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Drivers Of The Global Thirst For Milk

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Climate change mitigation efforts face increasing demand for animal source food consumption and dairy in particular. Therefore, it is necessary to understand the differences in dairy consumption levels and underlying drivers on a global scale. We attempt to estimate drivers of milk consumption by using a panel regression clustering approach and analyzing the relative importance by applying a Shorrocks-Shapley decomposition of the R-squared. Further, we show how the results change when we incorporate income projections for the years 2050 and 2100. Results suggest that, using a panel data set from 2000 to 2020 for 120 countries, socio-economic milk consumption drivers can be allocated to six different clusters with price elasticities ranging from -1.085 to 0.450 and income elasticities from -0.527 and 1.084. Decomposing the R-squared shows that the value of milk industry seems to explain most of the variance of milk consumption. When considering income projections until the mid and end century, we find that the share of young population gains statistical significance. Future research should investigate how fiscal climate change adaptation policies could be designed effectively while considering heterogeneous milk demand drivers.

Keywords: Global heterogeneous milk consumption, Driver analysis, Clustering panel data, Climate change mitigation policies, Shapley Values
JEL Codes: Q11, Q18, Q21
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1 Introduction

Inconsistent and unavailable food consumption data impedes accurate global food demand projections, which are important for future food security, nutrition, and health analysis (Bodirsky et al., 2020a). Within food demand analyses, the focus on dairy is of particular interest as the production of ASF is associated with excessive land and water use, as well as Greenhouse gas emissions (Poore & Nemecek, 2018). At the same time, it is estimated that six billion people consume some kind of dairy products on a regular basis (Bojovic & McGregor, 2022). In the next ten years, the demand for milk is expected to increase in low middle income countries by 2 percent, compared to 0.4 percent in high income countries (OECD, 2022). Moreover, the consumption of milk can serve as important source for micronutrients in low- and middle-income countries. A recent study found that milk consumption is associated with a reduced probability of being underweight and being stunted for children aged 6 to 59 month, but also acknowledge rather small effect sizes, substantial variation across countries, and the strongest associations for children from wealthier households (Herber et al., 2020). A further paper stated that growth in dairy consumption is associated with reduced rates of stunting (Haile & Headey, 2023).

In order to understand the analyze underlying drivers of milk consumption worldwide, we utilize a panel regression clustering algorithm in order to obtain cluster-specific estimates of drivers of global milk consumption. We find that milk consumption drivers of 120 countries from the period between the year 2000 to year 2020 can be grouped into six clusters. Additionally, we decompose the R-squared for each cluster according to the Shorrocks-Shapley values, which reveal highest relative importances of the value of milk industry per capita and the share of young population. Repeating the regressions with income projections for the mid and end of the century confirm strong and statistically significant associations between the milk industry per capita and milk consumption.

Food demand analyses, that cover multiple regions or countries, tend to group countries according to geographical proximity (Colen et al., 2018) or income classes (Milford et al., 2019; Muhammad et al., 2011). While income and geography constitute decisive variables for the heterogeneity in consumption levels of milk and ASFs in general (Bodirsky et al., 2020b; Milford et al., 2019; Parlasca & Qaim, 2022), there might be considerable differences in ASF consumption even within countries that share a similar location or income level. Previous clustering studies demonstrated that there are considerable differences in food consumption on country level already (Bertail & Caillavet, 2008; Mózner, 2014; Staudigel & Schröck, 2014).

In contrast to previous studies, we intend to cluster global food consumption based on the example of milk by considering various socioeconomic variables (Milford et al., 2019). Our approach adds further explanation to the existing literature about differences and drivers of these differences in milk consumption on a global scale. We find that milk is an inferior or luxury good for around one third of the world population, which should be taken into account when simulating fiscal climate change mitigation policies, such as a Carbon tax on food. We also show that the value of the milk industry per capita is strongly associated with the milk consumption within countries.

The remaining paper is structured as follows: Section 2 provides background information about existing dairy demand studies, climate change mitigation policies in the dairy sector, and previous cluster analyses of food and dairy consumption patterns. We explain the panel regression clustering method in Section 3. After a short description of the data in Section 4, we present results in Section 5. We discuss our choice of regressors, robustness checks, and the growing relevance of plant based dairy alternatives in Section 6. We draw conclusions in the last section.

2 Background

2.1 Dairy demand studies

A study from the year 2008 investigates dairy demand for France and Italy by employing an empirical demand system applied to consumer panel data. In general, they find ambiguous price and income elasticities for dairy consumption. French consumers have inelastic price elasticities towards fresh dairy products, and diverse price elasticities for cheese, ranging between -0.27 (processed cheese) and -1.22 (semi-hard cheese) as well as low income elasticities for fresh dairy products as well as processed dairy products. Authors identify similar trends but in general less statistically significant patterns for Italian consumers (Bouamra-Mechemache et al., 2008).

Davis et al. (2011) use purchasing data of the Nielsen's 2007 Homescan data to derive an empirical demand system to calculate elasticities for 16 dairy products while taking economic but also US specific demographic variables into account. Interestingly, expenditure for two dairy products (reduced-fat milk and ice cream) account for 42 percent of the total dairy expenditures. The authors calculate highly elastic own price elasticities for fluid milk products (-1.93 for whole milk, -1.73 for 1 percent milk and -1.6 for 2 percent milk), which are theoretically regarded as commodities with inelastic price elasticities. Expenditure elasticities suggest that milk commodities are normal commodities (for example, 1.01 for 1 percent milk to 1.12 for cottage cheese). With respect to the demographic variables, they find that purchases of whole and 2 percent milk products are positively associated by households with either children ages 6 and younger or and teenagers ages 13 to 17. Further, the purchase of most of the dairy products was positively associated with being white and different income categories, although depending on the commodity (higher income categories were associated with increased purchases of cheese products and butter as well as margarine) (Davis et al., 2011).

2.2 Climate change mitigation policies in the dairy sector

The dairy sector is characterized by multiple regulations across the supply chain, given the importance of dairy as part of the diet in many countries of the world and important contribution for combating global hunger in low income countries (FAO, GDP and IFCN, 2019; OECD, 2022). For many high income countries, the EAT Lancet diet recommends a limited intake of dairy per day due to a lack of clear positive association of milk or dairy intake on bone health or lower risk of non-communicable diseases (Springmann et al., 2020; Willett et al., 2019).

Further, the dairy production is also associated with high levels of Greenhouse gas emissions. At median, it takes 2.1 m^2 land and 197 litres of freshwater to produce one litre of milk. Further, milk production emits 2.7 kg CO_2 equivalents. The production of one kilogram of cheese at median takes up to 20.2 m^2 land, 1559.3 litres of freshwater and results in 18.64 kg CO_2 equivalents. Soy milk, which constitutes a prominent alternative to traditional milk, is associated with only 0.6 m^2 land use, 0.9 kg CO_2 equivalents GHG emissions, and one litre freshwater withdrawals per litre at median (Poore & Nemecek, 2018).

While most of the climate change mitigation policies related to the dairy sector focus on improving production efficiency, there are also climate change mitigation relevant policies on the demand side (Creutzig et al., 2021; FAO, GDP and IFCN, 2019). A Carbon tax on food (Pigouvian tax proportional to the emissions related to food production) on the consumer side can be an effective climate change-mitigation policy and the ultimate financial distributional effect depends heavily on the tax implementation (Roosen et al., 2022; Säll, 2018).

The majority of the existing literature that simulate a Carbon tax on food and dairy explicitly cover developed countries, where dairy production is highly industrialized, and thus, accompanied with lower emission levels compared to developing countries, where dairy productions tends to be less industrialized (FAO, GDP and IFCN, 2019). Estimated Carbon tax rates for milk range from 8.2 percent for Denmark (Edjabou & Smed, 2013), and around 15 percent for France and Sweden (Huang, 2022; Mosnier et al., 2019). Carbon tax rates for dairy are higher and can be quantified until up to 25 percent for the case of the UK, up to 19.27 percent for the case of France, and up to 30 percent for a simulation study in Sweden (Benedetti et al., 2022; Caillavet et al., 2019; Säll & Gren, 2015). However, the ultimate effect of the Carbon tax on food depends on how elastic the demand for milk is. If we estimate very elastic demand for milk in countries where alternative protein sources might be scarce, a Carbon tax on food should be accompanied with appropriate compensation measures.

Huang (2022) investigates the effect of a carbon tax on cow milk and PBD alternatives using home scanner data from the GFK consumer panel from consumers in Sweden. Assuming weak separability between fresh milk and other consumption commodities, the author employs as a first step an empirical demand system and as a second step, simulates Carbon taxes according to damage costs from CO_2equivalents for different types of milks. The most elastic own price elasticity was calculated for plant based milk (-4.546), while own price elasticities for fresh milk types ranged between -2.244 and -1.361. When categorising households according to their income, richest households were most price elastic for PBD alternatives and low fat milk. Results of different Carbon tax scenarios show that a Carbon tax on cow milk commodities would lead to a decrease of between 4.890 to 14.316 kg in the annual carbon footprint. A Carbon tax on PBD alternatives would, however, increase the corresponding carbon footprint due to the previously identified substitutional effects between plant-based milk and low-fat and standard milk.

2.3 Previous cluster analyses of food and dairy consumption

Previous studies clustered food consumption based on household surveys for France (Bertail & Caillavet, 2008), Russia (Staudigel & Schröck, 2014), Hungary (Mózner, 2014), as well as for dairy products in the US (Wolf et al., 2020). For the case of food consumption in Russia, five different household clusters were detected as result of hierarchical clustering and the Calinski/Harabasz-criterion. The identified clusters ranged from rural home producers to urban non growers. The study reveals most substantial differences in expenditure elasticities of 25.26 percent for meats and of 77.19 percent for milk and dairy products across the most distinct clusters (Staudigel & Schröck, 2014).

For the case of French fruit and vegetable consumption, six different household clusters were found based on using various information criteria. The different cluster memberships were explained mainly by adult equivalent income levels. Interestingly, for the as socioeconomically disadvantaged classified cluster, no correlation between expenditure and income and no statistically significant expenditure elasticities were found, suggesting a strong expenditure restriction with essentially no real choice in food consumption Bertail & Caillavet (2008). Regarding food consumption in Hungary, six different clusters were identified based on non hierarchical k-means clustering and described by differences in socio-demographic characteristics. Further, they calculate the ecological footprint of the different diets in each cluster. They find that the cluster with highest share of meat consumption within total food consumption is formed by elderly, urbanized, and the lowest income sextile. Interestingly, the cluster with the highest ecological footprint is a different cluster which is characterized by relatively high quantities of various different animal source foods and not the cluster with the highest relative meat consumption (Mózner, 2014).

3 Methods

In order to capture heterogeneous milk demand across the globe, we leverage the method developed by Christodoulou & Sarafidis (2017), where we first classify countries into clusters and then run separate regressions for each cluster. Further, we calculate Shapley values in order to assess the relative importance of which variables determine the cluster membership, after fitting a gradient boosting algorithm to the data.

3.1 Empirical specification

The number of k clusters and the optimal partition is unknown and determined based on minimizing the Model Information Criterion (MIC) through an iterative algorithm that takes the cluster k-means as the initial partition (Christodoulou & Sarafidis, 2017). The MIC is defined as follows:

$$MIC = N \ln \left(\frac{RSS}{N\overline{T}} \right) + \Omega \theta_N \tag{1}$$

where N is the number of countries, RSS is the sum of residual squares per cluster,$\overline{T}$ is the average time-series length, and $\sigma\theta_N$ is a penalty value and defined as $\Omega\theta_N = \frac{1}{3} \ln \frac{2}{3} \sqrt{N}$ since RSS is monotone increasing in the number of clusters (Boto-García & Mayor, 2022; Sarafidis & Weber, 2014). We display the RSS and the MIC for $\Omega = 1, 7$ in Table 2.

We attempt to explain milk consumption per capita/kg/year q_{ct} for each country c in year t in Equation 2 with milk price p_{ct}, GNI per capita y_{ct} and a vector of relevant socioeconomic control variables X_{ct} for each cluster $\omega = 1, ..., \Omega$. These controls include the share of young population, the share of the population that lives in urban areas, a trade openness indicator, and the value of the milk industry per capita (see more details in the Section 4, while μ_c represent country fixed effects and ϵ_c denotes the iid error term.

$$\log(q_{ct}) = \beta_{0,\omega} + \beta_{1,\omega}\log(p_{ct}) + \beta_{2,\omega}\log(y_{ct}) + \beta_{3,\omega}X_{ct} + \mu_{c,\omega} + \epsilon_{ct,\omega} \tag{2}$$

As a second step, we leverage the Shorrocks-Shapley decomposition of the R-squared. This metric quantifies how important each input variable is to a model for making certain predictions (to a certain cluster in our case) compared to the average prediction. In other words, the Shapley value is the average of all the marginal contributions to all possible coalitions (Shorrocks, 2012; Boto-García & Mayor, 2022; Elbers, 2023).

We conclude with a prediction by assuming the following relationship between milk consumption and income for years t 2050 and or 2100, country c, and scenario s:

$$\log(q_{ct}) = \beta_0 + \beta_1\log(p_{ct}) + \beta_2\log(y_{cst}) + \beta_3X_{ct} + \epsilon_{ct} \tag{3}$$

where $t = 2050, 2100$ and $s = SSP1, .., SSP5$. The Shared Socioeconomic Pathways scenarios (SSPs) are based on the work by O'Neill et al. (2017) and are widely in simulation models (Dietrich et al., 2019). The five scenarios vary by different combinations of challenges to climate change mitigation and adaptation. While SSP1 "Sustainability" is characterized by relatively small challenges to mitigation and adaptation, SSP3 "Regional Rivalry" represents the most substantial challenges for mitigation and adaptation (O'Neill et al., 2017).

4 Data

We summarize our variables in Table 1. We select milk consumption data per capita, price index, and the value of milk industry between the years 2000 and 2020 from the FAO. We source income data, the share of people living in urban areas, and young population (ages 0-14 as percent of total population) data for all available countries between the years 2000 and 2020 from the World Bank Database. We obtain retail prices for 2011 and 2017 from the International Comparison Program (ICP) database, which we used together with the FAO milk price index to approximate consumer prices for the remaining years between 2000 to 2020. We calculate the influence of the milk industry per capita as Value of the milk industry divided by population data from the World Bank. We complement our data the trade openness indicator from the KOF Swiss Economic Institute.

For the projection part of the paper, we use the SSP database from International Institute for Applied Systems Analysis (IIASA) (K.C. et al., 2024). From their database, we selected the variable "GDP in PPP per capita", generated from the OECD.

5 Results

5.1 Optimal amount of clusters

We identified a total of six different clusters according the criteria of the lowest MIC (as described in Section 3.1). We display results for RSS and MIC as recommended in (Christodoulou & Sarafidis, 2017) in Table 2.

Variable	Source
Milk consumption per capita	FAOSTAT Food balance sheets
Milk price	Price index from FAO
	ICP commodity prices
Share of young population	World Bank Population ages 0-14 (% of total population)
Share of people living in urban areas	World Bank Urban population (% of total population)
Trade openness	Trade Globalisation, de facto (KOFTrGIdf)
Value of the milk industry	Gross Production Value of the milk production and Population
Income Predictions	SSP Database

Table 1: Variables used in this paper with respective source

Omega	Total RSS	MIC
1	148.736	-296.604
2	108.359	-325.712
3	82.626	-349.349
4	72.850	-355.560
5	67.934	-355.045
6	65.121	-351.221
7	56.019	-360.389

Table 2: The sum of residual squares (RSS) and the Model Information Criterion (MIC) for each Omega.

	Milk consumption in kg (log)						
	Full Model	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6
Price milk (in USD log)	-0.307***	0.450***	-1.085***	-0.370***	-0.511***	-0.155***	-0.385*
	(0.03)	(0.08)	(0.08)	(0.05)	(0.12)	(0.02)	(0.16)
GNI per capita (in USD log)	0.313***	-0.527***	1.084***	0.356***	-0.517***	0.154***	0.358**
	(0.03)	(0.09)	(0.08)	(0.05)	(0.13)	(0.02)	(0.13)
Share of young population (in percent)	0.275***	-0.913***	0.848***	0.285***	0.520	0.136**	2.387***
	(0.06)	(0.15)	(0.13)	(0.08)	(0.30)	(0.04)	(0.26)
Urbanisation (in percent)	-0.092	0.212	-1.370***	-4.358***	-0.459	0.296***	4.433***
	(0.09)	(0.20)	(0.19)	(0.19)	(0.25)	(0.07)	(0.40)
Trade openness (in percent)	0.860***	0.986***	1.729***	0.164	-1.030*	-0.528***	-0.261
	(0.11)	(0.26)	(0.33)	(0.15)	(0.50)	(0.09)	(0.52)
Value of the milk industry per capita (in USD log)	0.353***	-0.045	0.723***	0.100*	0.840***	0.205***	0.074
	(0.02)	(0.07)	(0.07)	(0.04)	(0.07)	(0.02)	(0.09)
N (Observations)	1897	212	178	390	231	734	152
N (Countries)	120	16	10	22	14	47	11
r2	0.366	0.704	0.798	0.802	0.826	0.370	0.806
bic	152.410	-92.608	-60.913	-207.623	63.562	-1086.006	65.647
aic	2.614	-183.235	-146.821	-314.709	-29.383	-1210.166	-15.998

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3: Cluster panel regression results for six clusters and the Full model for the time period yr2000 to yr2020. Standard errors are in parentheses.

5.2 Estimation results

We display the results for the full model and the six clusters in Table 3 as well as in Figure 2. We illustrate the country memberships to each cluster in Figure 1. We estimate milk consumption per capita/kg/year by the price, GNI per capita, the share of young population, urbanisation, trade openness, and the value of the milk industry per capita. The size of the cluster varies between 10 and 47 allocated countries. The full model for the example of milk consumption is displayed in the first column in Table 3. The full model is consistent with economic theory with a negative price and a positive income association on milk consumption per capita/kg/year. We find statistically significant positive associations of the share of the young population and trade openness on milk consumption per capita/kg/year. On a global level, urbanisation has a negative but statistically insignificant association on milk consumption per capita/kg/year.

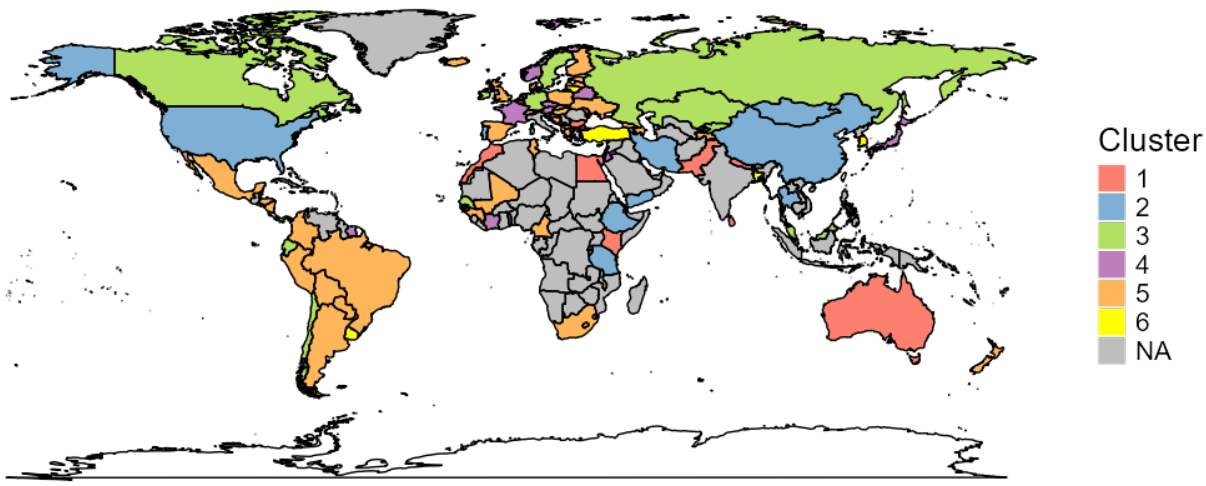

Figure 1: Graphical illustration of milk consumption driver cluster membership across the world for yr2000 to yr2020, Source: own compilation

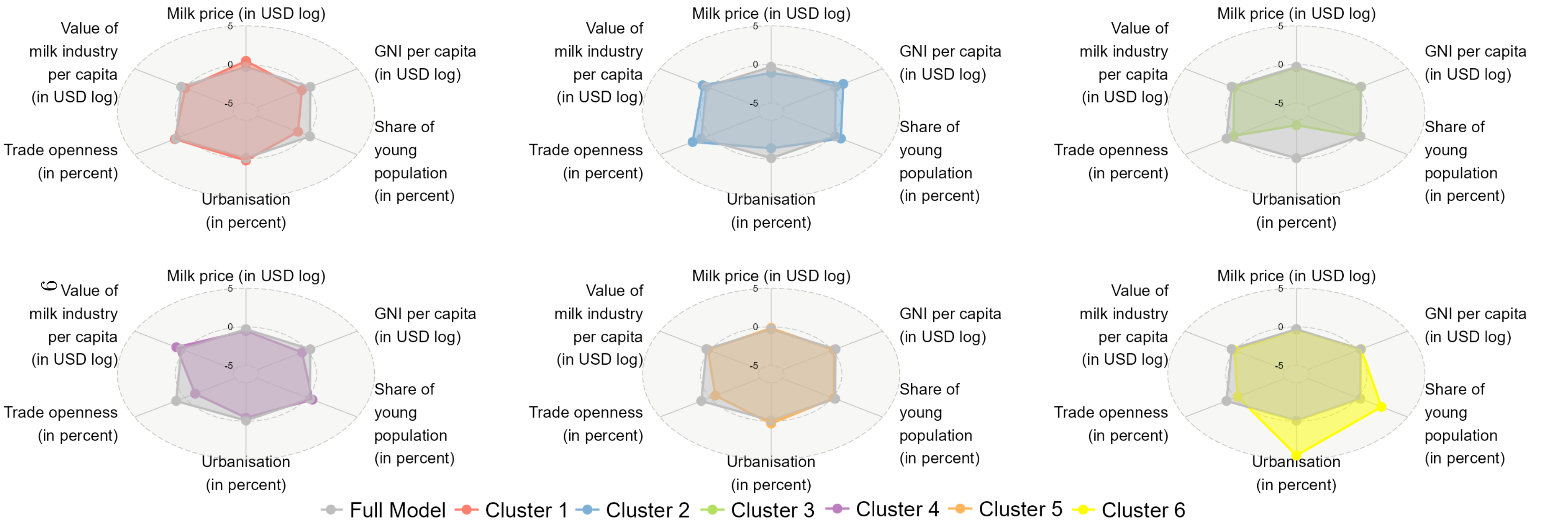

Figure 2: Coefficient estimates of milk consumption driver cluster membership across the world for yr2000 to yr2020, Source: own compilation

Cluster one entails 16 high milk consumption countries, such as Australia and Pakistan, but also some African countries (colored in red color in Figure 1). We display the regression results in the second column of Table 3. This cluster can be distinguished from other clusters by a negative and statistically significant association between the share of young population and milk consumption. This is the only cluster where milk consumption seems to be negatively affected by the value of the milk industry per capita, although this association in statistically insignificant. Contrary to economic theory, this cluster has reversed signs of the price and income elasticity (0.450 and -0.527 respectively).

The second cluster entails 10 countries in blue color in Figure 1 and the corresponding regression results are displayed in the third column of Table 3. These countries are characterized by being the most sensitive to price and income changes (-1.085 and 1.084 respectively) and geographically scattered around the world. As the estimated income elasticity exceeds unity, milk can be classified as luxury good for consumers in these countries. Interestingly, an increase in urbanisation rate is negatively associated with milk consumption per capita/kg/year. Another attribute of this cluster is that we find here the strongest positive association of trade openness and milk consumption per capita/kg/year.

Cluster three is described in the fourth column of Table 3 and illustrated in green colour in Figure 1, consisting of 14 countries mostly in the Northern hemisphere. These countries have the most negative and statistically significant association of urbanisation on milk consumption per capita/kg/year. Further, trade openness seems to have a positive but statistically insignificant association with milk consumption per capita/kg/year.

The fourth cluster is colored in purple in Figure 1 and quantified by the coefficients in column five in Table 3 and entails countries mostly in Europe. These countries are characterized by the highest association of the value of milk industry and milk consumption, while the positive association of share of young population and the negative association of trade openness are statistically insignificant. The negative income elasticity coefficient (-0.517) suggests that milk is an inferior good for these countries, meaning that with increasing income, consumers switch from milk to other (presumably more processed) dairy products.

Cluster five is the largest cluster, consisting of more than a third of all countries from the available sample. The countries are colored in orange in Figure 1 and described in the second last column of Table 3. Here we find statistically significant associations of all considered variables. We observe the lowest price and income elasticities in magnitude (-0.155 and 0.154 respectively). We find positive associations of the share of young population, urbanisation, and the milk industry but a negative association of trade openness on milk consumption per capita/kg/year.

The last cluster entails eleven countries in yellow color in Figure 1 and is the last column in Table 3. This cluster can be distinguished from other clusters because of the largest coefficient estimates in magnitude for the share of young population and urbanisation, while trade openness and the value of milk industry do not seem to relate too much to milk consumption per capita/kg/year.

In summary, we find heterogeneous associations of milk demand drivers across the globe. Price elasticities vary from -1.085 to 0.45. Income elasticities vary from -0.527 to 1.084, highlighting that milk seems to be an inferior good for consumers in Clusters 1 and 4, a normal good for consumers in Cluster 3, 5, and 6 and a luxurious good for consumers in Cluster 2. Cluster 4 and 5 share that they are both characterized by a negative association of urbanisation on milk consumption per capita/kg/year. Further, we find that for most of the clusters the value of the milk industry per capita has a positive association with milk consumption per capita/kg/year. These results are robust to different time periods. We find an equal amount of clusters for the time periods from year 2006 to 2015 and from year 2010 to 2020 (see Tables A2 and A3). The results are not robust to the time period from the year 2000 to 2010. There, we only identify three clusters, but most of the coefficients remain similar. We discuss this further in the discussion section.

5.3 Shapley decomposition

We calculate Shapley values, which show the relative importance of each feature to the R squared and are displayed in Table 4. Interestingly, we find that the the value of the milk industry per capita has the highest contribution to the R-squared for the full model and for all clusters besides the country-wise biggest Cluster 5. There, the share of young population has the biggest contribution to the R-squared. Surprisingly, the price variable has the second highest contribution to the R-squared only for the full model and Cluster 6. The income variable has the second highest contribution to the R-squared for Cluster 5. Otherwise, price and income variables do not seem to play an important role in explaining milk consumption per capita/kg/year.

	Full Model	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6
Urbanisation (in percent)	0.08	0.09	0.17	0.01	0.07	0.08	0.08
Share of young population (in percent)	0.03	0.04	0.06	0.11	0.14	0.28	0.03
GNI per capita (in USD log)	0.02	0.03	0.16	0.04	0.13	0.11	0.02
Trade openness (in percent)	0.01	0.01	0.01	0.02	0.00	0.04	0.01
Price milk (in USD log)	0.10	0.04	0.03	0.03	0.09	0.03	0.10
Value of the milk industry per capita (in USD log)	0.24	0.38	0.39	0.32	0.33	0.14	0.24

Table 4: SHAPley values for the full model and each cluster separately

5.4 Predictions

We further include income projections for five different scenarios for the year 2050 and the year 2100 in our estimations. We assume that other variables remain constant on the baseline year 2020. The results show similar coefficient sizes and significance levels across all scenarios and also for the years 2050 and year 2100. Regarding projections for the year 2050, most of the variables become statistically insignificant. The price variable, however, shows a negative association and the value of the milk industry shows a positive association with milk consumption, both variables are statistically significant. Regarding the results for the income projections for the year 2100, we find that the share of young population is statistically negatively associated with milk consumption except in the scenario SSP4.

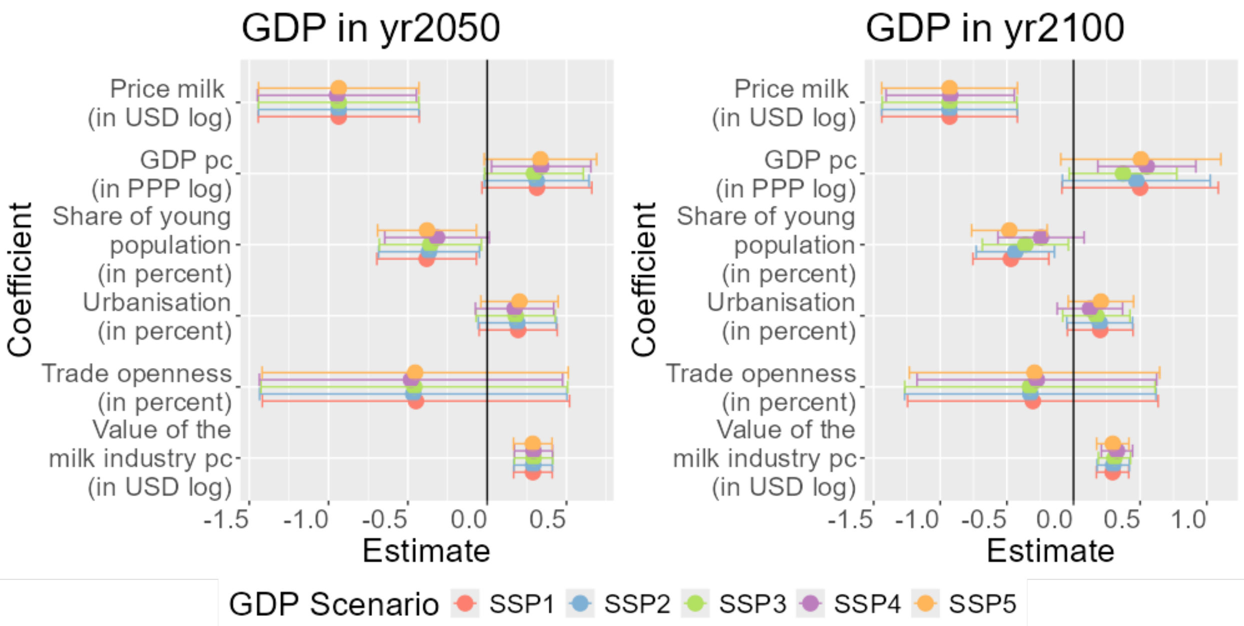

Figure 3: Regression results for GDP projections for the year 2050 (left) and the year 2100 (right) for different SSP scenarios.

6 Discussion

6.1 Choice of regressors

We base our inclusion on previous studies (Milford et al., 2019; McCullough et al., 2022) and data availability. We find that our model specification suffices for milk consumption, but the extension of the analysis to other dairy products such as yoghurts or cheese as well as other animal sourced foods should be accompanied by more sophisticate variables. The inclusion of the urbanization variable is contested in the literature. Several studies include urbanization in their food demand estimations (Ecker & Pauw, 2024) and acknowledge that urbanization affects animal source food consumption via circumstances that are accompanied with living in an urban environment, rather than urbanization itself (Milford et al., 2019; McCullough et al., 2022). These circumstances include different levels of physical activity levels, exposure to advertisement, or increased opportunity costs of food preparation at home (Cockx et al., 2018; Colen et al., 2018; Gouel & Guimbard, 2018). In case of fresh milk consumption, access to reliable electricity supply for refrigeration at home as well as access to modern retail venues that guarantee the cold chain are understood to be associated with increased milk consumption (Cheng et al., 2022).

Cheng et al. (2022) investigate income growth, employment structure, and the rise of modern markets as mediation channels of urbanization and dairy consumption for the case of Chinese residents using the Chinese Health and Nutrition Survey (CHNS) between the years 1989 to 2011. They find that income growth and transitioning from agricultural to non-agricultural employment serve as robust mediators between urbanization and dairy consumption. Modern markets do not seem to have a robust effect on milk consumption, and the authors attribute this circumstance to the Chinese consumers' consumption structure of dairy products (Cheng et al., 2022).

We hypothesize that milk consumption might be also driven by the amount of governmental support for the milk sector in each country. While there is some data about coupled and decoupled direct subsidies (in USD per 100 kg of milk) from the yearbooks of the International Farm Comparison Network (IFCN), we decided to exclude a subsidy variable in our present analysis due to low variance of the available data. Countries with the highest amount of decoupled and coupled subsidies throughout the years 2013 and 2019 are Norway, Switzerland, and Algeria with respectively 35.25, 33, and 15.75 USD per 100kg milk. In contrast, countries with the lowest subsidies for the same time period are Ireland, Denmark and Spain with 0.15, 0.1, and also 0.1 USD per 100kg of milk (IFCN, a,b,c,d,e,f,g).

Other studies found mixed effects of dairy subsidies on various outcome variabilities, such as profitability (Requena-i Mora & Barbeta-Viñas, 2023), technical efficiency (Latruffe et al., 2016), herd size (Petrick & Götz, 2019), or dairy product trade (Kondaridze & Luckstead, 2023). Concerning nine Western European countries in the period between the years 1990 and 2007, positive (negative) associations between subsidies and technical efficiency are found in Spain and Portugal (the UK and Belgium). For other countries, such as Germany and France, the study could identify further ambiguous associations (although statistically insignificant) (Latruffe et al., 2016). A study for the dairy sector in Russia and Kazakhstan revealed that current subsidy payments are not associated with heard growth (Petrick & Götz, 2019). Covering 49 exporting countries and 235 importing countries for a 17-year period between 2000 to 2016, another study found that a one percent increase in subsidies leads to a roughly 0.02 percent increase in trade for an average country. However, a lag policy analysis revealed that this effect vanishes after the second year of implementation and a lead-policy analysis showed that there seems to be an at least three year anticipatory effect.

6.2 The rising importance of plant based dairy alternatives

More recent studies about dairy demand in developed countries focus increasingly on also plant based dairy alternatives (PBDA) for Sweden (Huang, 2022), the US (Ghazaryanm et al., 2023; McCarthy et al., 2017; Wolf et al., 2020) or Europe (Hansen et al., 2023) as the per capita dairy consumption in the Western world is declining and the market share of PBDA is growing rapidly (Ramsing et al., 2023). In terms of the nutritional value, a recent study in the US found that nutritional values of soy milk are consistently comparable to the nutritional values of cow milk (Drewnowski, 2021).

Ghazaryanm et al. (2023) investigate whether dairy and PBDA are complementary or substitute products by using scanner data of US consumers. Conducting a weak separability test in an empirical demand system (LA-AIDS), they find that consumers do not distinguish between dairy and PBDA a priori. Additionally, calculated cross price elasticities suggest that dairy milk products are considered substitutes for PBDA. Dairy milk products seem to be overall substitutes for both, dairy products and PBDA. PBDA are complements to other PBDA (Ghazaryanm et al., 2023). Closely related to our work is a paper that analyses dairy and plant based alternatives demand in the US by conducting a k-means clustering analysis. Wolf et al. (2020) conducted a household survey in the US in order to link consumer preferences and various economic and demographic characteristics. They identify three distinct clusters according to the frequency of dairy and PBD alternative consumption. The most frequent dairy consumption cluster is characterized by the highest average age, highest share of male respondents, lowest household income, and smallest share of liberal political affiliation. This cluster indicated also a low willingness to substitute dairy with PBDA. Interestingly, the flexitarian cluster is characterized by the youngest average age, highest years of education, highest annual household income, and highest share of liberal political affiliation. The cluster with the most frequent consumption of PBDA is characterized by the highest share of female respondents, other demographic characteristics are always in between the most frequent dairy consumption and the flexitarian cluster. It is not surprising to observe the highest share of females in the most frequent PBDA consumption cluster since the consumption of animal source foods seems to be associated with masculinity (De Backer et al., 2020). Interestingly, the highest share of respondents where household member follow a vegetarian, vegan, or any diet are grouped to the flexitarian and not in the plant based cluster (Wolf et al., 2020). A paper from the year 2017 analysed the personal values towards the purchase of dairy vs PBD alternative beverages of almost thousand US consumers. Consumers who purchase exclusively PBD alternative beverages declared lower environmental footprints and animal welfare as reasons for their choice. Consumers who purchase cow dairy beverages perceived their purchase as staple food consumption (McCarthy et al., 2017).

Another study evaluated preferences towards PBDA of 3,086 responses across six European countries who are either showed interest in consuming or consumed PBDA already. Findings show that consumer who consume PB meat alternatives are more likely to consumer PBDA across all European countries. Consumers who actively informed themselves about food choices and product groups where more likely to consume PBDA more often in Germany, Denmark, and Poland and more likely to intend PBD alternative consumption in Spain and Italy. Organic food consumers were also more likely to consume PBDA in Spain and Italy, as perceived quality played a role for these consumer groups. Consumers seemed to be risk averse in terms of taste expectations as consumers with a strong preference for better taste were less likely to consume PBDA (Hansen et al., 2023).

6.3 Cluster analysis

We repeat the calculations for three time windows: years from 2000 to 2010, from 2005 to 2015, and from 2010 to 2020. The full models for each time window are displays in the first columns in Tables 3, A1, A2, and A3. We observe statistically significant associations of prices and incomes on milk consumption. The price elasticities range from -0.307 for the time period between the years 2000 to 2020 to -0.192 for the time period from 2010 to 2020. The income elasticities vary between 0.195 and 0.313. The magnitude of the coefficient estimate of the value of milk industry per capita is the smallest for the latest time period. The association of trade openness and the share of young population with milk consumption is positive across all time windows. The analysis of cluster formation for different time windows highlights the ambiguous association of urbanization on milk consumption. As mentioned earlier, we observe different amounts of clusters and cluster formation across consecutive time windows. While we find equally optimal amounts of distinct clusters for the time periods between the years 2005 and 2015 as well as 2010 and 2020, we only identify three clusters for the time period between the years 2000 and 2010. We hypothesize that this could be attributed to the time trend, and that drivers of milk consumption patterns diverged increasing with time.

Unfortunately, panel data is scarce for countries located in Sub Saharan Africa. Cluster analysis could help to predict cluster memberships in the absence of complete panel data, which could be a promising avenue for future research. If Shapley values reveal that variables, where data is missing, are less important for predicting cluster membership than variables, were data is available, one could infer cluster membership in the absence of data.

7 Conclusions

We apply a panel regression clustering approach to classify global milk consumption and summarize milk demand drivers in six different clusters. When decomposing the R-squared, we find high importance of the value of the milk industry per capita of a country and low relative importances of price and income variables. While milk can be classified as a normal good for consumers in the majority of countries (n=80), milk seems to be an inferior good for consumers in 30 countries, and a luxurious good for consumers ten countries. Our work suffers from several limitations such as the restriction to only milk (and not dairy or other animal source foods), or the lack of potentially important demand shifters. Our findings could contribute to more reliable estimates for global food demand projections. The results can serve as a basis for estimations of global fiscal climate change mitigation policies, such as a climate motivated tax on food. The above mentioned ranking of demand shifters as well as differences in income elasticities should be taken into account when simulating fiscal climate change mitigation policies. Future research about global food demand and simulations of fiscal should further exploit the potentials of cluster analysis in order to design effective climate change mitigation policies.

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Appendix

	Milk consumption in kg (log)			
	Full Model	Cluster 1	Cluster 2	Cluster 3
Price milk (in USD log)	-0.266***	-0.218***	0.156	-0.653***
	(0.04)	(0.03)	(0.15)	(0.08)
GNI per capita (in USD log)	0.267***	0.218***	-0.109	0.355***
	(0.04)	(0.03)	(0.11)	(0.09)
Share of young population (in percent)	0.180*	-0.117	1.085***	1.063***
	(0.08)	(0.06)	(0.27)	(0.19)
Urbanisation (in percent)	0.055	-0.380***	-2.309***	1.098***
	(0.12)	(0.09)	(0.37)	(0.29)
Trade openness (in percent)	0.599***	-0.010	1.469***	0.226
	(0.13)	(0.11)	(0.36)	(0.26)
Value of the milk industry per capita (in USD log)	0.252***	0.068***	0.149	0.562***
	(0.03)	(0.02)	(0.11)	(0.06)
N (Observations)	1061	571	197	293
N (Countries)	111	61	21	29
R2	0.377	0.394	0.703	0.587
BIC	-729.164	-1033.080	-84.056	-99.449
AIC	-813.603	-1106.986	-139.870	-162.012

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A1: Cluster panel regression results for three clusters and the full model for the time period yr2000 to yr2010. Standard errors are in parentheses.

	Milk consumption in kg (log)						
	Full Model	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6
Price milk (in USD log)	-0.267***	-0.390*	-0.238***	-0.011	-0.095	0.057	0.023
	(0.06)	(0.18)	(0.04)	(0.29)	(0.09)	(0.05)	(0.16)
GNI per capita (in USD log)	0.288***	0.135	0.251***	-0.376	0.292*	-0.320***	0.014
	(0.06)	(0.29)	(0.05)	(0.55)	(0.13)	(0.07)	(0.15)
Share of young population (in percent)	0.614***	1.414**	-0.302**	1.895	0.675	0.321*	0.733*
	(0.16)	(0.51)	(0.10)	(0.99)	(0.43)	(0.14)	(0.34)
Urbanisation (in percent)	-0.115	-6.941***	-0.855***	-0.588	-3.251***	-1.105***	-1.036
	(0.27)	(1.11)	(0.18)	(2.56)	(0.50)	(0.19)	(0.72)
Trade openness (in percent)	0.837***	-0.390	0.324	-0.112	0.368	0.789***	-2.343*
	(0.25)	(0.86)	(0.20)	(1.02)	(0.44)	(0.16)	(0.91)
Value of the milk industry per capita (in USD log)	0.265***	0.569***	0.078*	-0.100	0.435***	0.153**	0.001
	(0.05)	(0.11)	(0.04)	(0.20)	(0.09)	(0.06)	(0.12)
N (Observations)	906	115	264	48	115	234	130
N (Countries)	108	13	35	7	13.000	26	14
R2	0.384	0.857	0.377	0.964	0.581	0.703	0.790
BIC	70.683	33.588	-514.173	3.897	-70.034	-429.085	-38.891
AIC	-6.261	-10.331	-571.388	-26.043	-113.953	-484.370	-84.772

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A2: Cluster panel regression results for three clusters and the full model for the time period yr2006 to yr2015. Standard errors are in parentheses.

	Milk consumption in kg (log)						
	Full Model	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6
Price milk (in USD log)	-0.192***	-0.207***	-1.589**	0.034	-0.375***	-0.005	-0.184*
	(0.04)	(0.04)	(0.52)	(0.04)	(0.08)	(0.30)	(0.08)
GNI per capita (in USD log)	0.195***	0.161***	1.311*	-0.115	0.203*	-0.980**	0.217*
	(0.04)	(0.04)	(0.57)	(0.06)	(0.09)	(0.29)	(0.10)
Share of young population (in percent)	0.065	-0.121*	7.568**	0.947***	-1.878***	-1.633	1.261***
	(0.07)	(0.06)	(2.03)	(0.11)	(0.18)	(1.04)	(0.17)
Urbanisation (in percent)	-0.343*	-0.630***	2.190	1.484***	-2.070***	2.563	2.139***
	(0.15)	(0.13)	(1.59)	(0.19)	(0.26)	(2.11)	(0.37)
Trade openness (in percent)	0.325*	-0.382**	-1.266	0.304	0.380	2.397*	-0.281
	(0.13)	(0.12)	(1.65)	(0.18)	(0.23)	(1.10)	(0.24)
Value of the milk industry per capita (in USD log)	0.246***	0.252***	1.361*	0.175**	0.205***	1.283***	0.024
	(0.03)	(0.04)	(0.51)	(0.05)	(0.04)	(0.32)	(0.07)
N (Observations)	836	309	40	153	172	44	118
N (Countries)	104	38	4	18	22	7	15
R2	0.186	0.359	0.828	0.560	0.627	0.825	0.801
BIC	-1133.004	-715.375	7.722	-366.796	-366.973	-17.669	-247.769
AIC	-1208.662	-775.108	-19.300	-415.283	-417.333	-46.216	-292.100

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A3: Cluster panel regression results for three clusters and the full model for the time period yr2010 to yr2020. Standard errors are in parentheses.