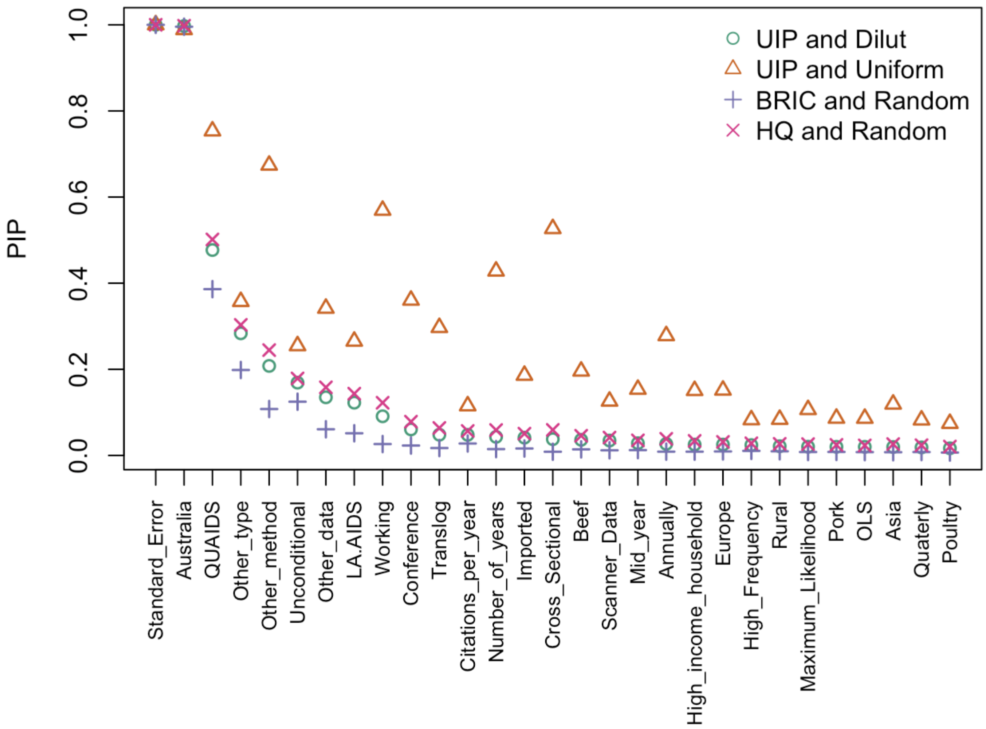
Figure B.4: Correlation matrix - Hicksian fish & seafood



Note: The figure displays a correlation matrix with coefficients among different independent variables, which are described in Table 5.1.

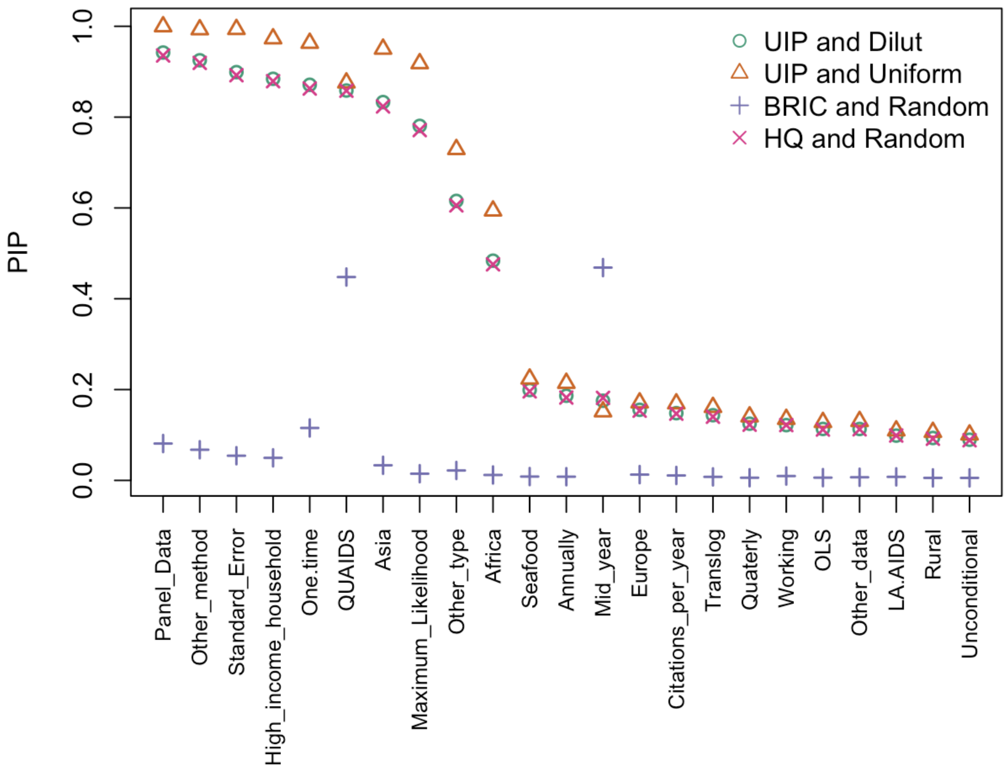
B.2 BMA results - priors comparison

Figure B.5: BMA results for Marshallian meat category - different priors



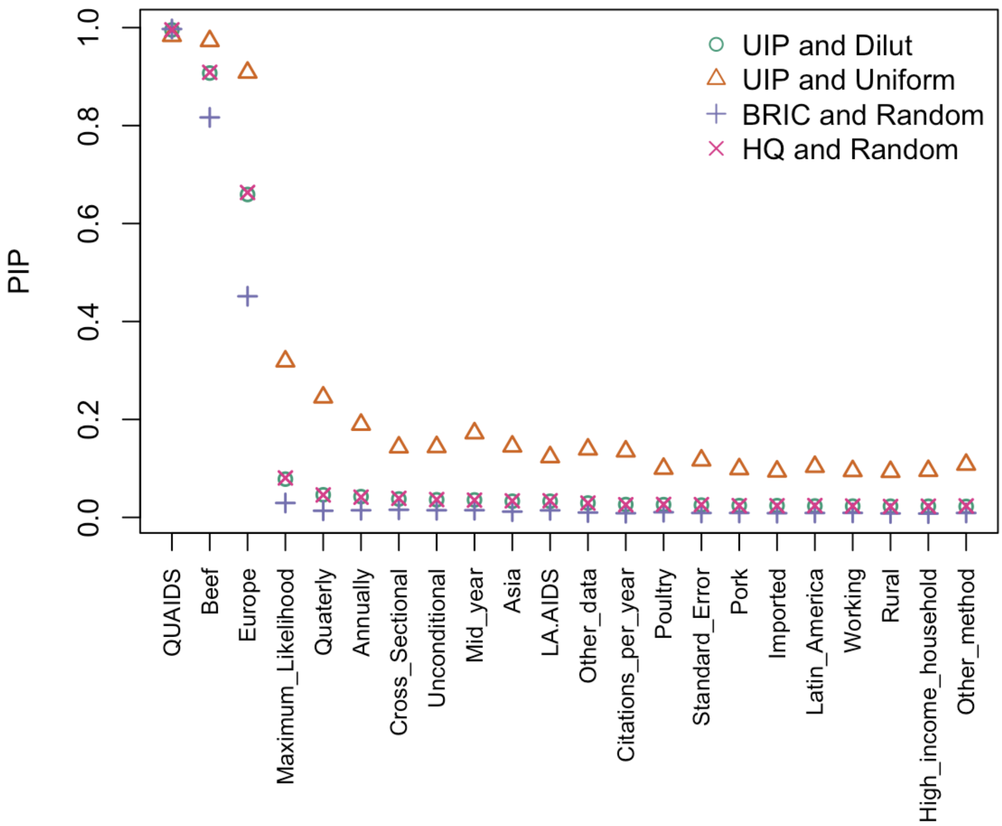
Note: This figure shows the posterior inclusion probability of each variable across different priors.

Figure B.6: BMA results for Marshallian fish & seafood category - different priors



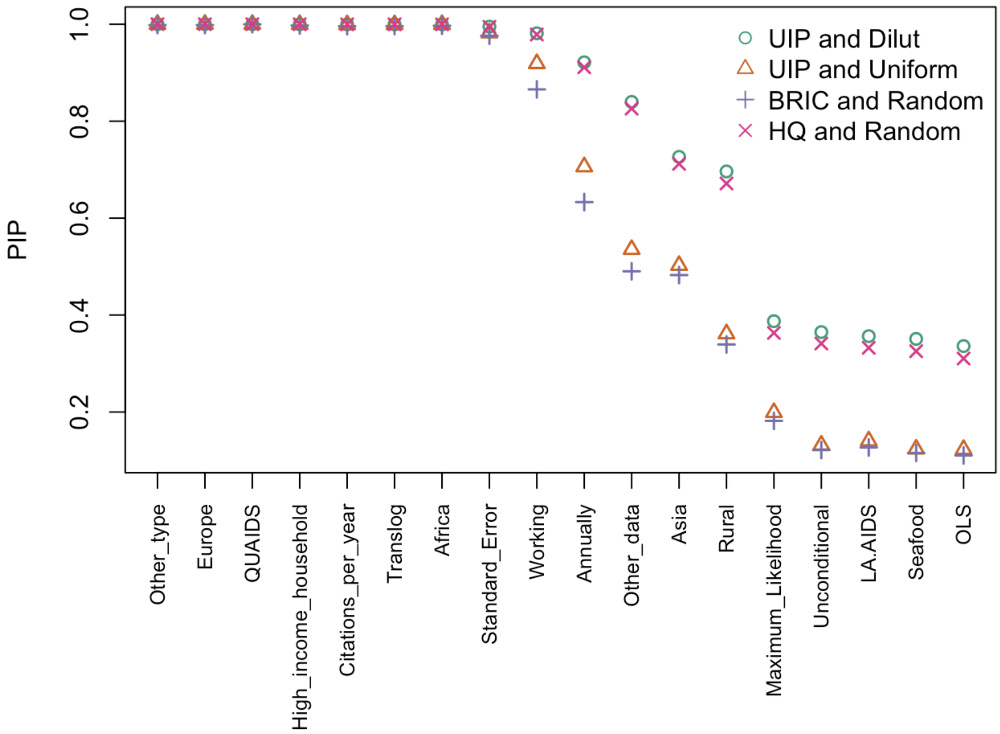
Note: This figure shows the posterior inclusion probability of each variable across different priors.

Figure B.7: BMA results for Hicksian meat category - different priors



Note: This figure shows the posterior inclusion probability of each variable across different priors.

Figure B.8: BMA results for Hicksian fish & seafood - different priors



Note: This figure shows the posterior inclusion probability of each variable across different priors.

B.3 Variance Inflation Factors (VIFs)

Table B.1: Variance Inflation Factors (VIFs) for different categories

Variable	VIFs			
	Marshallian		Hicksian	
	Meat	Fish & Seafood	Meat	Fish & Seafood
Standard Error	1.45	2.00	1.85	1.55
Poultry	1.82	-	1.96	-
Pork	1.82	-	1.77	-
Beef	2.29	-	2.19	-
Seafood	-	1.90	-	1.68
Unconditional	2.04	1.61	3.49	1.61
LA/AIDS	5.45	2.57	3.09	5.47
QUAIDS	4.00	3.62	4.96	4.84
Translog	8.83	7.82	-	7.28
Other type	8.85	7.97	-	4.29
Maximum Likelihood	3.55	4.50	1.98	5.62
OLS	2.19	4.02	-	4.38
Other method	4.15	6.92	3.08	-
Panel Data	-	5.82	-	-
Cross-Sectional	4.65	-	4.42	-
High Frequency	4.83	-	-	-
Quarterly	2.34	2.80	3.41	-
Annually	3.61	3.31	4.83	4.32
One-time	-	4.10	-	-
Number of years	8.14	-	-	-
Mid-year	6.05	3.20	8.30	-
Rural	1.25	1.40	1.32	1.55
High-income household	1.41	1.54	1.61	1.78
Imported	1.52	-	2.11	-
Scanner Data	5.01	-	-	-
Other Data	2.21	1.61	4.48	2.48
Asia	3.94	4.77	3.75	7.85
Europe	3.57	6.10	1.71	9.37
Australia	5.46	-	-	-
Africa	-	3.79	-	8.06
Latin America	-	-	1.47	-
Working	1.89	2.02	2.09	1.96
Conference	5.14	-	-	-
Citations per year	5.33	2.16	4.62	3.10