



The World's Largest Open Access Agricultural & Applied Economics Digital Library

This document is discoverable and free to researchers across the globe due to the work of AgEcon Search.

Help ensure our sustainability.

Give to AgEcon Search

AgEcon Search
<http://ageconsearch.umn.edu>
aesearch@umn.edu

Papers downloaded from AgEcon Search may be used for non-commercial purposes and personal study only. No other use, including posting to another Internet site, is permitted without permission from the copyright owner (not AgEcon Search), or as allowed under the provisions of Fair Use, U.S. Copyright Act, Title 17 U.S.C.

No endorsement of AgEcon Search or its fundraising activities by the author(s) of the following work or their employer(s) is intended or implied.



Citation: Frontuto, V., Felici, T., Andreoli, V., Bagliani, M. M. & Corsi, A. (2025). Is there an Animal Food Kuznets Curve, and does it matter? *Bio-based and Applied Economics* 14(1): 19-35. doi: 10.36253/bae-16172

Received: May 24, 2024

Accepted: September 23, 2024

Published: June 13, 2025

Data Availability Statement: All relevant data are within the paper and its Supporting Information files.

Competing Interests: The Author(s) declare(s) no conflict of interest.

Associated Editor: Oriana Gava
Editor in Chief: Silvia Coderoni

ORCID

VF: 0000-0002-0627-9511
TF: 0000-0002-3779-4225
VA: 0000-0001-9163-011X
MMB: 0000-0003-4918-8852
AC: 0000-0002-8519-6721

Is there an Animal Food Kuznets Curve, and does it matter?

VITO FRONTUTO^{1*}, TOMMASO FELICI², VANIA ANDREOLI³, MARCO MARIA BAGLIANI^{1, #}, ALESSANDRO CORSI¹

¹ Department of Economics and Statistics, Università degli Studi di Torino, Torino 10153, Italy

² Utrecht University School of Economics (U.S.E), Kriekenpitplein 21-22, 3584 EC Utrecht, The Netherlands

³ School of Biological Sciences, University of Western Australia, 35 Stirling Hwy, Crawley, WA 6009, Australia

[#] Sadly, Prof. Marco Maria Bagliani, passed away in July 2024 while this paper was under revision. We wish to dedicate this paper to a dear colleague and friend.

*Corresponding author. E-mail address: vito.frontuto@unito.it

Abstract. Proteins from animal sources, including meat, and plant-based foods are essential for a healthy human diet. However, animal-based proteins have significantly higher environmental impacts (e.g., greenhouse gas emissions, deforestation, and water usage) and health risks (e.g., obesity, type 2 diabetes, kidney stones and cardiovascular diseases) compared to plant-based proteins. The consumption patterns of these proteins are strongly influenced by income levels. This study introduces the concept of an Animal Food Kuznets Curve by systematically analyzing the relationship between income and animal-based protein consumption. Utilizing a novel panel dataset spanning 28 years and covering 79 countries, we uncover an inverted U-shaped relationship between income and the consumption of animal-based and meat proteins. Our findings indicate that the turning points occur around 43,000-45,000 US\$, corresponding to the 90th and 95th percentiles of the per capita income distribution in the sample. At these income levels, protein consumption is estimated at approximately 25 g/day for meat and 52 g/day for animal-based proteins, as compared to recommended total protein intake of 45-56 g/day. These insights highlight the critical need for targeted policy interventions, such as taxes, nudges, and informational campaigns to promote sustainable dietary choices across all income levels. Our study provides empirical evidence for the importance of integrating economic and environmental policies to enhance global food sustainability.

Keywords: protein consumption, consumption drivers, Environmental Kuznets Curve, mixed effects model, panel data.

JEL Codes: Q54, Q56, C23.

1. INTRODUCTION

Over the past 50 years, the global consumption of animal-based proteins, including meat, eggs, dairy, and seafood, has significantly increased in

both absolute and per capita terms (Bonnet et al., 2020; Marques et al., 2018; Pais et al., 2021). This growth has been mainly driven by increased meat consumption (Bonnet et al., 2020; Sans and Combris, 2015). According to OECD and FAO (2023), global per capita meat consumption has nearly doubled, rising by 87 percent from about 23 kg per person per year in 1961 to 43 kg per person per year in 2021. Similarly, other animal-based foods have seen increases, with milk consumption by 16 percent and egg consumption by 129 percent. This tendency is in accordance with the nutrition transition featuring increasing demand for animal-based foods when income rises (Popkin, 1993). However, diets rich in animal-based protein have been linked to adverse health and environmental outcomes (Tilman and Clark, 2014), while diets with a higher composition of plant-based proteins are associated with less damaging impacts (Galli and Moretti, 2024). Several studies have called for urgency in shifting protein consumption from animal-based sources to plant-based sources (Willett et al., 2019), especially in upper-middle income countries with sustained economic growth rates (Duro et al., 2020). Indeed, the increase in global meat consumption (kg/year per capita) between 1961 and 2021 has been driven mainly by countries with rapid economic growth such as South Korea (1,935 percent), China (1,774 percent) and Indonesia (398 percent). Several studies have demonstrated that the first global protein transition, marked by a significant increase in demand for animal-based protein over the last century, was closely linked to changes in real income (Sans and Combris, 2015). The more recent second nutrition transition, characterized by a stabilization or decline in animal-based protein consumption, particularly meat (Godfray et al., 2018; Marques et al., 2018; Vranken et al., 2014), may also be attributed to similar factors. Economic growth has initially promoted animal-based consumption and then it has slowed it down. This brought some scholars to claim the existence of an Environmental Kuznets Curve (EKC) for animal-based food consumption, which could be named Animal Food Kuznets Curve (AFKC). According to the EKC original theory, the environmental impact of economic growth increases in the first phase and subsequently declines (Grossman, 1995; Grossman and Krueger, 1991). If such a trend proved true for animal-based food consumption, it would decrease the urgency of policies aiming at curbing its consumption since income growth would automatically lead to its decline. Nevertheless, the existence of an AFKC is to be empirically verified, and its actual effect on global consumption is to be assessed.

This paper aims at investigating interactions between protein consumption and income over the last

30 years. The research uniquely analyses protein intake from animal-based, meat and plant-based sources to understand the dynamics of change and the predominant factor of variation, i.e., income. While the existing literature has predominantly focused on meat consumption and its correlation with income (York and Gossard, 2004; Vranken et al., 2014), there is a noticeable gap concerning the consumption of protein from different sources. This paper aims to bridge this gap by comprehensively exploring differences in protein consumption across animal-based, meat and plant-based sources using a global panel dataset covering 28 years and 79 countries. The originality of this study is further highlighted by the application of the linear mixed effect model. This methodological advancement addresses cross-sectional dependence in errors within large panel datasets, thus enhancing the accuracy of parameter estimates compared to conventional fixed effects models.

2. NEGATIVE IMPACTS OF ANIMAL-BASED PROTEIN CONSUMPTION

Animal-based products are an essential source of nutrients – proteins, among others – to humans. However, among protein-rich foods, those of animal-based sources produce higher greenhouse gas (GHG) emissions (Dyer and Desjardins, 2022; Errickson et al., 2021), use more land (Van Zanten et al., 2018) and water (Mekonnen and Gerbens-Leenes, 2020), cause more acidification and eutrophication (Godfray et al., 2018; Poore and Nemecek, 2018). Among animal-based foods, meat has a higher environmental damage potential than those derived from eggs, milk and seafood (de Vries and de Boer, 2010). Among meats, beef proteins have the highest impact on the environment (de Vries and de Boer, 2010; Gaillac and Marbach, 2021).

There is an urgent need for transitioning to more sustainable protein sources, such as protein of vegetal sources – pulses, legumes and novel protein-rich foods (McClements and Grossmann, 2021) – which have a lower environmental impact (Mazac et al., 2022). Plant-based diets can reduce GHG emissions by 49%, land use by 76%, scarcity-weighted freshwater withdrawals by 19%, acidification by 50% and eutrophication by 49% (Poore and Nemecek, 2018).

Another reason to reduce consumption of animal-based products, particularly meat, is related with the potential adverse effects of its excessive consumption on human health. A higher availability of animal-based protein consumption would benefit food-insecure countries, where fewer alternatives are available to access nutrients

and micronutrients. Here, a higher animal-based protein consumption would increase food and nutritional security. By contrast, the developed world, if anything, consumes an excessive amount of proteins (Aiking and de Boer, 2020). For instance, while the Lancet Commission on healthy diets suggests that an “adequate protein intake for adults is 0.8 g/kg bodyweight, which is 56 g/day for a 70-kg individual” (Willet et al., 2019) and the European Food Safety Authority (EFSA) sets an average requirement intake of 46 g protein per capita per day (Agostini et al., 2012), protein intake in the EU is around 82 g per day, of which 49 g from animal-based sources and 33 g from plant-based sources (Simon et al., 2024). This aspect highlights substantial inequalities of the food systems between developing and developed world, and also represents an increased risk for human health. Meat consumption contributes to global obesity (You and Henneberg, 2016), higher risks of type 2 diabetes (Malik et al., 2016), kidney stones (Asoudeh et al., 2022), cardiovascular disease mortality (Zheng et al., 2022), cancer mortality (Huang et al., 2021) in the specific, colorectal, breast and prostate cancer (Cellura et al., 2022; Gonzalez et al., 2020) and more generally all-cause mortality (Sun et al., 2021). Conversely, diets rich in plant-based proteins, such as legumes, nuts and seeds, while sufficient to achieve full protein adequacy in the developed world (Mariotti and Gardner, 2019), seem to confer protection against the incidence of cancers (Gonzalez et al., 2020) and to reduce global mortality (Springmann et al., 2016). Increasing the share of plant-based proteins will provide significant health and environmental co-benefits (Bonnet et al., 2020; Stylianou et al., 2021). This study aims to assess the relationships between income and different protein sources to highlight potential differences that can be useful to understand the impact of policies. The paper will discuss the relationship between food consumption and income using existing literature, which, however, rarely took into consideration protein sources other than meat, and explains the theory behind the model in Section 3. We will then outline the data and the econometric strategy we chose to apply to describe this relationship in Section 4. The results of the estimated models are presented in Section 5 and their implications are discussed in Section 6 and 7.

3. THE RELATIONSHIP BETWEEN ANIMAL-BASED PROTEIN CONSUMPTION AND INCOME

Rising real Gross Domestic Product (GDP at constant prices) over the last century has been identified as the root-cause of a global nutrition transition. The tran-

sition encompasses a shift towards animal-based sourced proteins in general (Gerbens-Leenes et al., 2010; Sans and Combris, 2015) and proteins from meat in particular (Milford et al., 2019; York and Gossard, 2004). As income increases, consumers tend to shift their dietary preferences toward more resource-demanding foods (Tilman and Clark, 2014). This transition is taking place at different stages and paces worldwide (Gerbens-Leenes et al., 2010). Consumption of animal-based foods is much higher in developed countries than in developing and least developed countries. However, the upward trend is more pronounced in developing countries (Henchion and Zimmermann, 2021), where the rise above the poverty line occurs at a faster pace than it did in developed countries (Sans and Combris, 2015; Drewnowski and Poulaing, 2018). Meanwhile, in higher income countries a “second nutrition transition” seems to occur (Pais et al., 2021; Vranken et al., 2014). In these countries, the consumption of animal-based proteins, especially from meat, seems to stagnate or decline when reaching a high level of income. Vranken et al. (2014) and Cole and McCoskey (2017) have therefore found evidence of an inverted U-shape relationship between meat consumption and income, indicating that the consumption of unsustainable proteins could reach a maximum and then decline. Therefore, these studies suggested that meat protein consumption follows an EKC. Arguably, the reasons for an AFKC differ from those of the EKC. The latter is justified by the increasing environmental impact of the shift from an agricultural to an industrial economy, followed by a decreasing impact due to resources-saving technological progress and increasing environmental awareness. In the case of the AFKC, the same reasons do not apply, and the determinants have to be ascribed to the factors mentioned above.

The reasons behind this decline can be attributed to several factors: i) increasing awareness of the health risks associated with high meat consumption, ii) concerns about the environmental impact of meat production, including greenhouse gas emissions, deforestation, and water usage, iii) growing awareness of animal welfare, iv) the rising availability and popularity of plant-based meat alternatives, v) the spread of popular dietary trends, such as vegetarianism, veganism, and flexitarianism.

We therefore present a model of animal-based food consumption that incorporates the above reasons for an inverted U-shaped consumption-income pattern for animal-based food (AF) consumption. The theoretical model sheds light on past trends in AF consumption and the reasons that render possible an AFKC. Nevertheless, while the model may justify the existence of an AFKC, it does not predict it unequivocally.

The model (for a formal presentation see Appendix 1) assumes that utility from AF consumption has two components. The first one directly stems from its consumption per se, due to its taste and appetite value. Utility is therefore a positive function of animal-based food consumption, so that its marginal utility is positive, but decreasing, due to increasing satiation: additional AF consumption provides less and less additional utility. The second component is the nutritional and health one. According to the nutritional literature, consumption of animal-based proteins has initially a positive effect on nutrition and health (receding from famine, mortality declines, see e.g., Mathijs, 2015) but, at higher levels, it brings several adverse health effects (e.g., cardiovascular risks, obesity-related issues). Hence, if consumers are aware of and care about the negative impacts of high animal-based food consumption on health, this component of utility has an inverted U-shape. In addition, as mentioned above, concern for animal welfare and for the environment can be reasons for a lower utility associated with large animal-based food consumption (Frank, 2008). In this model, for simplicity we include these effects in the health one.

The model assumes that a consumer maximizes his/her utility subject to a budget constraint. The equilibrium condition states that the marginal utility from AF consumption per se, plus the marginal utility stemming from the variation in nutrition-health due to the effect on consumers' health of an additional AF consumption, equals the additional utility that could be drawn from other goods that could be purchased with the animal-based food price, i.e., the marginal opportunity cost of AF.

The marginal utility of AF consumption per se decreases when AF increases, and reaches a lower bound at zero for satiation, when further consumption provides no additional utility. The marginal utility from nutritional-health benefits also decreases with AF consumption and remains positive as long as the marginal health benefit is positive, then it becomes negative. When the marginal health benefits, at high consumption levels, become negative, they may determine a decrease in overall utility if disutility from health damages prevails over utility due to taste. In this case, an inverted U-shape of the income-consumption relationship results.

The model implies that a decrease in the AF price relative to all other prices (i.e., a decrease in real AF price) leads to higher AF consumption. This explains what actually happened in the past (FAO, 2009) when the relative price of AF declined with reference to other food prices.

The crucial question for the existence of an AFKC is nevertheless the shape of the relationship between

income and AF consumption. Among necessities, animal-based food is more expensive than plant-based food. At low-income levels, a higher income allows a shift from cheap staple food to animal-based food, as empirically observed in all countries in the initial stages of development and as a general trend in the recent decades (Sans and Combris, 2015; Delgado et al., 2009; among others).

However, the model cannot unambiguously predict a priori whether a further income growth leads to an increase or decrease of AF consumption, because the resulting equilibrium will depend on how the marginal utilities of AF of other consumptions and of nutrition-health react to income, and on their interrelationships. The model allows for the existence of an AFKC, but does not imply its necessity. The form of the income-AF consumption relationship has therefore to be determined empirically.

Plant-based protein consumption also increases with income at the initial stages of development. However, its increase is presumably slower than the one of animal-based proteins, since income growth allows consumption of the more expensive animal-based proteins, so that in the diet the share of animal-based proteins grows. If consumption of animal-based proteins declines at high income levels, it is possible that plant-based protein consumption will increase as a substitute. The relationship between plant-based protein consumption and income must also be determined empirically.

4. MATERIALS AND METHODS

4.1. Variables and data

We employ a balanced panel dataset covering 79 countries from 1991 to 2018 (Table A.1 in Appendix 2). We draw on data from the Food and Agriculture Organization (FAO) New Balance Sheets (NBSs; FAO, 2021), where food supply quantities are used as proxies for consumption (Cole and McCoskey, 2017; You and Henneberg, 2016). These quantities are measured in grams per capita per day and reflect food reaching consumers, with the caveat that actual consumption may be lower due to waste and spoilage during preparation. The study classifies protein consumption into three types: "meat protein" from poultry, pork, goat, mutton and bovine; "animal-based protein" encompassing all animal products including dairy and eggs; and "plant-based protein" derived from cereals, vegetables, fruits, beans, nuts, seeds, roots and spices.

We explore potential determinants of protein consumption across three principal dimensions: economic, socio-cultural, and land use. In the economic dimen-

sion, the primary focus is income expressed by GDP per capita (p.c.) at chained Purchasing power parities (PPPs) measured in million constant 2017 US\$. The data are collected from the Penn World Table (Feenstra et al., 2015), a set of national-accounts data to measure real GDP across countries and over time. In the presence of an inverted U-shape, i.e. Kuznets curve, we expect positive estimated coefficients for the linear terms and negative coefficient for the quadratic terms. In addition to income p.c., we recognize the substantial influence of food prices on protein consumption patterns. To capture this influence, we build national price indexes using data from FAOSTAT (FAO, 2022b). Specifically, we select the price of the most consumed item within each of the three protein sources (meat, animal-based and plant-based) for every country and year under study and build an index using the first year of the time series (1991) as base year. This approach aims to quantify how variations in food prices across different protein sources impact dietary choices and consumption behaviors globally. Indeed, our hypothesis is to observe a negative coefficient for the price index meaning that an increase in prices determines a reduction in protein consumption. In addition to own price for each protein source, we have also tested relative prices. In fact, as suggested by FAO (2009) over the last 50 years there has been a decline in the prices of livestock products relative to those of other products, making consumption of animal-based and plant-based foods more affordable than meat even without rising income. A third economic variable used in our empirical application is the trade openness, built as the ratio of imports and exports over national GDP. Our hypothesis is to observe a positive effect of trade on the three proteins consumption due to the likely larger availability of different products and thus protein sources.

Beyond economic factors, social and cultural influences could also shape protein consumption patterns. We integrate several key variables to explore these dimensions. First, the religious beliefs were incorporated by using the percentage of population adhering to Islam as a proxy to understand dietary restrictions that may affect consumption preferences, for example by reducing meat consumption and increasing plant-based protein intakes. Second, we integrate the percentage of women participating in the labour force as an indicator of evolving food preparation practices. Third, the percentage of adults with tertiary education levels is used to capture the influence of educational attainment on dietary preferences and awareness of nutritional choices, potentially affecting protein intake patterns. We hypothesize that more educated people tend to prefer diets with more

plant-based food for both health and environmental concerns. However, we are aware that education is strongly correlated with income levels.

Finally, to further explore other contextual conditions likely influencing protein consumption, the study includes two proxies of land use: the harvested area per capita as a measure for the relevance of the agricultural sector for self-provision of proteins and the percentage of the population living in urban areas. These variables are used to examine the impact of urbanization on dietary habits and access to diverse food options, including protein sources.

Table 1 provides a comprehensive list of variables used in the study, and their descriptive statistics and sources. Unlike the typical practice in Environmental Kuznets Curve (EKC) literature, the study uses variables in their original levels instead of logarithmic transformations, aligning with findings by Hasanov et al. (2021).¹

4.2. Econometric strategy

Since the mid-1950s, scholars testing the Kuznets Curve (KC) hypothesis on various environmental and non-environmental indicators have primarily used cross-sectional data and longitudinal data with fixed effects estimators (e.g., Vranken et al. (2014) for consumption of meat protein). However, traditional panel data estimators assume cross-sectional independence, basing the models on homogeneous coefficients and yielding inconsistent estimated parameters (Heck and Thomas, 2020).

Indeed, cross-sectional units may exhibit shared characteristics, such as spatial effects, omitted common factors, or socioeconomic networks interaction leading to cross-sectional dependence, calling for estimators that account for intercepts and slopes heterogeneity. The literature on heterogeneous panels has evolved along two main strands: i) the application of mean group (MG) estimators (Pesaran and Smith, 1995) and subsequent modifications (Augmented MG and Common Correlated Effects MG; Teal and Eberhardt, 2010), ii) the application of multilevel or mixed effect models to panel data (McCulloch et al., 2001).

The key distinction between panel models (such as MG estimators) and mixed effects models lies in the treatment of the independent variables. In mixed effects

¹ Hasanov (2021) argues that in non-linear logarithmic Environmental Kuznets Curves (EKC), the signs of estimated coefficients and the statistical significance of lower-order polynomial terms can vary arbitrarily based on the units of measurement chosen for the independent variables. Consequently, Hasanov suggests that researchers should first study the EKC in levels considering the potential issues with the logarithmic specification.

Table 1. List of variables with descriptive statistics.

Variable	Description	Mean	Std.	Min	Max	Source
<i>Dependent variables</i>						
MeatProt	Per capita Meat-based Protein consumption (g/day)	16.4	11.1	1.2	46.9	FAO (2021)
AnimalProt	Per capita Animal-based Protein consumption (g/day)	35.2	21.4	3.2	79.7	FAO (2021)
PlantProt	Per capita Plant-based Protein consumption (g/day)	44.0	10.1	22.9	82.7	FAO (2021)
<i>Independent variables</i>						
GDPPc	Per capita expenditure-side real GDP at chained PPPs (000 US\$)	16.6	16.3	0.4	90.3	Penn world table (Feenstra et al., 2015)
GDPPc ²	Squared GDPPc	541.7	880.9	0.2	8154.2	Penn world table (Feenstra et al., 2015)
Price Index	Animal-based products	0.99	0.16	-0.88	2.65	
	Meat products	0.98	0.17	-0.45	2.50	
	Plant-based products	1.11	0.52	-2.73	4.67	FAO (2022b)
Trade	(Imports+exports) / GDP (%)	68.7	34	13.8	227.4	World Bank (2022a)
Education	Share of post-secondary education (%)	10.2	8.9	0.15	48.3	World Bank (2022b)
PerMus	Share of Muslims over population (%)	23.4	35.7	0	99.8	ARDA (2022)
PerFemWork	Share of female employment (%)	40.2	9.3	10.7	56	World Bank (2022c)
Urbanization	Share of people living in urban areas (%)	58.6	22.2	5.5	95.3	World Bank (2022d)
HarvArea	Harvested area/population (per capita ha)	0.172	0.2	0	1.4	FAO (2022a)
<i>N. obs.</i>	2212					
<i>N. groups</i>	79					

Sources: FAO, Penn World Table, World Bank, ARDA and own calculation.

models, independent variables are treated as non-random variables, whereas in panel data models, they are always assumed to be random. Another significant difference is in estimating the average effects (invariant between individuals) and individual (or random) effects. In the case of MG estimators, individual-specific ordinary least-squares (OLS) regressions are estimated then the individual-specific parameters are averaged across the panel to determine an overall effect. In the case of mixed effect models, the estimated parameters are the common effect with the random effects representing individual deviations from this average, inferred from estimated variances and covariances (Dinda, 2004).

A meta-analysis conducted by Saqib and Benhmad (2021) on more than five hundred studies concluded that the econometric strategy does not significantly impact the test of the EKC hypothesis. However, they highlighted the greater reliability of longitudinal data and the robustness of methods that deal with heterogeneous panels such as MG estimators and mixed effect models.

In this paper, we employ a mixed effect model because of our focus on the variation in regression coefficients rather than a global behaviour as an average of country-specific dynamics. Country-specific estimates, limited by the income ranges, cannot properly identify the curvature of a general function. To account for

intercept and slopes heterogeneity in parameters the unknown parameters are decomposed in a fixed term γ (constant across countries) and a random term δ (specific for each country). Thus, the relationship between protein consumption per capita (animal-, plant-based and meat) and GDP per capita is modelled as:

$$(Proteins/P)_{it} = (\gamma_{s0} + \delta_{s0i}) + (\gamma_{s1} + \delta_{s1i}) (GDP/P)_{sit} + (\gamma_{s2} + \delta_{s2i}) (GDP/P)_{sit}^2 + \sum_{j=3}^J \beta_{sij} X_{sijt} + \varepsilon_{it} \quad (1)$$

where $s = a, m, p$ identifies the protein source (animal-, plant-based and meat), $i=1, \dots, N$ indicates the countries, $t=1, \dots, T$ the time periods, GDP is defined as above and P is population, X_j the j -covariates. Note that $\frac{GDP^2}{P}$ represents the potential non-linear effect of GDP per capita on proteins consumption and it is used in the Kuznets framework to check the inverted U-shaped curvature of the relation.

This model has been estimated using maximum likelihood estimators for the three sources of protein (Rabe-Hesketh and Skrondal, 2008) and likelihood-ratio tests have been employed to compare different models and to validate the use of random coefficients. Moreover, the models are first estimated with an unstructured random-effects covariance matrix, which allows for distinct variances and covariances between all random-

effects covariates. However, inconsistent estimations for the plant-based protein model necessitated an identity covariance structure, assuming equal variances.

According to the literature on testing the nature of the time-series to select the appropriate panel estimator (Perman and Stern, 2003; Eberhardt, 2012), the model of equation [1] was tested relative to: i) cross-sectional dependence; ii) presence of unit roots (i.e., stationarity); iii) long-run relationship (i.e., cointegration).

To select the appropriate test for investigating unit roots, we initially checked the cross-sectional dependence of the series using the Pesaran test (Pesaran, 2021) under the null hypothesis of cross-sectional independence. Most variables exhibited cross-sectional dependence (except for trade) (see Table A.2 in Appendix 3). Subsequently, we tested the stationarity of the series by implementing the modified pCADF test (Costantini and Lupi, 2013) which consider cross-sectional dependence under the null hypothesis of non-stationarity. The results suggested that the null hypothesis of non-stationarity can be rejected only after transforming the series in their first differences except for the urbanization rate and the education (Table A.3 in Appendix 3). Then, we checked the cointegration assumption to prevent the regression from providing biased statistical evidence of the relationship among variables. Cointegration was investigated through various tests, including the Phillips-Perron, the Modified Phillips-Perron, the Augmented Dickey-Fuller tests (Pedroni, 1999; Pedroni, 2004) and the so-called Westerlund test (Westerlund, 2005) by assuming the presence of cross-sectional dependences (Table A.4 in Appendix 3). The rejection of the null hypothesis of all these tests indicates that our models are cointegrated. The findings support the selection of the mixed effect model as appropriate to estimate heterogeneous coefficients for intercepts and slopes.

5. RESULTS

Table 2 presents the estimated coefficients of the model of meat animal-based and plant-based protein consumption which exhibit overall significance. Likelihood-ratio tests have been applied to compare different models and different covariates. Education and urbanization rate turned out to be non-stationary even when transformed in their first differences and were therefore not used to avoid spurious estimated coefficients (see Table A.3 in the Appendix 3). Prices for the three protein sources are not statistically significant and hence are not included in our preferred specification in Table 2 (see Table A.5 for the estimated coefficients of model includ-

ing prices).² Table 2 also reports the estimated standard deviations for the intercept, the GDP per capita and the GDP^2 per capita coefficients. All of these standard deviations are statistically significant, indicating the intercept and slopes heterogeneity and thus supporting the use of the mixed effects model.

The most important determinant of meat protein consumption is per capita income, with both its estimates of the linear and the quadratic term highly significant. The estimates indicate that a thousand dollar increase in per capita income induces a 0.725 g/day increase in meat protein consumption. Notably, the negative sign of the squared term suggests that meat protein consumption does increase with income, but at a decreasing pace.

Among the variables aside from income, the Trade and the percentage of Muslims are significant. Specifically, every additional percentage point in the ratio of imports plus exports over GDP implies a 0.008 g/day increase in the average meat protein consumption. A percentage point increase in the share of Muslims over the population translates into a 0.11 g/day decrease in the average meat protein consumption, *ceteris paribus*. These results are consistent with Andreoli et al. (2021) and Milford et al. (2019). Female participation, however, does not show statistical significance, as in Milford et al. (2014).

The positive sign of the GDP parameter and the negative sign of the GDP^2 parameter, both significant, suggest the existence of an inverted U-shaped relationship, thus supporting the existence of an AFKC where meat protein consumption increases with per capita income up to a maximum before decreasing. A crucial point for assessing the policy implications of the AFKC is nevertheless determining the level of the turning point. This can be calculated as $-\hat{\gamma}_1/(2 \bullet \hat{\gamma}_2)$ where $\hat{\gamma}_1$ is the estimated parameter of per capita income and $\hat{\gamma}_2$ the estimated parameter of its square.³ This simple calculation results in a turning point of 42,923 US\$,⁴ located between the 90th and the 95th percentiles of the per capita income distribution in the whole sample, and above the 80th percentile of the income distribution in the last year of the panel (2018). It could be argued that the turning point should also be estimated consid-

² We used version 18 of STATA for Windows to carry out the analysis of the data in this paper. The mixed command has been used to estimate the mixed models presented in Table 2.

³ The formula for the maximum income in the estimated second-degree equation is obtained by setting the derivative of the equation to zero and solving for the income variable.

⁴ To present a more concise table of results, the coefficients have been rounded to three decimal places. Consequently, the turning point value derived from rounded coefficients differs from the one presented in the text, which uses estimated coefficients to six decimal places.

Table 2. Results of the models of protein consumption.

Indep. variables	Dependent variables					
	Meat Protein		Animal-based Protein		Plant-based Protein	
	Coef.	Std.Err.	Coef.	Std.Err.	Coef.	Std.Err.
GDPPc	0.725***	0.135	1.255***	0.206	1.506***	0.419
GDPPc ²	-0.008***	0.003	-0.015***	0.004	-0.003	0.002
Trade	0.008***	0.003	0.019***	0.005	0.032**	0.005
HarvArea	1.097	1.317	1.930	1.863	-15.479***	1.739
PerMus	-0.105***	0.0281	-0.177***	0.484	0.212***	0.421
PerFemWork	-0.008	0.033	0.058	0.048	0.113**	0.046
Constant	11.092***	2.191	25.517***	3.689	30.675***	2.613
sd(GDPPc)	1.086	0.124	1.686	0.161	3.644	0.361
sd(GDPPc ²)	0.021	0.006	0.030	0.004	0.005	0.002
sd(Constant)	13.364	1.414	25.170	2.378	12.892	1.120
sd(Residual)	1.541	0.028	2.167	0.035	2.093	0.034
N. obs.	2212		2212		2212	
N. groups	79		79		79	
Wald Chisq(6)	78.33***		108.10***		194.50***	
Log likelihood	-4533.46		-5302.99		-5300.83	

*; **; *** indicate that statistics are significant at the 10%, 5% and 1% level of significance respectively.

ering the variation of the estimated parameters. Unfortunately, the turning point results from the ratio of two normal random variables, which results in a Cauchy distribution, whose expected value and variance are undefined. However, its mode and median are defined, and the distribution is symmetrical. We therefore perform a Monte Carlo simulation of the median turning point. We randomly draw couples of $\hat{\gamma}_1$ and $\hat{\gamma}_2$ parameters from a bivariate normal distribution, calculate the turning point, repeated for 1000 draws, and individuate the median turning point of these simulations. By repeating the procedure 10,000 times we obtain an empirical distribution of the medians, from which we calculate their mean and standard deviation. The result of 42,891 US\$ is sensibly similar to the simple calculation from the estimated parameters. The standard deviation is relatively modest, 318 US\$, and the range went from a minimum of 41,867 to a maximum of 44,159 US\$. The minimum value is around the 90th percentile.

Comparisons with previous studies reveal similar turning point estimates, i.e. 46,000-66,000 constant 2017 International US\$ p.c. (Andreoli et al., 2021); 36,375-49,848 constant 2005 US\$ p.c. (Cole et al., 2013); 35,000-53,000 constant 2005 international US\$ p.c. (Vranken et al., 2014), indicating consistency across analyses. However, employing mixed effects models alongside Monte Carlo simulation produces more efficient estimates with reduced variability.

Table 3. Predicted protein consumption at the turning points.

	Meat Protein	Animal-based Protein
Mean	24.61	51.62
Min	16.16	35.02
Max	29.57	61.96
Mean-SD	20.45	43.79
Mean+SD	28.76	59.45

Furthermore, the results allow us to predict the meat protein consumption corresponding to the turning point, by using the estimated parameters and the per capita income of the turning point and setting the other variables at their mean. To appreciate the variation of the prediction, we also calculate the predicted consumption when the other variables are taken at the minimum and maximum of their observed values,⁵ and when they are taken at their mean plus/minus their standard deviation. Table 3 presents the results.

The calculated meat protein consumption at the income turning point and the mean of the other variables is 24.61 g/day, slightly below the 75th percentile. The maximum value (29.57 g/day) is between the 85th

⁵ When calculating the maximum and minimum consumption, variables with a negative parameter were taken as positive, so to identify the maximum possible range.

and the 90th percentile, while the minimum (16.16 g/day) is between the 55th and the 60th percentile.

The results of the model of animal-based protein consumption (Table 2) are similar to the ones of meat protein consumption, as meat constitutes about 30 percent of total animal-based protein intake. The Trade variable has a significant and positive impact on consumption, higher than for meat (every additional percentage point in the ratio of imports plus exports over GDP implies a 0.019 g/day increase in the average meat protein consumption). Similarly, the share of Muslims over the population is significant and negative, suggesting that a 1 percent increase in the share generates 0.17 g/day decrease in animal-based protein consumption. Both per capita income and its square estimated parameters are significant, with larger absolute values than the respective parameters of meat consumption, thus suggesting a more rapid increase but also a faster slowing down of the growth. The turning point is located at 41,928 US\$, slightly lower than the turning point of meat consumption, but still within the 90th and the 95th percentile of income distribution. Strictly considered, the results indicate that the consumption of animal-based products other than meat start declining at a lower income level than meat consumption. However, the small difference in the turning point, along with the likely variation in the estimates, suggest that in practice there is no appreciable difference in the behaviour of meat relative to the other animal-based proteins.

Animal-based protein consumption at the turning point, calculated as above (Table 3), is 51.62 g/day, falling between the 70th and 75th percentile, for the whole panel and 2018. The maximum (61.95 g/day) and the minimum (35.02 g/day) values are located over the 80th percentile and between the median and the 60th percentile, respectively, for both the panel and the 2018 distribution. Also, it should be considered that the adequate total protein intake for average adults suggested by the Lancet Commission on healthy diets is 56 g/day (Willet et al., 2019) and the average requirement intake set by the EFSA is 46 g total protein per capita per day (Agostoni et al., 2012).

In contrast, the results of the model for plant-based proteins (Table 2) differ from the previous ones mainly in the fact that the quadratic term of GDP turns out not to be statistically different from zero, meaning that the AFKC hypothesis is not confirmed in this case and that plant-based protein consumption increases linearly with income. Among the other estimated coefficients, the openness to international trade positively influences plant-based protein consumption, possibly due to the exposure to consumption models or via their

increased availability. Every additional percentage point in the ratio of imports plus exports over GDP implies a 0.03 g/day increase in the average plant-based protein consumption. The per capita harvested area negatively impacts plant-based protein consumption, as one per capita hectare more induces a decrease of consumption of 15.5 g/day.

Nevertheless, one per capita hectare is more than 5-fold the average (0.17), so the size of the estimated parameter should be related to the one of the marginal effects in the covariate. A possible -admittedly questionable- explanation of this counterintuitive finding is that when more land is available it is mainly devoted to cereal crops rather than pulses. Consistently with the negative effect on animal-based protein consumption, the share of Muslims over the population has a positive and significant effect, as a one percent increase of their share induces a 0.21 g/day increase in the average plant-based protein consumption. Since the squared per capita income parameter, although exhibiting a negative sign, is non-significant, no turning point can be consistently predicted, with plant-based protein consumption increasing linearly with income, at a rate of 1.50 g/day increase for every additional thousand dollars.

6. DISCUSSION

The empirical results suggest the existence of an inverted U-shaped relationship between animal-based and meat protein consumption and per capita income and a linear relationship between per capita income and plant-based protein consumption. Both models of animal-based and meat protein consumption capture an initial increase in the amount of protein from these sources as income grows. Taste, appetite and the need to increase protein consumption for optimal nutrition can also be considered responsible for this initial increase. As consumers have a rising purchasing power from a growing income, they diversify their bundle of goods and increase their consumption of foods rich in proteins, as also observed by the theory of nutrition transition (Popkin, 1993). In particular, within the diet composition, the animal-based food proportion increases and the plant-based one decreases, as shown by all historical records. However, the historical experience of developed countries shows that consumption keeps increasing until it reaches an amount that may cause negative externalities, consistently with the theoretical model presented.

Nevertheless, we found that the inversion of the trends is predicted at very high-income levels. This is consistent with both the assumption of the positive effect

of income on the taste-appetite driver of consumption and with the negative health effects at high income levels.

Our investigation also found a linear increase of plant-based protein consumption with income. The increase of plant-based protein consumption is lower than that of animal-based and meat but it is continuous. It is possible in fact that when animal-based and meat protein consumption decline plant-based proteins act as substitutes. In fact, the popularity of novel protein consumption with plant-based origins has been recently observed (McClements and Grossmann, 2021).

A somewhat counterintuitive result is that meat protein consumption actually starts declining at a slightly higher income level than animal-based protein consumption. A tentative explanation can relate these trends to a composition effect of rising incomes. At low-income levels, a rising income allows consumption of “non-meat” animal-based proteins (eggs, dairy, fish, etc., generally cheaper than meat) in addition to plant-based ones, as also suggested by the higher income parameter of animal-based than meat protein consumption. As income further rises, meat consumption becomes affordable, and substitutes for “non-meat” animal-based protein consumption, up to the point that the latter starts to decline. This has been empirically observed before (e.g., see Akpalu and Okyere, 2022) and is consistent with the theory of nutrition transition (Dagevos and Voordouw, 2017).

The high level of the turning points, especially the one of meat protein consumption, have important sustainability implications related to the environment and health, with significant consequences for policy makers. Even though the consumption of unsustainable protein reaches a peak and decreases, the peak is at a very high level of income. The majority of the world population is positioned well below the income turning point and still has a long way to go before it reaches the level that, according to our results, decreases the consumption of unsustainable proteins. Thus, the global level of meat and animal-based protein consumption is expected to grow for at least the near future and with that, the impacts on health and the environment. Hence, income growth does not warrant a decrease in animal-based protein consumption sufficient to curb its environmental impact.

7. CONCLUSIONS AND POLICY IMPLICATIONS

This study analysed how animal-based protein consumption is determined by per capita income. We modelled this relationship empirically through a panel of 79 countries over 28 years, distinguishing between meat and more generally animal-based proteins. In addition,

we also modelled the relationship between plant-based proteins and per capita income.

Our main goal was determining whether an Animal Food Kuznets Curve (AFKC) exists, according to which animal-based protein consumption increases with income and then declines. Our results suggested that an AFKC exists, since the estimates show an initial increasing and then decreasing significant trend of animal-base food (AF) consumption relative to real income. It was also possible to calculate the per capita income level at which AF protein consumption starts to decline, corresponding to 42-43,000 US\$, i.e., over the 90th percentile of the per capita income distribution. By contrast, plant-based protein consumption monotonically increases with income.

Some limitations of this study are acknowledged. We tried to build indexes for prices using the price of the most consumed item in every type of protein source, but they turned out to be non-significant, so we were forced to proxy them with variables whose relationship with prices could be weak. Other explanatory factors, in particular income, have had a much more pronounced effect on animal-based foods consumption than prices, resulting in the limited influence of prices on protein consumption found in this study and previous literature (inter alia Mildford et al., 2019). We adopted Mildford et al.’ (2019) argument that in addition to income, natural conditions can be an important determinant of protein consumption. We therefore included per capita harvested area as a control, like Cole and McCoskey (2017). The socio-cultural determinants of diets are arguably important and, even if we tested several, most were correlated with income and others were not significant. This may be due to the inadequacy of those variables to represent the actual socio-cultural determinants.

Despite these limitations, this study is consistent with previous literature and has important policy implications. The policy interest in detecting an AFKC is because such a trend, in principle, would decrease the concern for the environmental and health impacts of animal-based food (AF) consumption. If a rising income would curb AF consumption, policies aiming at reducing it would be less urgent. Unfortunately, the income levels at which we found that AF starts to decline are so high that it is unlikely that this trend can cope with the environmental and health impacts that the growing consumption is creating. More so, because most of the predictable growth of animal-based protein consumption will take place in developing countries. For these countries, the path for reaching income levels determining an inversion of the trend is still long. The inescapable policy implications that the negative environmental impacts of animal-based food consumption must be tackled direct-

ly. Interventions can be envisaged on the production side from a technical point of view, since for instance some techniques allow lower GHG emissions from bovines (Thomson and Rowntree, 2020). Changing the production mix could also help since the environmental impact of poultry and pigs is lower than that of bovines. However, supply is driven by demand, and this calls for interventions on consumers both regarding the type of animal-based products and the quantity of consumption. The regulation of meat and animal-based consumption is one of the major challenges that countries must face in the coming decades (Willett et al., 2019) with the goal of a protein transition reducing the share of animal-based proteins in human diets (Simon et al., 2024). Bonnet et al. (2020) discuss the justification for meat regulation and the different tools that can be used. Their discussion includes economic tools such as taxes (see also Funke et al., 2022), nudging, and informational instruments. There is also an extensive literature on the effects of labelling and information on health and environmental impacts of food, and especially meat (e.g., Canavari and Coderoni, 2020; Edenbrandt and Lagerkvist, 2021; Bazoche et al., 2023). The results are mixed but generally suggest an albeit limited effectiveness of these policies. Regardless, our results suggest that an explicit policy in this regard is needed, since it cannot be expected that income growth will curb excessive consumption of animal-based food.

REFERENCES

Aiking, H., & de Boer, J. (2020). The next protein transition. *Trends in Food Science & Technology* 105: 515-522. <https://doi.org/10.1016/j.tifs.2018.07.008>.

Akpalu, W., & Okyere, M. A. (2022). Fish protein transition in a coastal developing country. *Environmental and Resource Economics*. <https://doi.org/10.1007/s10640-022-00669-y>.

Andreoli, V., Bagliani, M., Corsi, A., & Frontuto, V. (2021). Drivers of protein consumption: A cross-country analysis. *Sustainability* 13(13): 7399. <https://doi.org/10.3390/su13137399>.

Asoudeh, F., Talebi, S., Jayedi, A., Marx, W., Najafi, M. T., & Mohammadi, H. (2022). Associations of total protein or animal protein intake and animal protein sources with risk of kidney stones: A systematic review and dose-response meta-analysis. *Advances in Nutrition* 13(3): 821-832. <https://doi.org/10.1093/advances/nmac013>.

Association of Religion Data Archive (ARDA) (2022). Religious Demographics – National Profiles. <https://www.thearda.com/search-the-arda?sr=0&m=150&searchterms=muslims&specData=0&specItem=InternationalData>. Accessed December 16, 2022.

Bazoche, P., Guinet, N., Poret, S., & Teyssier, S. (2023). Does the provision of information increase the substitution of animal proteins with plant-based proteins? An experimental investigation into consumer choices. *Food Policy* 116: 102426.

Bonnet, C., Bouamra-Mechemache, Z., Réquillart, V., & Treich, N. (2020). Viewpoint: Regulating meat consumption to improve health, the environment and animal welfare. *Food Policy* 97: 101847. <https://doi.org/10.1016/j.foodpol.2020.101847>.

Canavari, M., & Coderoni, S. (2020). Consumer stated preferences for dairy products with carbon footprint labels in Italy. *Agricultural and Food Economics* 8(1): 1-16. <https://link.springer.com/article/10.1186/s40100-019-0149-1>.

Cellura, M., Cusenza, M. A., Longo, S., Luu, L. Q., & Skurk, T. (2022). Life cycle environmental impacts and health effects of protein-rich food as meat alternatives: A review. *Sustainability* 14(2): 979. <https://doi.org/10.3390/su14020979>.

Cole, J. R., & McCoskey, S. (2017). Does global meat consumption follow an environmental Kuznets curve? *Sustainability: Science, Practice and Policy* 9(2): 26-36. <https://doi.org/10.1080/15487733.2013.11908112>.

Costantini, M., & Lupi, C. (2013). A simple panel-CADF test for unit roots. *Oxford Bulletin of Economics and Statistics* 75(2): 276-296. <https://doi.org/10.1111/j.1468-0084.2012.00690.x>.

Dagevos, H., & Voordouw, J. (2017). Sustainability and meat consumption: Is reduction realistic? *Sustainability: Science, Practice and Policy* 9(2): 60-69. <https://doi.org/10.1080/15487733.2013.11908115>.

de Vries, M., & de Boer, I. J. M. (2010). Comparing environmental impacts for livestock products: A review of life cycle assessments. *Livestock Science* 128(1-3): 1-11. <https://doi.org/10.1016/j.livsci.2009.11.007>.

Drewnowski, A., & Poulain, J. P. (2018). What lies behind the transition from plant-based to animal protein? *AMA Journal of Ethics* 20(10): E987-993. <https://doi.org/10.1001/amajethics.2018.987>.

Duro, J. A., Lauk, C., Kastner, T., Erb, K.-H., & Haberl, H. (2020). Global inequalities in food consumption, cropland demand and land-use efficiency: A decomposition analysis. *Global Environmental Change* 64: 102124. <https://doi.org/10.1016/j.gloenvcha.2020.102124>.

Dyer, J. A., & Desjardins, R. L. (2022). The GHG protein ratio: An indicator whose time has come. *High-*

lights of Sustainability 1(2): 105-112. <https://doi.org/10.54175/hsustain1020008>.

Eberhardt, M. (2012). Estimating panel time-series models with heterogeneous slopes. *The Stata Journal* 12(1): 61-71. <https://doi.org/10.1177/1536867X1201200105>.

Edenbrandt, A. K., & Lagerkvist, C. J. (2021). Is food labelling effective in reducing climate impact by encouraging the substitution of protein sources? *Food Policy* 101: 102097. <https://doi.org/10.1016/j.foodpol.2021.102097>.

Errickson, F., Kuruc, K., & McFadden, J. (2021). Animal-based foods have high social and climate costs. *Nature Food* 2(4): 274-281. <https://doi.org/10.1038/s43016-021-00265-1>.

FAO (2009). The state of food and agriculture: livestock in the balance. Food and Agriculture Organization. Rome.

FAO (2021). Food Balances Sheets. <https://www.fao.org/faostat/en/#data/FBS>. Food and Agriculture Organization. Rome. Accessed September 20, 2021.

FAO (2022a). Crops and livestock products - area harvested. <https://www.fao.org/faostat/en/#data/QCL>. Food and Agriculture Organization. Rome. Accessed September 10, 2021.

FAO (2022b). Consumer Price Indices. <https://www.fao.org/faostat/en/#data/CP>. Accessed March 15, 2022.

Feenstra, R., Inklaar R. and Timmer M. P. (2015). The Next Generation of the Penn World Table. *American Economic Review* 105(10): 3150-3182. [10.1257/aer.20130954](https://doi.org/10.1257/aer.20130954). Accessed December 16, 2022.

Frank, J. (2008). Is there an “animal welfare Kuznets curve”? *Ecological Economics* 66(2-3): 478-491. <https://doi.org/10.1016/j.ecolecon.2007.10.017>.

Funke, F., Mattauch, L., van den Bijgaart, I., Godfray, H. C. J., Hepburn, C., Klenert, D., Springmann, M., & Treich, N. (2022). Toward optimal meat pricing: Is it time to tax meat consumption? *Review of Environmental Economics and Policy* 16(2): 219-240. <https://doi.org/10.1086/721078>.

Gaillac, R., & Marbach, S. (2021). The carbon footprint of meat and dairy proteins: A practical perspective to guide low carbon footprint dietary choices. *Journal of Cleaner Production* 321: 128766. <https://doi.org/10.1016/j.jclepro.2021.128766>.

Galli, F. & Moretti, M. (2024). Narratives shaping the protein transition. *Nature Food* 5(1): 7-8. <https://doi.org/10.1038/s43016-023-00914-7>.

Gerbens-Leenes, P. W., Nonhebel, S., & Krol, M. S. (2010). Food consumption patterns and economic growth. Increasing affluence and the use of natural resources. *Appetite* 55(3): 597-608. <https://doi.org/10.1016/j.appet.2010.09.013>.

Godfray, H. C. J., Aveyard, P., Garnett, T., Hall, J. W., Key, T. J., Lorimer, J., Pierrehumbert, R. T., Scarborough, P., Springmann, M., & Jebb, S. A. (2018). Meat consumption, health, and the environment. *Science* 361(243): eaam5324. <https://doi.org/10.1126/science.aam5324>.

Gonzalez, N., Marques, M., Nadal, M., & Domingo, J. L. (2020). Meat consumption: Which are the current global risks? A review of recent (2010-2020) evidences. *Food Research International* 137: 109341. <https://doi.org/10.1016/j.foodres.2020.109341>.

Grossman, G. M. (1995). Pollution and growth: What do we know? In Goldin, I. & Winters L. A. (Eds.), *The economics of sustainable development* (pp. 19-50). Cambridge University Press.

Grossman, G. M., & Krueger, A. (1991). Environmental impacts of a North American Free Trade Agreement. Working paper no. 3914. National Bureau of Economic Research, Cambridge, MA. <https://doi.org/10.3386/w3914>.

Hasanov, F. J., Hunt, L. C., & Mikayilov, J. I. (2021). Estimating different order polynomial logarithmic environmental Kuznets curves. *Environmental Science and Pollution Research International* 28: 41965 - 41987. <https://doi.org/10.1007/s11356-021-13463-y>.

Hayek, M. N., Harwatt, H., Ripple, W. J., & Mueller, N. D. (2020). The carbon opportunity cost of animal-sourced food production on land. *Nature Sustainability* 4(1): 21-24. <https://doi.org/10.1038/s41893-020-00603-4>.

Henchion, M., & Zimmermann, J. (2021). Animal food products: policy, market and social issues and their influence on demand and supply of meat. *Proceedings of the Nutrition Society* 80(2): 252-263. <https://doi.org/10.1017/S00296651200007971>.

Huang, Y., Cao, D., Chen, Z., Chen, B., Li, J., Guo, J., Dong, Q., Liu, L., & Wei, Q. (2021). Red and processed meat consumption and cancer outcomes: Umbrella review. *Food Chemistry* 356: 129697. <https://doi.org/10.1016/j.foodchem.2021.129697>.

Jones, B. A., Grace, D., Kock, R., Alonso, S., Rushton, J., Said, M. Y., McKeever, D., Mutua, F., Young, J., McDermott, J., & Pfeiffer, D. U. (2013). Zoonosis emergence linked to agricultural intensification and environmental change. *Proceedings of the National Academy of Sciences* 110(21): 8399-8404. <https://doi.org/10.1073/pnas.1208059110>.

Lakdawalla, D., & Philipson, T. (2009). The growth of obesity and technological change. *Economics & Human Biology* 7(3): 283-293. <https://doi.org/10.1016/j.ehb.2009.08.001>.

Lakdawalla, D., Philipson, T., Bhattacharya, J. (2005). Welfare-enhancing technological chan-

ge and the growth of obesity. *American Economic Review* 95(2): 283-293. <https://doi.org/10.1257/000282805774670266>.

Lombardi, G. V., Berni, R., & Rocchi, B. (2017). Environmental friendly food. Choice experiment to assess consumer's attitude toward "climate neutral" milk: the role of communication. *Journal of Cleaner Production* 142: 257-262. <https://doi.org/10.1016/j.jclepro.2016.05.125>.

Machovina, B., Feeley, K. J., & Ripple, W. J. (2015). Biodiversity conservation: The key is reducing meat consumption. *Science of the Total Environment* 536: 419-431. <https://doi.org/10.1016/j.scitotenv.2015.07.022>.

Malik, V. S., Li, Y., Tobias, D. K., Pan, A., & Hu, F. B. (2016). Dietary protein intake and risk of type 2 diabetes in US men and women. *American Journal of Epidemiology* 183(8): 715-728. <https://doi.org/10.1093/aje/kwv268>.

Mariotti, F., & Gardner, C. D. (2019). Dietary protein and amino acids in vegetarian diets - A review. *Nutrients* 11(11). <https://doi.org/10.3390/nu1112661>.

Marques, A. C., Fuinhas, J. A., & Pais, D. F. (2018). Economic growth, sustainable development and food consumption: Evidence across different income groups of countries. *Journal of Cleaner Production* 196: 245-258. <https://doi.org/10.1016/j.jclepro.2018.06.011>.

Mathijs, E. (2015). Exploring future patterns of meat consumption. *Meat Science* 109: 112-116. <https://doi.org/10.1016/j.meatsci.2015.05.007>.

Mazac, R., Meinilä, J., Korkalo, L., Järviö, N., Jalava, M., & Tuomisto, H. L. (2022). Incorporation of novel foods in European diets can reduce global warming potential, water use and land use by over 80%. *Nature Food* 3(4): 286-293. <https://doi.org/10.1038/s43016-022-00489-9>.

McClements, D. J., & Grossmann, L. (2021). The science of plant-based foods: Constructing next-generation meat, fish, milk, and egg analogs. *Comprehensive Review in Food Science and Food Safety* 20(4): 4049-4100. <https://doi.org/10.1111/1541-4337.12771>.

Mekonnen, M. M., & Gerbens-Leenes, W. (2020). The water footprint of global food production. *Water* 12(10): 2696. <https://doi.org/10.3390/w12102696>.

Milford, A. B., Le Mouel, C., Bodirsky, B. L., & Rolinski, S. (2019). Drivers of meat consumption. *Appetite* 141: 104313. <https://doi.org/10.1016/j.appet.2019.06.005>.

OECD and FAO (2023). OECD-FAO Agricultural Outlook 2023-2032. Paris, OECD. <https://openknowledge.fao.org/handle/20.500.14283/cc6361en>.

Pais, D. F., Marques, A. C., & Fuinhas, J. A. (2021). Drivers of a new dietary transition towards a sustainable and healthy future. *Cleaner and Responsible Consumption* 3: 100025. <https://doi.org/10.1016/j.clrc.2021.100025>.

Pedroni, P. (1999). Critical values for cointegration tests in heterogeneous panels with multiple regressors. *Oxford Bulletin of Economics and Statistics* 61(S1): 653-670. <https://doi.org/10.1111/1468-0084.0610s1653>.

Pedroni, P. (2004). Panel cointegration: asymptotic and finite sample properties of pooled time series tests with an application to the PPP hypothesis. *Econometric Theory* 20(3): 597-625. <https://doi.org/10.1017/S0266466604203073>.

Perman, R., & Stern, D. I. (2003). Evidence from panel unit root and cointegration tests that the Environmental Kuznets Curve does not exist. *Australian Journal of Agricultural and Resource Economics* 47: 325-347. <https://doi.org/10.1111/1467-8489.00216>.

Pesaran, M. H. (2021). General diagnostic tests for cross-sectional dependence in panels. *Empirical Economics* 60(1): 13-50. <https://doi.org/10.1007/s00181-020-01875-7>.

Pesaran, M. H., & Smith, R. (1995). Estimating long-run relationships from dynamic heterogeneous panels. *Journal of Econometrics* 68(1): 79-113. [https://doi.org/10.1016/0304-4076\(94\)01644-F](https://doi.org/10.1016/0304-4076(94)01644-F).

Poore, J., & Nemecek, T. (2018). Reducing food environmental impacts through producers and consumers. *Science* 360: 987-992. <https://doi.org/10.1126/science.aaq0216>.

Popkin, B. M. (1993). Nutritional patterns and transitions. *Population and Development review* 19(1): 138-157. <https://doi.org/10.2307/2938388>.

Rabe-Hesketh, S., & Skrondal, A. (2008). Multilevel and longitudinal modeling using Stata. 2nd edition. *Biometrics* 64: 1310-1310. https://doi.org/10.1111/j.1541-0420.2008.01138_15.x.

Sans, P., & Combris, P. (2015). World meat consumption patterns: An overview of the last fifty years (1961-2011). *Meat Science* 109: 106-111. <https://doi.org/10.1016/j.meatsci.2015.05.012>.

Saqib, M., & Benhmad, F. (2021). Updated meta-analysis of environmental Kuznets curve: Where do we stand? *Environmental Impact Assessment Review* 86: 106503. <https://doi.org/10.1016/j.eiar.2020.106503>.

Shepon, A., Eshel, G., Noor, E., & Milo, R. (2018). The opportunity cost of animal-based diets exceeds all food losses. *Proceedings of the National Academy of Sciences* 115(15): 3804-3809. <https://doi.org/10.1073/pnas.1713820115>.

Simon, W. J., Hijbeek, R., Frehner, A., Cardinaals, R., Talsma, E. F., & Van Zanten, H. H. (2024). Circular

food system approaches can support current European protein intake levels while reducing land use and greenhouse gas emissions. *Nature Food* 5(5): 402-412. <https://doi.org/10.1038/s43016-024-00975-2>.

Springmann, M., Godfray, H. C., Rayner, M., & Scarborough, P. (2016). Analysis and valuation of the health and climate change cobenefits of dietary change. *Proceedings of the National Academy of Sciences* 113(15): 4146-4151. <https://doi.org/10.1073/pnas.1523119113>.

Stylianou, K. S., Fulgoni, V. L., & Jolliet, O. (2021). Small targeted dietary changes can yield substantial gains for human health and the environment. *Nature Food* 2(8): 616-627. <https://doi.org/10.1038/s43016-021-00343-4>.

Sun, Y., Liu, B., Snetselaar, L. G., Wallace, R. B., Shadyab, A. H., Kroenke, C. H., Haring, B., Howard, B. V., Shikany, J. M., Valdiviezo, C., & Bao, W. (2021). Association of major dietary protein sources with all-cause and cause-specific mortality: Prospective cohort study. *Journal of the American Heart Association* 10(5): e015553. <https://doi.org/10.1161/JAHA.119.015553>.

Swain, M., Blomqvist, L., McNamara, J., & Ripple, W. J. (2018). Reducing the environmental impact of global diets. *Science of the Total Environment* 610-611: 1207-1209. <https://doi.org/10.1016/j.scitotenv.2017.08.125>.

Teal, F., & Eberhardt, M. (2010). Productivity analysis in global manufacturing production. Department of Economics Discussion Paper Series. University of Oxford.

Thomson, L. R., & Rowntree, J. E. (2020). Invited Review: Methane sources, quantification, and mitigation in grazing beef systems. *Applied animal science* 36(4): 556-573. <https://doi.org/10.15232/aas.2019-01951>.

Tilman, D., & Clark, M. (2014). Global diets link environmental sustainability and human health. *Nature* 515(7528): 518-522. <https://doi.org/10.1038/nature13959>.

Van Boeckel, T. P., Brower, C., Gilbert, M., Grenfell, B. T., Levin, S. A., Robinson, T. P., Teillant, A., & Laxminarayan, R. (2015). Global trends in antimicrobial use in food animals. *Proceedings of the National Academy of Sciences* 112(18): 5649-5654. <https://doi.org/10.1073/pnas.1503141112>.

Van Zanten, H. H. E., Herrero, M., Van Hal, O., Roos, E., Muller, A., Garnett, T., Gerber, P. J., Schader, C., & de Boer, I. J. M. (2018). Defining a land boundary for sustainable livestock consumption. *Global Change Biology* 24(9): 4185-4194. <https://doi.org/10.1111/gcb.14321>.

Vranken, L., Avermaete, T., Petalios, D., & Mathijs, E. (2014). Curbing global meat consumption: Emerging evidence of a second nutrition transition. *Environmental Science & Policy* 39: 95-106. <https://doi.org/10.1016/j.envsci.2014.02.009>.

Westerlund, J. (2005). New simple tests for panel cointegration. *Econometric Reviews* 24(3): 297-316. <https://doi.org/10.1080/07474930500243019>.

Willett, W., Rockström, J., Loken, B., Springmann, M., Lang, T., Vermeulen, S., Garnett, T., Tilman, D., DeClerck, F., Wood, A., Jonell, M., Clark, M., Gordon, L. J., Fanzo, J., Hawkes, C., Zurayk, R., Rivera, J. A., de Vries, W., Majele Sibanda, L., ... Murray, C. J. L. (2019). Food in the Anthropocene: the EAT-Lancet Commission on healthy diets from sustainable food systems. *The Lancet* 393(10170): 447-492. [https://doi.org/10.1016/s0140-6736\(18\)31788-4](https://doi.org/10.1016/s0140-6736(18)31788-4).

World Bank (2022a). Export and Import data. <https://databank.worldbank.org/export-and-import-data/id/42cf7c81>. Accessed December 16, 2022.

World Bank (2022b). Educational attainment, at least completed post-secondary, population 25+, total (%) (cumulative). <https://data.worldbank.org/indicator/SE.SEC.CUAT.PO.ZS>. Accessed December 16, 2022.

World Bank (2022c). Labor force participation rate, female (% of female population ages 15+) (modeled ILO estimate). <https://data.worldbank.org/indicator/SL.TLF.CACT.FE.ZS>. Accessed December 16, 2022.

World Bank (2022d). Urban population (% of total population). <https://data.worldbank.org/indicator/SP.URB.TOTL.IN.ZS>. Accessed December 16, 2022.

York, R., & Gossard, M. H. (2004). Cross-national meat and fish consumption: exploring the effects of modernization and ecological context. *Ecological Economics* 48(3): 293-302. <https://doi.org/10.1016/j.ecolecon.2003.10.009>.

You, W., & Henneberg, M. (2016). Meat in modern diet, just as bad as sugar, correlates with worldwide Obesity: An ecological analysis. *Journal of Nutrition & Food Sciences* 6(4): 1000517. <https://doi.org/10.4172/2155-9600.1000517>.

Zhang, M., Feng, J. C., Sun, L., Li, P., Huang, Y., Zhang, S., & Yang, Z. (2022). Individual dietary structure changes promote greenhouse gas emission reduction. *Journal of Cleaner Production* 366: 132787. <https://doi.org/10.1016/j.jclepro.2022.132787>.

Zheng, J., Zhu, T., Yang, G., Zhao, L., Li, F., Park, Y. M., Tabung, F. K., Steck, S. E., Li, X., & Wang, H. (2022). The isocaloric substitution of plant-based and animal-based protein in relation to aging-related health outcomes: A systematic review. *Nutrients* 14(2): 272. <https://doi.org/10.3390/nu14020272>.

APPENDIX 1

In formal terms, the model of AF consumption assumes the consumer maximizes his/her utility subject to a budget constraint:

$$\begin{aligned} \text{Max } U[a, H(a), C] \\ \text{s.t.: } C + p_a I = I \end{aligned} \quad [A1]$$

where a is animal-based protein consumption, H indicates health-nutrition components of utility as a function of animal food consumption, C is expenditure for all other consumption goods, I is income, p_a is the price of a and the price of C is taken as numeraire. The usual general assumptions hold: $U'_a > 0$, $U''_a < 0$; $U'_C > 0$, $U''_C < 0$; $U'_H > 0$, $U''_H < 0$. To represent the U-shape of nutritional-health benefits, it is assumed that $H'_a \geq 0$ for $a \leq \bar{a}$, $H'_a < 0$ for $a > \bar{a}$ where \bar{a} is the animal-based protein consumption yielding the maximum nutrition-health benefit; H''_a is assumed < 0 .

The first order conditions (FOCs) is:

$$U'_a + U'_H H'_a = p_a U'_C \quad [A2]$$

Equation [A2] simply states that, at equilibrium, the marginal utility from consumption of AF (the first left-side term), plus the marginal utility from the nutritional-health benefits from its consumption (the second left-side term) is equal to the additional utility that could be drawn from other goods that could be purchased with the animal food price, i.e., the marginal opportunity cost of AF (the right-side term).

The effect of income on AF consumption can be computed as the derivative of a with respect to I in eqn. [A2]. The result is nevertheless a complex function of the second direct and cross derivatives of a , H , C , and its sign cannot be unambiguously determined, it can be positive or negative.

APPENDIX 2

Table A.1. List of countries analysed.

Country	ISO CODE
Algeria	DZA
Argentina	ARG
Australia	AUS
Austria	AUT
Bangladesh	BGD
Bolivia	BOL
Brazil	BRA
Belize	BLZ
Cameroon	CMR
Canada	CAN
Cabo Verde	CPV
Sri Lanka	LKA
Chile	CHL
China	CHN
Colombia	COL
Congo	COG
Cyprus	CYP
Denmark	DNK
Dominican Republic	DOM
Ecuador	ECU
Egypt	EGY
El Salvador	SLV
Finland	FIN
France	FRA
Gambia	GMB
Germany	DEU
Ghana	GHA
Greece	GRC
Guinea	GIN
Honduras	HND
Hungary	HUN
India	IND
Indonesia	IDN
Iran (Islamic Republic of)	IRN
Ireland	IRL
Israel	ISR
Italy	ITA
Côte d'Ivoire	CIV
Japan	JPN
Jordan	JOR
Kenya	KEN
Cambodia	KHM
Republic of Korea	KOR
Lao People's Democratic Republic	LAO
Lebanon	LBN
Madagascar	MDG
Malaysia	MYS
Mali	MLI
Mauritius	MUS
Mexico	MEX
Morocco	MAR
Mozambique	MOZ
Namibia	NAM
Nepal	NPL
Netherlands	NLD
New Zealand	NZL
Nicaragua	NIC
Niger	NER
Nigeria	NGA

Country	ISO CODE
Norway	NOR
Pakistan	PAK
Panama	PAN
Paraguay	PRY
Peru	PER
Philippines	PHL
Poland	POL
Portugal	PRT
Rwanda	RWA
Saudi Arabia	SAU
South Africa	ZAF
Spain	ESP
Sweden	SWE
Switzerland	CHE
Togo	TGO
Turkey	TUR
United Kingdom	GBR
United States of America	USA
Burkina Faso	BFA
Uruguay	URY

APPENDIX 3

Table A.2. Test of cross-sectional dependence of variables.

Variable [#]	Pesaran test
AnimalProt	2.678***
MeatProt	2.398**
PlantProt	2.798***
GDPPc	9.247***
GDPPc ²	16.342***
Trade	0.158
HarvArea	5.03***
PerFemWork	3.804***
Urbanization	1.948*
Education	85.837***
Animal-based Price Index	12.883***
Meat Price Index	6.536***
Plant-based Price Index	24.181***

[#]The percentage of Muslim (PerMus) has not been tested because time invariant.

^{*}, ^{**}, ^{***} stand for the significance level of 10%, 5% and 1% respectively. The null hypothesis is the absence of cross-sectional dependence.

Table A.3. Unit root test on variables and their first difference.

Variable	pCADF test	Variable	pCADF test
AnimalProt	2.965	Δ AnimalProt	-8.341***
MeatProt	1.408	Δ MeatProt	-10.136***
PlantProt	3.616	Δ PlantProt	-19.977***
GDPPc	5.426	Δ GDPPc	-3.426***
GDPPc ²	6.295	Δ GDPPc ²	-1.592*
Trade	4.052	Δ Trade	-7.158**
HarvArea	2.232	Δ HarvArea	-7.700***
PerFemWork	1.631	Δ PerFemWork	-2.565***
Urbanization	4.302	Δ Urbanization	6.272
Education	11.310	Δ Education	3.016
Animal-based Price Index	-12.225***	Δ Animal-based Price Index	-20.497***
Meat Price Index	-12.825***	Δ Meat Price Index	-5.473***
Plant-based Price Index	-16.698***	Δ Plant-based Price Index	-9.583***

^{*}, ^{**}, ^{***} stand for the significance level of 10%, 5% and 1% respectively. The null hypothesis is non-stationarity.

Table A.4. Cointegration test assuming cross-sectional dependence.

Test name	AnimalProt	MeatProt	PlantProt
<i>Pedroni</i>			
Modified Phillips–Perron t	4.590***	3.697***	1.88**
Phillips–Perron t	-7.509***	-8.279***	-9.710***
Augmented Dickey–Fuller t	-8.99***	-10.195***	-10.324***
<i>Westerlund</i>			
Variance ratio	-2.579 ***	-2.751***	-1.6434*

^{*}, ^{**}, ^{***} indicate that statistics are significant at the 10%, 5% and 1% level of significance respectively. The null hypothesis is no-co-integration.

Table A.5. Results of the full models of protein consumption.

Indep. variables	Dependent variables					
	Animal-based Protein		Meat Protein		Plant-based Protein	
	Coef.	Std.Err.	Coef.	Std.Err.	Coef.	Std.Err.
GDPPc	1.256***	0.206	0.725***	0.135	1.505***	0.419
GDPPc ²	-0.015***	0.004	-0.008**	0.003	-0.002	0.001
Trade	0.018***	0.005	0.008**	0.003	0.032***	0.004
HarvArea	1.190	1.862	1.087	1.317	-15.486***	1.738
PerMus	-0.177***	0.048	-0.105***	0.028	0.211***	0.421
PerFemWork	0.057	0.047	-0.008	0.033	0.111**	0.046
Price Index (animal-based)	0.304	0.289				
Price Index (meat)			0.065	0.200		
Price Index (plant-based)					-0.184	0.148
Constant	25.245***	3.697	11.033***	2.199	30.910***	2.619***
sd(GDPPc)	1.686	0.161	1.087	0.125	3.644	0.361
sd(GDPPc ²)	0.029	0.003	0.021	0.006	0.005	0.002
sd(Constant)	25.17	2.378	13.369	1.415	12.894	1.119
sd(Residual)	2.167	0.035	1.541	0.028	2.092	0.033
N. obs.	2212		2212		2212	
N. groups	79		79		79	
Wald Chisq(6)	109.25***		78.31***		196.14***	
Log likelihood	-5302.43		-4533.41		-5300.07	

*, **, *** indicate that statistics are significant at the 10%, 5% and 1% level of significance respectively.