Globalisation and national trends in nutrition and health - a grouped fixed effects approach to inter-country heterogeneity

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August 2016

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We are grateful for financial support from the INRA Metaprogrammes Did'it and Glofoods.

Abstract

This paper estimates the effect of globalisation on nutritional components of the diet and health outcomes using a panel dataset of 70 countries spanning 42 years (1970-2011). Our key methodological contribution is the application of the grouped fixed effects estimator developed by Bonhomme and Manresa (2015), which enables us to better control for unobserved time-varying heterogeneity. Our results indicate that a one standard deviation increase in the index of social globalisation is associated with an increase of animal protein of about 20.4%. In contrast, economic globalisation has no effect on the composition of the diet. Moreover, we do not find significant effects on diabetes prevalence or mean Body Mass Index. Our findings indicate that social aspects of globalisation, such as food advertising, deserve greater attention in the nutrition transition discourse.

Keywords: nutrition transition, globalisation, overweight, grouped fixed effects

1 Introduction

Globalisation has substantially altered food systems around the world, yet consequences for nutrition and health are not well understood. This paper estimates the relationship between globalisation, food supply, and health outcomes for a large sample comprising 70 high and middle income countries between 1970 and 2011.

Not only has food supply significantly increased over the past 40 years but the composition of the diet has been undergoing a profound shift. Diets have become less dominated by carbohydrates[1] while intake of animal protein, animal fat, and free fat[2] has been increasing.

While this nutrition transition has advanced the most in high income countries, the transition speed is faster in middle income countries. Figure 1 shows that the amount of energy (kcal/capita/day) derived from animal protein rose by 70% (from 80.7 to 137.4) in upper and by 33% (from 603 to 79.9) in lower middle income countries compared to 25% (from 194.0 to 243.3) in high income countries.
Similarly, figure 2 reveals that vegetable fat is increasingly replaced by free fat and animal fat. Supply of of free fat doubled (from 190.1 to 382.0) in upper middle income countries and rose by 78% (from 135.4 to 240.8) in lower middle income countries while it only increased by 30% (from 446.5 to 578.6) in high income countries. Supply of animal fat also increased but to a smaller extent than free fat. Finally, supply of sugar grew by 25% in lower middle and by 23% in upper middle income countries compared to no significant change in high income countries since 1970 (see figure 3).

The nutrition transition constitutes an important risk-factor for non-communicable diseases such as cardiovascular diseases (CVD) and diabetes. High intakes of fat and sugar contribute to overweight, which in turn is an important risk factor for diabetes and CVD (WHO, 2015b). In 2012 17.5 million people died from CVD ranking them as the number one cause of death globally. More than three quarters of CVD deaths take place in low- and middle-income countries causing substantial economic costs (WHO, 2015a). As a consequence, the World Health Organisation (WHO) regards obesity and related diseases as a growing threat all over the world replacing traditional public health concerns such as undernutrition and infectious diseases (WHO, 2000).

[1] Carbohydrates are sugars, and starches found in fruits, grains, and vegetables. Products rich in carbohydrates are cereals, pasta, rice, bread, corn, peas, and lentils.

[2] We classified oil, butter, and cream as free fats, as these are not part of a food item but individuals can choose the quantity of free fats in their diet.

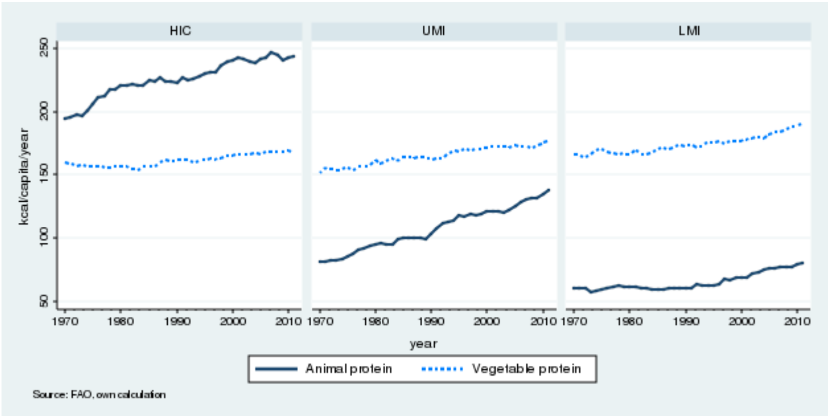

Figure 1: Composition of protein supply by income group, 1970-2011

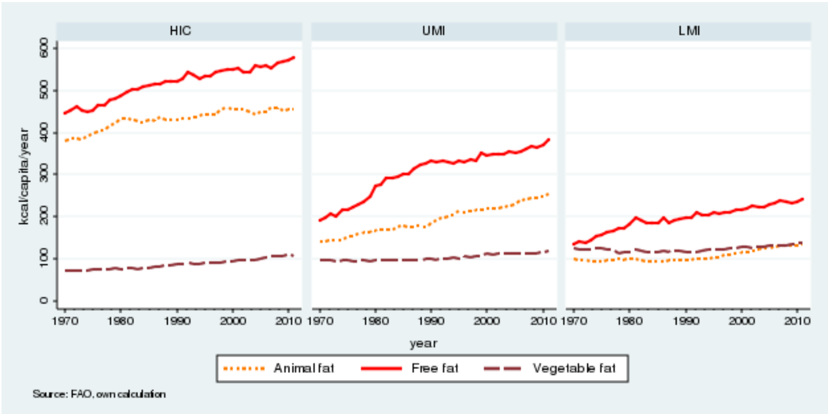

Figure 2: Composition of fat supply by income group, 1970-2011

Globalisation has been held responsible for the nutrition transition (Hawkes, 2006; Popkin, 2006; Bishwajit et al.). The existing evidence for this claim, however, consists mostly of case studies linking observed changes in diets to free trade agreements (Hawkes and Thow, 2008; Thow and Hawkes, 2009; Thow et al., 2011) and trends in foreign direct investments (FDI) in the food industry (Hawkes, 2006). These case studies typically solely focus on economic aspects and fail to take into account the multifaceted nature of globalisation.

However, theoretical work from Olivier et al. (2008) suggests that it is crucial to separately analyse economic and social facets of globalisation and its impact on diets. In their model, a cultural good (e.g. a country's cuisine) has in addition to an economic value also a positive cultural externality. This cultural externality increases the more people belong to this culture because it reinforces a sense of belonging and facilitates social exchange within the community.

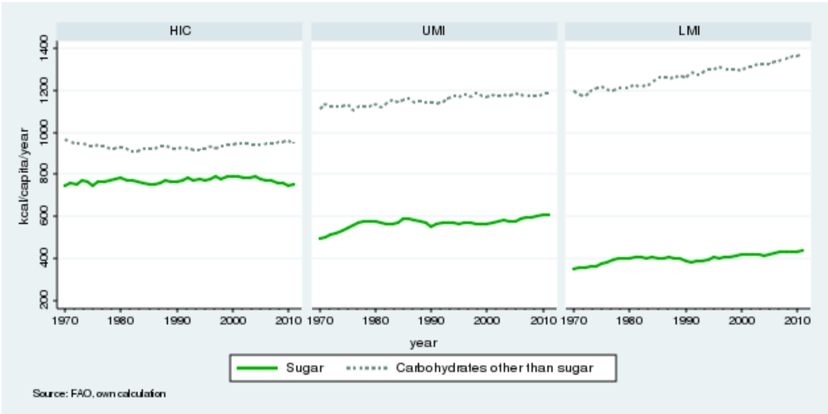

Figure 3: Composition of carbohydrates supply by income group, 1970-2011

The model predicts two opposing effects of economic and social integration. Economic integration causes cultural divergence across countries. As a consequence of economic integration individuals face the world market price for the cultural good, which is lower than the price under autarky because the local economy does not have a comparative advantage in producing this cultural good. The reduction in price increases demand for the cultural good. With more individuals consuming this cultural good and thus belonging to this culture its cultural externality increases, which makes the cultural good even more attractive. In the long-run, everyone in the country consumes the same cultural good, so economic integration leads to cultural homogeneity within a country and cultural divergence across countries.

In contrast, social integration causes cultural convergence across countries. The most frequently consumed cultural good under autarky experiences a decline of its attached cultural externality when the country becomes socially integrated into the world. This is the case because the worldwide share of people consuming this cultural good is lower than the share in the domestic country. Consequently, individuals in the domestic country reduce their consumption because they perceive the price of this cultural good as too high given its now lower value of cultural externality. The same process happens analogously in other countries so that overall, the dominance of a specific culture in a country declines and the countries become more culturally diverse.

Considering model predictions of Olivier et al. (2008), we use the KOF Index of globalisation constructed in Dreher (2006) which allows us to separately analyse the effect of the social and economic dimension of globalisation. In order to better control for unobserved time-varying heterogeneity we use the Grouped Fixed Effects (GFE) estimator developed by Bonhomme and Manresa (2015). The GFE estimator endogenously groups countries together that share similar time profiles of food supply. Thereby, we can control for time-varying unobserved heterogeneity that is common within groups of countries.

Our results suggest that social globalisation has a positive and significant effect on the supply of animal protein but no effect on free fat or sugar. The magnitude of the effect on animal protein is considerable, as a one standard deviation increase in the index of social globalisation is associated with an increase of energy (kcal/capita/day) derived from animal protein of 20%. In contrast, economic globalisation has no significant effect on the composition of the diet. Moreover, we document a relatively strong convergence trend across countries for animal protein, and to a lesser extent for free fat and sugar.
Subsequent analysis suggests that the effect of social globalisation on animal protein is stronger for richer countries. Moreover, the positive effect of social globalisation seems to be driven by personal contacts with foreigners and information flows via telephone and TV.
Regarding health outcomes, we do not find significant effects of social or economic globalisation on diabetes prevalence and mean Body Mass Index (BMI).

Our paper contributes to the following strands of literature.
First, this paper is most closely related to a recent study from Costa-i-Font and Mas (2014) who estimated the effect of globalisation on calorie intake and obesity using data from 26 mostly OECD countries from 1989 until 2004. Results of their pooled ordinary least-squares (OLS) regression suggest that globalisation is positively associated with calorie intake.
We make a methodological contribution by applying the grouped fixed effects estimator, which allows us to better control for unobserved time-varying heterogeneity than pooled OLS. For example, food advertising expenditure is likely to be correlated with globalisation (e.g. number of households with television) and has been found to be positively associated with absolute calorie intake (Folkvord et al., 2016; Pettigrew et al., 2013). Moreover, we contribute to this literature by separately analysing the effect of social and economic globalisation on the composition of the diet.

Second, this paper relates to the literature on the relationship between overweight and globalisation. Three studies (Costa-i-Font and Mas, 2014; Miljkovic et al., 2015; Vogli et al., 2014) use country-level data on BMI and overweight between 1980 and 2008. Goryakin et al. (2015) pooled Demographic Health Surveys and restricts its sample to women. Using country fixed effects[3] these studies conclude that the effect of social globalisation is positive and significantly larger in magnitude than the effect of economic globalisation.
Results on the effect of economic globalisation are mixed. Two studies (Vogli et al.,

[3] Costa-i-Font and Mas (2014) used pooled OLS

2014; Miljkovic et al., 2015) report a positive effect of economic globalisation on overweight. But Goryakin et al. (2015) documents a small negative significant effect for women. These contradicting findings are likely to stem from different samples, time periods, and (non-)inclusion of individual covariates.
We add to the literature by better controlling for time-variant unobserved heterogeneity. Moreover, to the best of our knowledge this is the first study analysing the effect of globalisation on diabetes prevalence.

The rest of the paper is structured as follows. Section two describes data and section three the estimation strategy. Results and discussion are presented in sections four and five. Section six concludes.

2 Data

2.1 Food supply data

Given that we observed the strongest trends for animal protein, free fat, and sugar, we restrict our attention to these three outcome variables. These dietary components are also particularly associated with negative health outcomes. High intake of sugar increases the risk of type two diabetes and overweight (Imamura et al., 2015; Te Morenga et al., 2013). Animal fat and free fats are associated with increased risk of coronary heart disease mortality (de Souza et al., 2015; Leren, 1968), and animal protein elevates the risk of type two diabetes (Malik et al., 2016).

The per capita food supply, expressed in kilocalories (kcal) per day, is a measure of the average number of calories available for human consumption, including all food groups. We obtained these data from the food balance sheets of the FAO for the time period of 1961 until 2011[4]. A food balance sheet indicates total supply by reporting the total quantity produced of each basic food item, adjusted for imports. On the utilisation side, a distinction is made between quantities exported, fed to livestock, used for seed, losses during storage and transportation, and food supply available for human consumption. However, the amount of food actually consumed may be lower depending on the degree of losses in the household.
In addition to the kilocalories available for human consumption of each food item, the dataset also contains the amount of fat and protein (grams/capita/day) of each food item, which we subsequently converted into kcal/capita/day.
In a second step, we determined for each food item its dominant type of fat and

[4] We drop data for the years 2012 and 2013 because they contain a large number of missing values. Access to FAO balance sheet data: http://faostat3.fao.org/download/FB/FBS/E

protein. More precisely, we divided proteins into vegetable and animal proteins according to their source. For fat, we differentiated between animal and vegetable origin and distinguished these from free fats that are not bound in a product. In particular, we classified vegetable oils, fish oil, butter, and cream as free fats. Finally, we separated sugar from other carbohydrates.

2.2 Health outcomes

For health outcomes we focus on diabetes prevalence and BMI. Data was obtained from the Global Burden of Metabolic Risk Factors of Chronic Diseases Collaborating Group, which is a worldwide network of clinical and public health researchers[5]. The dataset covers the time period of 1980 to 2008 and is constructed by collecting data from health examination surveys and epidemiologic studies. The researchers used a Bayesian hierarchical model to estimate mean BMI and diabetes prevalence over time, by age group, sex, and country. Final data is age-standardised corresponding to the 2000-2025 world population (Finucane et al., 2011).

The BMI is a simple index of weight-for-height that is commonly used to classify overweight and obesity in adults. It is defined as the weight in kilograms divided by the square of the height in metres (kg/m^2). Diabetes is defined as having a mean fasting plasma glucose value of 7.0 mmol/L or greater, or use of a glucose-lowering drug.

2.3 KOF Index of globalisation

Globalisation is a global process including "economic integration, transfer of policies across borders, transmission of knowledge, [and] cultural stability" (Al-Rodhan and Stoudmann, 2006). We use the KOF Index of globalisation developed by Dreher (2006)[6], as it allows us to distinguish between the social and economic dimension of globalisation. This is important in order to test the model predictions of Olivier et al. (2008).

The variables social and economic globalisation take values on a scale from 1 to 100 and higher values indicate a higher level of globalisation. Economic globalisation consists of two sub-dimensions: Data on actual flows (1) which includes trade, foreign direct investments, portfolio investment, and income payments to

[5] We thank the research group for sharing their data. Access to data: https://www1.imperial.ac.uk/publichealth/departments/ebs/projects/eresh /majidezzati/healthmetrics/metabolicriskfactors/.

[6] We thank the KOF team for sharing their data. Access to data: http://globalisation.kof.ethz.ch/.

foreign nationals. The second sub-dimension consists of data on trade openness (2) measured by an index of hidden import barriers, mean tariff rate, taxes on international trade, and capital account trade openness.
Social globalisation is also constructed as a composite index with three sub-dimensions. It contains data on personal contacts (1) measured by telephone traffic, transfers, share of foreign population, and international letters. The second sub-dimension is data on information flows (2) including Internet users per day, television, and trade in newspapers. The final sub-dimension of social globalisation is data on cultural proximity (3) consisting of the number of McDonald's restaurants and Ikea stores as well as trade in books.

Over the past 40 years globalisation has intensified across the world. Figure 4 shows that all countries experienced a sharp upwards trend of globalisation since the 1990s. Interestingly, we observe a parallel increasing trend for both dimensions of globlisation while the model of Olivier et al. (2008) predicts that economic and social globalisation have opposing effects on the diet.

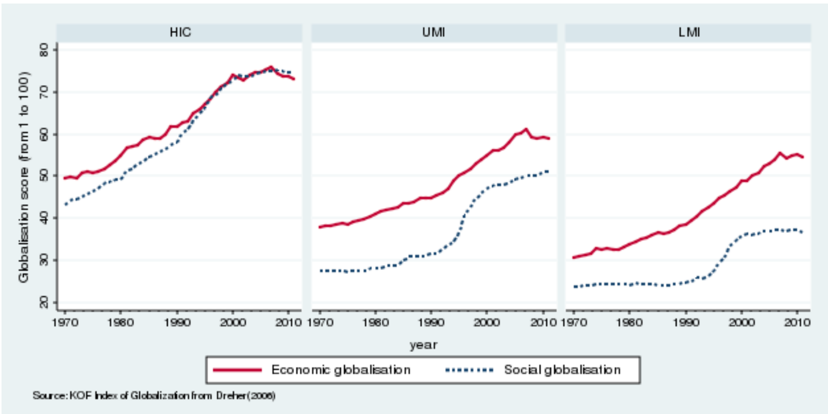

Figure 4: Social and economic globalisation by income group, 1970-2011

Social and economic globalisation exhibit a high correlation of about 0.84 and the sub-dimensions cultural proximity and information flows are also strongly correlated (0.74). In order to rule out that coefficients are unstable because of multicollinearity, we verified that all of our variables exhibit a variance inflation factor substantially smaller than the rule of thumb of 10.

2.4 Descriptive Statistics

Our estimation sample includes 2940 observations from 70 countries. We dropped all countries containing missing values in any of the outcome variables or covariates.

Consequently, this balanced sample contains 42 observations for every country, from 1970 until 2011 and covers 76% of the worldwide population. 40% of the countries in our sample are high income countries and 60% are middle income countries.

Table 1 reports the descriptive statistics for all variables. On average 143 kcal/capita/day are derived from animal protein, 359 kcal/capita/day from free fat, and 598 kcal/capita/day from sugar. In our sample, the mean score of economic globalisation is 52 points and higher than social globalisation (44 points) on a scale from 0 to 100. Mean GDP per capita is about 10,500 USD.

In order to estimate the effect of globalisation on health outcomes, the sample has to be reduced to the time period 1980 to 2008 resulting in a sample size of $N = 2494$[7]. In our sample around 8% of the population suffer from diabetes. Mean BMI is 24.5, which is slightly lower than the cut-off point of $>= 25$ for overweight as defined by the WHO (WHO, 2015b).

Table 1: Summary Statistics, nutrition sample

	Mean	SD	Min	Max
Outcome variables				
Animal protein (kcal/capita/day)	143.03	85.26	22.00	422.72
Free fat (kcal/capita/day)	358.81	194.75	16.92	975.33
Sugar (kcal/capita/day)	598.14	211.65	71.49	1077.74
Covariates				
Social globalisation	44.06	20.65	6.83	92.31
Personal contacts	48.61	19.43	8.81	90.61
Information flows	51.65	21.11	4.40	97.83
Cultural proximity	31.53	30.58	1.00	95.95
Economic globalisation	52.14	17.17	17.27	97.09
GDP per capita[a]	10.50	13.22	0.14	69.09
Income groups				
High income	0.41	0.49	0	1
Upper middle income	0.27	0.44	0	1
Lower middle income	0.31	0.46	0	1
Sample				
Number of countries	70			
Number of years	42			
N	2940			

[a] GDP per capita (constant 2005 in 1000 USD).

[7] see table 6 in the Appendix for summary statistics of the smaller health outcome sample.

3 Estimation strategy

3.1 Grouped Fixed Effects (GFE) estimator

Our objective is to estimate the relationship between globalisation, the composition of the diet, and health outcomes. The main challenge for our identification strategy are unobservable country characteristics that affect a country's level of globalisation as well as its food supply. For example, cultural norms and unobserved trends in food innovation may both affect a country's openness and its dietary habits.

A common solution to this problem is the application of country and year fixed effects that control for time-invariant unobservable country characteristics as well as time trends common for all countries. This approach implies the relatively strong assumption that all unobserved country characteristics are constant over time and that year-specific characteristics are common to all countries.

A less restrictive approach is the grouped fixed effects (GFE) estimator developed by Bonhomme and Manresa (2015). The GFE estimator relaxes the strict assumption that year-specific shocks are common to all countries. It only requires that year-specific characteristics are common to all countries within a group. Yet, across groups the year-specific characteristics can differ.
In practise, countries in the sample are first allocated into different groups. Then, in the regression equation, each group dummy is interacted with each year dummy. Thereby, the GFE estimator can control for unobservable time-varying country characteristics that follow a group-specific time pattern. The main identifying assumption is that the number of distinct country-specific time patterns of unobserved heterogeneity is equal to the number of groups. In other words, all countries have to follow one of the group specific time-varying paths of unobserved heterogeneity.

For our research question, the GFE estimator constitutes an attractive alternative to a country and year fixed effects model. It allows for year-specific shocks that are different across groups of countries. It is plausible to assume that not all countries faced the same year-specific shocks but rather that clusters of countries experienced similar developments over time.
For example, in the early 1990s, the former "Eastern Block" countries opened their markets and became exposed to "Western diet" at roughly the same time. Similarly, expansion of supermarkets in the developing world occurred in several waves starting in the 1990s. The first wave hit major cities in richer countries in Latin America. 10 years later supermarkets entered the markets of countries in East and South-east Asia, and poorer countries in Latin America (Reardon et al., 2003).

Our regression equation takes the following form:

$$y_{it} = \beta_1 globalisation_{it} + \beta_2 GDPpc_{it} + \beta_3 (GDPpc_{it})^2 + \alpha_{g_i t} + v_{it},$$

where y_{it} denotes the outcome variables for country i and year t. In particular, we have three outcome variables, the log of animal protein (1), free fat (2), and sugar (3). Our coefficient of interest is β_1 indicating the effect of globalisation on food supply while controlling for GDP per capita and GDP per capita squared[8]. We use two main indicators for globalisation, namely social globalisation and economic globalisation. $\alpha_{g_i t}$ denotes the group-specific time fixed effect which includes group fixed effects as well as year fixed effects. v_{it} denotes the error term.

3.2 Estimation procedure

An important feature of the GFE estimator is that group membership is not predetermined (e.g. classification according to income groups) but group membership is estimated according to a least-squares criterion. More precisely, countries whose time profiles of the outcome variable - net of the effect of covariates - are most similar are grouped together. The number of groups g must be small compared to the number of countries.

Bonhomme and Manresa (2015) propose two heuristic algorithms for sorting the countries into groups. Algorithm 1 is a clustering algorithm consisting of two alternating steps. Algorithm 2 uses a variable neighbourhood search method, which significantly reduces computation time. Moreover, Bonhomme and Manresa (2015) demonstrate that algorithm 2 is also more reliable than algorithm 1 as it correctly identifies the global minimum even with a large number of groups[9]. This mitigates the concern that heuristic methods can lead to non-optimal solutions.

Algorithm 1
Algorithm 1 is a clustering algorithm. It coincides with the k-means algorithm, if the model has no covariates (when $\theta = 0$) and it alternates between two steps.

Step 1 - assignment step
In the beginning, a starting value of the parameter values (θ^0, α^0) is chosen.

[8] The GDP per capita variable is obtained from the World Development Indicators database published by the World Bank. Access to data: http://data.worldbank.org/data-catalog/world-development-indicators.

[9] Bonhomme and Manresa (2015) show that the heurisitc algorithm 2 yields the same objective function and grouping than exact algorithms such as the repetitive branch and bound algorithm of Brusco and Steinley (2007) or the column generation algorithm of (Aloise et al., 2012) even when $G = 10$.

Countries are sorted into groups by minimizing the sum of squared residuals over all years for each country i:

$$g_i = \text{argmin}_{g\in\{1,\ldots,G\}} \sum_{t=1}^{T} (y_{it} - x_{it}\theta - \alpha_{gt})^2$$

In the case of 42 years and 2 groups, for each country the residuals are computed 42 times while assuming the country is sorted into group 1 and hence using α_{1t}. The residuals across all 42 years are then summed and compared to the sum obtained when repeating this exercise using α_{2t}, that is assuming that this particular country had been sorted into group 2 instead of group 1. Finally, the country is sorted into that group in which it achieved the smallest sum of residuals over these 42 years. This assignment step thus results in an initial grouping g_i^s where $s = 0$.

Step 2 - update step
In the update step the initial grouping g_i^0 is used to estimate a new set of coefficients $(\theta^{s+1}, \alpha^{s+1})$. Then, s is set to $s = s+1$ initializing a new assignment step. Algorithm 1 thus alternates between an assignment step and an update step. This loop stops when the difference between the old and the new coefficients is close to zero.

The drawback of algorithm 1 is that the solution depends on the initial starting value. In order to ensure a reliable solution the entire exercise is simulated many times where a different starting value is chosen for each simulation This can result in very long computation times.

Algorithm 2
Given this drawback of algorithm 1 Bonhomme and Manresa (2015) propose the more efficient algorithm 2 that incorporates a variable neighbourhood search method.

Step 1 - starting value of parameters
First, a starting value of the parameters (θ^0, α^0) is chosen and algorithm 1 is used to obtain an initial grouping of the countries γ_{init}.

Step 2 - neighbourhood jump
The key feature of algorithm 2 is the inclusion of a neighbourhood jump, where n countries are randomly reallocated to n randomly selected groups to obtain a new grouping γ'. These random jumps allow for an efficient exploration of the objective function. In the beginning $n = 1$, so only one country is reallocated to another group. The newly obtained grouping γ' is then used to perform an update step to obtain new parameter values (θ', α').

Step 3 - local search
With these new parameter values (θ', α') algorithm 1 is applied. Then, a local search is performed in order to assure that algorithm 1 found the best local solution.

To this end every country i is subsequently re-assigned to all groups except its 'own' group. For example, in the case of 3 groups algorithm 1 finds the optimal solution that country A is grouped into group 1. Then, the local search re-assigns country A to group 2 and subsequently to group 3 and checks every time whether the objective function of country A decreases as a result of this re-assignment.
If this local search results in any improvement of the objective function, the resulting new grouping is labelled γ'' and the initial grouping is set to $\gamma_{init} = \gamma''$. Subsequently, step 2, the neighbourhood jump, is repeated by keeping n constant, followed by a new local search.
If the local search does not lead to any re-assignment we can be sure that algorithm 1 found a local minimum. In a next step, the neighbourhood jump is repeated by setting $n = n + 1$. This means that now 2 countries are randomly reallocated to 2 randomly selected groups.

Steps 2 and 3 are performed $iter_{max}$ times by setting n back to $n = 1$ once $neigh_{max}$ has been reached. For algorithm 2 the choice of starting values of the parameters is less important than for algorithm 1. Therefore, following Bonhomme and Manresa (2015), we run algorithm 2 with $N_s = 10$, where N is the number of starting values[10].

Given that algorithm 2 delivers faster and more reliable estimates than algorithm 1 we use algorithm 2 for our main results and set N_s,$neigh_{max}$, and $iter_{max}$ all equal to 10. In order to account for the fact that group membership has been estimated the variance covariance matrix is computed by using bootstrapping with 100 replications[11]. Group-specific coefficients are obtained with algorithm 1 with 2000 simulations[12].

3.3 Choice of the number of groups

The choice of the optimal number of groups is a balancing task. While a higher number of groups reduces the objective function it increases the potential for overfitting (Brusco et al., 2008). In order to determine the optimal number of groups we estimated our main regression for $G = 1$ until $G = 12$ and calculated the Bayesian information criterion (BIC)[13]. The BIC assesses the overall fit of a

[10] In contrast, we run algorithm 1 with $N = 2000$ starting values.

[11] Bootstrapped standard errors are obtained by setting $neigh_{max} = 10$,$N_{sim} = 5$, and $iter_{max} = 5$

[12] To this end we converted the Matlab code "Heterogenous_coeffB.m" provided by Bonhomme and Manresa (2015) into a Stata do file, which is shared on request.

[13] $BIC(G) = \frac{1}{NT} * Objectivefunction_G + \hat{\sigma}^2 \frac{GT+N+K}{NT} ln(NT)$ where G is the number of groups, $Objectivefunction_G$ is the sum of squared residuals of the regression with G groups, N is the number of countries in the sample, T is the number of years, and K is the number of covariates.

model and introduces a penalty term for the number of parameters.
Bonhomme and Manresa (2015) checked the performance of the BIC for the GFE estimator and concluded that it performs reasonably well. In particular, they find that the BIC provides an upper bound on the true number of groups, if T (years) grows at a slower rate than N (countries), which is the case for our sample.

Tables 7,8, and 9 show that the specification with $G = 9$ number of groups yields the lowest BIC for all 3 outcome variables. We thus regard $G = 9$ as the upper bound of the true number of groups. Next, we analyse the stability of the coefficients. Figure 5 shows that the values of the coefficients do not vary much between $G = 6$ and $G = 9$. Moreover, with $G = 6$ groups the objective function decreased already by about 80% compared to OLS. A further increase of the number of groups does not cause a further significant improvement of the objective function. Given these indicators, we choose $G = 6$ as our optimal specification. Conducting the same analysis for our health outcome variables we chose $G = 8$[14].

Interestingly, the second to last row of tables 7,8, and 9 show that the objective function of grouped fixed effects regressions is lower than the one of country and year fixed effects as soon as $G \geq 6$. This suggests that some cross-country heterogeneity is time-varying in our sample.
The last row shows the objective function when grouping countries into high, upper middle and, lower middle income countries. The value of the objective function is substantially larger suggesting that grouping according to income does not capture much of unobserved time-varying heterogeneity.

4 Results

This section reports estimation results for nutrition and health outcomes.

4.1 Nutrition outcomes

Our results suggest that social globalisation has a positive and significant effect on animal protein but no effect on free fat and sugar. We do not find any statistically significant effect of economic globalisation. These results are partly in line with the

This BIC formula defines the number of parameters as the number of group-specific time effects (GT), the number of common parameters (K), and the number of group membership variables (N). $\hat{\sigma}^2$ is an estimate of the variance of the error term v_{it} and it is computed with $G_{max} = 12$.
$\hat{\sigma}^2 = \frac{1}{NT - G_{max}T - N - K} Objective function_{G_{max}}$.

[14] Figure 8 in the Appendix plots the coefficients for different number of groups.

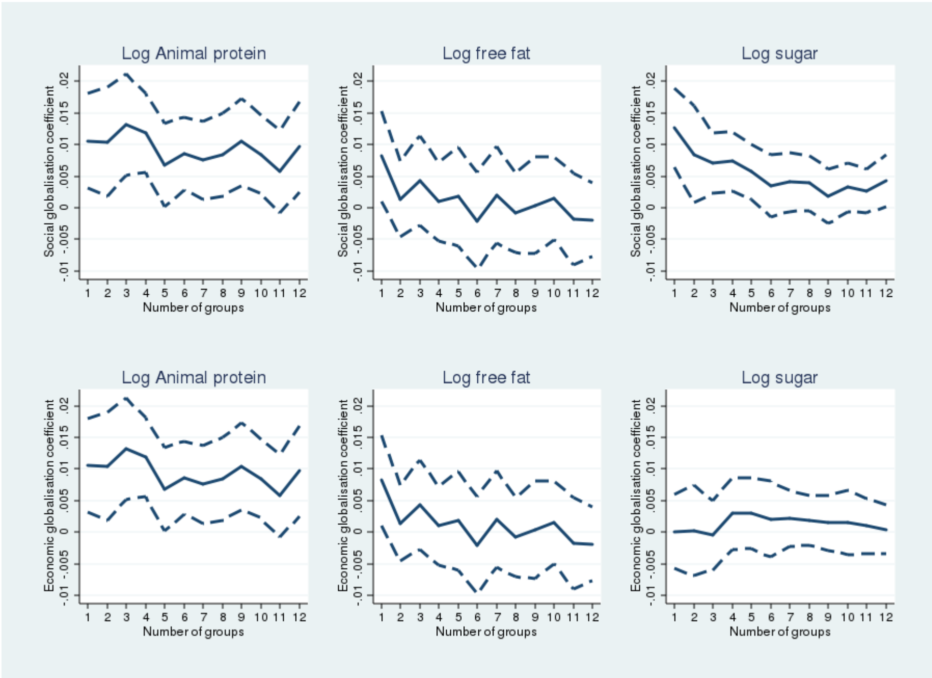

Figure 5: Coefficients of economic and social globalisation

model predictions of Olivier et al. (2008). Our results confirm the model prediction of a positive relationship between social globalisation and cultural convergence but our empirical analysis does not reveal a significant negative impact of economic globalisation.

Table 2 presents our main results for nutrition outcomes. Columns 1, 4, and 7 report results from a OLS regression with year fixed effects. Social globalisation is positively associated with the log of animal protein, free fat, and sugar and the coefficient is significant at the 5% or 1% level. In contrast, the coefficient of economic globalisation is only significant for animal protein at the 10% level.
Results of country and year fixed effects regressions are presented in columns 2,5, and 7. The coefficient of social globalisation remains positive but loses its significance for the log of free fat and sugar. The coefficient of economic globalisation becomes insignificant.
Controlling for grouped time effects (columns 3, 6, and 9) the coefficient of social globalisation is only significant at the 1% level for animal protein. Compared to the FE specifications it remains stable in magnitude. An additional point on the social globalisation index is associated with an increase of animal protein (kcal/capita/day) by 0.9%. A one standard deviation increase (20.65) on the index of social globalisation increases on average animal protein by about 20.4%. A

one standard deviation increase in the score of social globalisation approximately corresponds to a jump from the social globalisation level of Croatia to that of Singapore or from Turkey to France (values of 2011).
The effect of economic globalisation is never significant for any of the outcome variables. The positive sign of the coefficient of GDP per capita and the negative sign of the coefficient of its squared term suggests an inverted U-shape of the relationship between GDP and the outcome variables. The turning point for animal protein is at 22,500 USD GDP per capita. This value is very similar to the mean GDP per capita of high income countries in the sample over the period 1970 until 2011 (22,295 USD).

Table 2: Globalisation and nutrition outcomes

	Animal protein (log)			Free fat (log)			Sugar (log)		
	OLS	FE	GFE	OLS	FE	GFE	OLS	FE	GFE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Social glob.	0.011***	0.009***	0.009***	0.008**	0.002	-0.002	0.013***	0.003	0.004
	(0.004)	(0.003)	[0.003]	(0.004)	(0.003)	[0.004]	(0.003)	(0.002)	[0.003]
Economic glob.	0.005*	0.000	0.003	-0.002	-0.002	0.003	0.000	0.000	0.002
	(0.003)	(0.002)	[0.002]	(0.003)	(0.003)	[0.003]	(0.003)	(0.002)	[0.003]
GDP p.c.[a]	0.054***	0.006	0.045**	0.058***	0.000	0.053**	0.020***	0.002	0.015
	(0.009)	(0.014)	[0.019]	(0.014)	(0.023)	[0.022]	(0.007)	(0.010)	[0.013]
(GDP p.c.)^2	-0.001***	-0.000	-0.001**	-0.001***	-0.000	-0.001**	-0.000***	-0.000	-0.000
	(0.000)	(0.000)	[0.000]	(0.000)	(0.000)	[0.000]	(0.000)	(0.000)	[0.000]
Country FE	no	yes	no	no	yes	no	no	yes	no
Year FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Group FE	no	no	yes	no	no	yes	no	no	yes
Group-year FE	no	no	yes	no	no	yes	no	no	yes
N	2,940	2,940	2,940	2,940	2,940	2,940	2,940	2,940	2,940
Objective	346.31	65.43	64.50	507.17	109.82	109.76	253.01	48.08	41.78
Adjusted R^2	0.722	0.946	0.944	0.549	0.900	0.895	0.522	0.907	0.915

Robust standard errors in round brackets. Bootstrapped standard errors in square brackets (100 replications). GFE results obtained with algorithm 2 and $G = 6$ groups.
[a] GDP per capita (constant 2005 in 1000 USD).

4.2 Health outcomes

Results for nutrition outcomes are presented in table 3. We do not find significant effects of social or economic globalisation on diabetes prevalence and mean BMI. Pooled OLS results suggest a positive and significant association between social globalisation and diabetes prevalence and mean BMI. But applying country and year fixed effects (column 2) or grouped fixed effects (column 3) renders the coefficients of social globalisation insignificant. Interestingly, the FE results

(column 2) indicate a negative significant effect of economic globalisation on diabetes prevalence and mean BMI. Applying the GFE estimator, which controls for a part of the time-varying unobserved heterogeneity, this negative effect becomes insignificant.
Our results do not support findings of Miljkovic et al. (2015); Vogli et al. (2014); Costa-i-Font and Mas (2014) and Goryakin et al. (2015) who report a positive and significant association between social globalisation and different measures of overweight.

Table 3: Globalisation and health outcomes

	Diabetes prevalence			Mean BMI		
	OLS	FE	GFE	OLS	FE	GFE
	(1)	(2)	(3)	(4)	(5)	(6)
Social globalisation	0.040**	0.003	-0.014	0.065***	-0.005	0.008
	(0.019)	(0.015)	[0.019]	(0.015)	(0.005)	[0.013]
Economic globalisation	-0.008	-0.038***	-0.003	0.007	-0.015***	0.012
	(0.013)	(0.015)	[0.012]	(0.012)	(0.005)	[0.009]
GDP per capita[a]	-0.159***	-0.080	-0.041	-0.032	0.001	-0.009
	(0.039)	(0.067)	[0.076]	(0.038)	(0.020)	[0.049]
$(\text{GDP per capita})^2$	0.001**	0.001	0.000	-0.000	-0.000	-0.000
	(0.001)	(0.001)	[0.001]	(0.001)	(0.000)	[0.001]
Country FE	no	yes	no	no	yes	no
Year FE	yes	yes	yes	yes	yes	yes
Group FE	no	no	yes	no	no	yes
Group-year FE	no	no	yes	no	no	yes s
N	2,494	2,494	2,494	2,494	2,494	2,494
Objective	6,635.44	1,191.44	696.59	4,372.31	198.61	261.38
Adjusted R^2	0.325	0.874	0.923	0.436	0.973	0.963

Robust standard errors in round brackets. Bootstrapped standard errors in square brackets. Results obtained with algorithm 2 and $G = 8$ groups.
[a] GDP per capita (constant 2005 in 1000 USD).

4.3 Convergence across country groups

Next, we are addressing the question of whether countries are converging towards a homogeneous nutritional profile. Figures 1 , 2, and 3 already suggested that middle income countries have not yet reached the levels of animal protein, free fat, and sugar, which are prevalent in high income countries. But we have also seen that they experience larger growth rates than high income countries. So, is the gap shrinking between middle and high income countries? Figure 6 shows the coefficient of variation[15] over time for the nutrition outcome variables. Animal

[15] the coefficient of variation is defined as the ratio of the standard deviation to the mean.

protein exhibits a strong convergence trend over time. The coefficient of variation moderately declines for free fat and sugar. This suggests that middle income countries are catching up to high income countries regarding supply of animal protein, and to a smaller extent with respect to free fat and sugar.

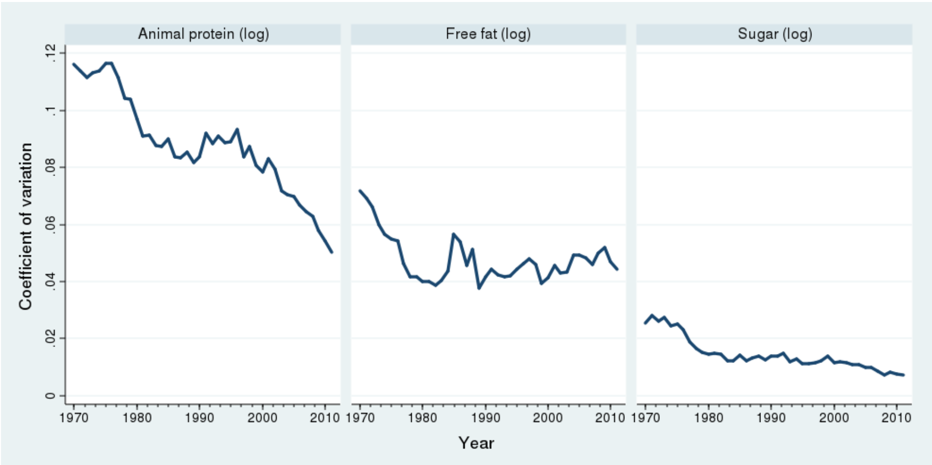

Figure 6: Coefficient of variation for nutrition outcomes, 1970-2011

The observed convergence for animal protein, free fat, and sugar can only be partly explained by globalisation and GDP. Figure 7 plots the difference between groups over time. The difference is calculated as the sum of the group dummy and the grouped time effect[16]. We find that after controlling for globalisation and GDP, the difference across country groups continues to converge for all three outcome variables. This suggests that other factors partly explain the observed convergence of countries with respect to their diet.

5 Discussion

Our results suggest that social globalisation has a positive effect on animal protein while economic globalisation has no effect on the nutrition composition. This result is only partly in line with the model developed by Olivier et al. (2008) predicting a positive effect of social globalisation but a negative effect of economic globalisation on cultural convergence.

[16] e.g. for group 3 and year 1971 it is the sum of $group_3$ and $group_3 * year_{1971}$ relative to the base group, group 1.

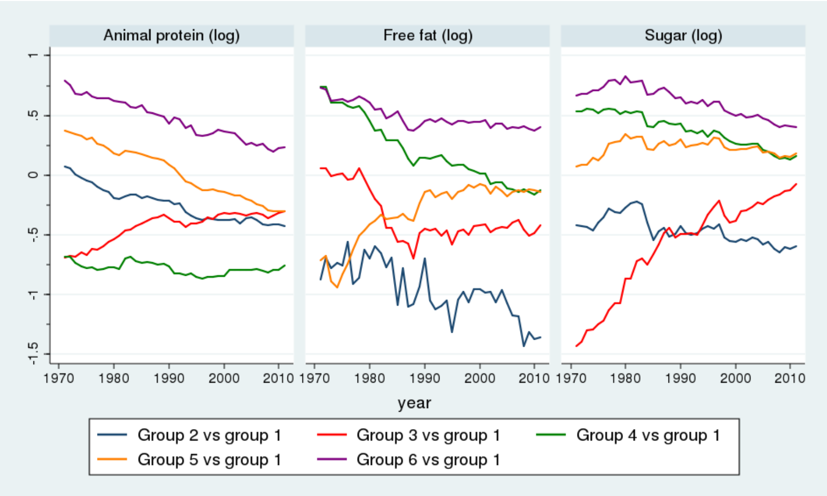

Figure 7: Convergence of groups for nutrition outcomes, 1970-2011

In order to understand better the drivers behind the positive effect of social globalisation we investigate whether social globalisation has a different effect on the diet for different groups of countries. To this end, we interacted the variable social globalisation with the group indicator variables.
Table 4 presents the impact of social globalisation for different groups. For animal protein and free fat only the interaction term for group 6 is positive and significant. For both outcome variables group 6 consists of high and upper middle income countries[17]. This suggests that the effect of social globalisation on the supply of animal protein and free fat is stronger for richer than for poorer countries.
A different picture emerges for sugar. The coefficient of the interaction terms with group 3 is significant and the largest in magnitude, followed by the interaction term with group 4. Group 3 consists of 12 mostly upper and lower middle income countries[18] suggesting that the effect of social globalisation on sugar is driven by middle income countries. The composition of group 4 is more diverse as it consists of 7 high as well as lower middle income countries[19].

[17] For animal protein these are Australia, Barbados, Chile, Finland, France, Greece, Ireland, Israel, Italy, Japan, Malta, Netherlands, Portugal, Spain, USA, Venezuela, Brazil, Colombia, Costa Rica, Ecuador, Fiji, Gabon, Malaysia, Panama, and the lower middle income country Guyana. For free fat these are Argentina, Austria, Canada, France, Germany, Greece, Israel, Italy, Norway, Portugal, Spain, USA, Venezuela, Algeria, Brazil, Costa Rica, Dominican Republic, Ecuador, Fiji, Malaysia, Paraguay, Tunisia, Turkey, and the lower middle income countries Cote d'Ivoire, Morocco, and Nigeria.
[18] These are Algeria, Thailand, Tunisia, Cameroon, Egypt, El Salvador, Guatemala, Kenya, Mauritania, Morocco, and the high income countries Korea and Norway.
[19] These are Iceland, Ireland, USA, Uruguay, Cote d'Ivoire, Ghana, India.

One potential concern is that these results do not capture a different impact of social globalisation for different groups but simply reflect that different groups exhibit substantial differences in their median level of social globalisation. In other words the groups may just be at different stages of social globalisation.
The box plot in figure 9 mitigates this concern. Group 6 for free fat and groups 3 and 4 for sugar do not exhibit substantially different levels of social globalisation compared to the other groups. Only group 6 for animal protein shows a slightly elevated median value, so the results of animal protein should be interpreted with some caution.

Table 4: Heterogeneous effects by group, grouped fixed effects

	Animal protein (log)	Free fat (log)	Sugar (log)
	(1)	(2)	(3)
Social globalisation*group 6	0.018**	0.027**	0.003
	(0.008)	(0.011)	(0.012)
Social globalisation*group 5	0.018	-0.001	0.005
	(0.025)	(0.010)	(0.005)
Social globalisation*group 4	-0.007	0.002	0.014**
	(0.009)	(0.013)	(0.006)
Social globalisation*group 3	0.000	0.009	0.023**
	-(0.016)	(0.016)	(0.012)
Social globalisation*group 2	0.009	-0.002	0.002
	(0.014)	(0.010)	(0.009)
Social globalisation*group 1	0.008	0.002	0.01
	(0.016)	(0.021)	(0.010)
Economic globalisation	0.004	0.002	0.000
	(0.007)	(0.006)	(0.004)
GDP per capita[a]	0.036**	0.048**	0.011
	(0.015)	(0.020)	(0.013)
(GDP per capita)^2	-0.000*	-0.001**	0.000
	(0.000)	(0.000)	(0.000)
Countries in group 6	25	26	5
Countries in group 5	5	11	26
Countries in group 4	19	7	7
Countries in group 3	6	4	12
Countries in group 2	5	14	13
Countries in group 1	10	8	7
N	2940	2940	2940

Results obtained with algorithm 1 and 2000 randomly generated starting values. Clustered standard errors based on the large-T normal approximation in parentheses. Regressions include group FE, year FE and, group-year FE.
[a] GDP per capita (constant 2005 in 1000 USD).

Finally, we analyse the impact of the different subcomponents of the globalisation index in order to better understand the underlying mechanisms. Table 5 presents results from estimating the effect of different subcomponents of the social globalisation index on animal protein, free fat, and sugar. We find that the positive effect of social globalisation on animal protein is driven by personal contacts (e.g. tourism, telephone traffic, foreign population and transfers) and information flows (e.g. number of Internet and telephone users per 1000 people) while cultural proximity (e.g. measured by number of McDonald's and IKEA stores) does not seem to play a role.

We do not find any significant effects for free fat which mirrors the non-significant effect of social globalisation on free fat presented earlier. Finally, we find a positive and significant effect of information flows on sugar. This may hint at the role of media and advertising in influencing dietary habits.

Overall, the effects of the subcomponents for free fat and sugar carry positive as well as negative signs and thus are likely to cancel each other out in the composite social globalisation variable. This could explain why we do not find significant effects of social globalisation on free fat and sugar in our main regression.

Table 5: Subcomponents of social globalisation, grouped fixed effects

	Animal protein (log)	Free fat (log)	Sugar (log)
	(1)	(2)	(3)
Personal contacts	0.006*	0.008	-0.003
	(0.003)	(0.005)	(0.003)
Information flows	0.006*	0.001	0.009***
	(0.003)	(0.004)	(0.003)
Cultural proximity	0.001	-0.002	-0.000
	(0.001)	(0.001)	(0.001)
Economic globalisation	0.001	-0.007*	0.003
	(0.002)	(0.004)	(0.002)
GDP per capita	0.055***	0.055***	0.005
	(0.014)	(0.018)	(0.010)
(GDP per capita)^2	-0.001***	-0.001***	-0.000
	(0.000)	(0.000)	(0.000)
N	2940	2940	2940

Bootstrapped standard errors in parentheses. Results obtained with algorithm 2.
Regressions include group FE, year FE and, group-year FE.
[a] GDP per capita (constant 2005 in 1000 USD).

6 Conclusion

This paper contributes to explaining the causes of changing nutrition patterns by estimating the effect of globalisation on the composition of the diet and health outcomes. Globalisation has often be held responsible for changing diets and associated negative health outcomes such as obesity, diabetes, and cardiovascular diseases. However, existing evidence only concentrated on economic aspects of globalisation and mostly consisted of case studies about trade liberalisations and FDI.

We provide empirical evidence on the impact of globalisation on the supply of animal protein, free fat, and sugar as well as on diabetes and mean BMI by using a panel of 70 high and middle income countries from 1970 until 2011.
In order to better account for unobserved time-varying heterogeneity we apply a grouped fixed effects estimator developed by Bonhomme and Manresa (2015). This estimator endogenously groups countries together by minimizing a least-squares criterion and subsequently controls for group-specific time-varying unobserved heterogeneity.

Our results indicate that the social dimension of globalisation has a positive and significant effect on animal protein while economic globalisation has no impact on the composition of the diet. This finding is relevant for economies given the negative health consequences of a meat-intensive diet and associated healthcare costs as well as the environmental impact of meat production.
Moreover, we find that the gap countries between countries strongly converged over time for animal protein and to a lesser extent for free fat and sugar. While globalisation and GDP are partly responsible for this convergence process, additional factors must play a role that require further analysis.
We further show that the effect of social globalisation on animal protein is stronger for richer than for poorer countries and that it is driven by personal contacts with foreigners and information flows via telephone and Internet. We do not find any significant effects of globalisation on health outcomes.

Given that social globalisation seems to be the main driver of changing diets, further research should focus on factors related to the social dimension of globalisation, such as food advertising on television and the Internet.

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7 Appendix

Table 6: Summary statistics, health sample

	Mean	SD	Min	Max
Outcome variables				
Diabetes prevalence	8.39	2.00	3.18	21.82
Mean BMI	24.57	1.78	19.47	28.74
Covariates				
Economic globalisation	54.69	18.11	9.94	99.16
Social globalisation	46.92	21.28	6.85	93.68
GDP per capita[a]	11.75	14.80	0.22	86.13
Income groups				
High income	0.42	0.49	0.00	1.00
Upper middle income	0.29	0.45	0.00	1.00
Lower middle income	0.29	0.45	0.00	1.00
Sample				
Number of countries	86			
Number of years	29			
N	2494			

[a] GDP per capita (constant 2005 in 1000 USD).

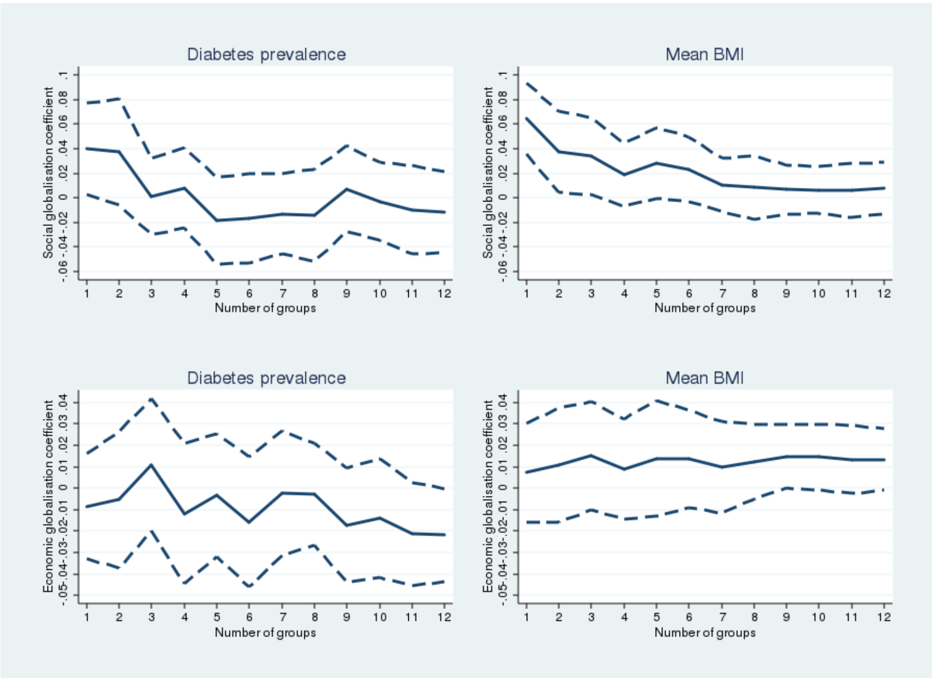

Figure 8: Coefficients of economic and social globalisation

Table 7: GFE estimates, animal protein (log)

Number of groups	Objective function	BIC	Social globalisation	Economic globalisation	GDP[a] per capita	(GDP per capita)^2
1	346.31	0.1227	0.011***	0.005*	0.054***	-0.001***
			(0.004)	(0.003)	(0.009)	(0.000)
2	183.28	0.0691	0.010**	-0.001	0.037***	-0.001*
			(0.004)	(0.004)	(0.013)	(0.000)
3	124.53	0.0509	0.013***	0.002	0.026	-0.000
			(0.004)	(0.003)	(0.018)	(0.000)
4	93.17	0.0420	0.012***	0.001	0.045**	-0.001**
			(0.003)	(0.002)	(0.018)	(0.000)
5	76.62	0.0382	0.007**	0.003	0.061***	-0.001***
			(0.003)	(0.003)	(0.017)	(0.000)
6	64.50	0.0358	0.009***	0.003	0.045**	-0.001**
			(0.003)	(0.002)	(0.019)	(0.000)
7	57.09	0.0351	0.008**	0.003*	0.074***	-0.001***
			(0.003)	(0.002)	(0.018)	(0.000)
8	50.90	0.0348	0.008**	0.003	0.073***	-0.001***
			(0.003)	(0.002)	(0.020)	(0.000)
9*	45.77	0.0348	0.010***	0.004	0.069***	-0.001***
			(0.004)	(0.002)	(0.023)	(0.000)
10	42.80	0.0356	0.008***	0.003	0.070***	-0.001**
			(0.003)	(0.003)	(0.022)	(0.000)
11	39.58	0.0363	0.006*	0.003	0.016	-0.000
			(0.003)	(0.003)	(0.022)	(0.000)
12	37.08	0.0373	0.010***	0.003	0.042**	-0.000
			(0.004)	(0.002)	(0.020)	(0.000)
Country & year FE	69.15		0.010***	0.003*	0.010	-0.000
			(0.002)	(0.002)	(0.013)	(0.000)
Income groups[b]	266.18		0.009***	0.002	0.021**	-0.000**
			(0.003)	(0.003)	(0.011)	(0.000)

The table reports the value of the objective function and the GFE coefficient for various number of groups. Computation using algorithm 2 with 100 Bootstrap iterations. The * marks the regressions with the minimum BIC value.

[a] GDP per capita (constant 2005 in 1000 USD).

[b] Countries grouped into high income, upper middle, and lower middle income countries.

Table 8: GFE estimates, free fat (log)

Number of groups	Objective function	BIC	Social globalisation	Economic globalisation	GDP[a] per capita	(GDP per capita)^2
1	507.17	0.1798	0.008**	-0.002	0.058***	-0.001***
			(0.004)	(0.003)	(0.014)	(0.000)
2	235.15	0.0899	0.001	-0.004	0.054***	-0.001***
			(0.003)	(0.003)	(0.012)	(0.000)
3	181.39	0.0743	0.004	-0.002	0.045**	-0.001**
			(0.004)	(0.003)	(0.019)	(0.000)
4	150.57	0.0665	0.001	0.002	0.047**	-0.001**
			(0.003)	(0.004)	(0.020)	(0.000)
5	127.89	0.0614	0.002	-0.000	0.055***	-0.001**
			(0.004)	(0.004)	(0.020)	(0.000)
6	109.76	0.0579	-0.002	0.003	0.053**	-0.001**
			(0.004)	(0.003)	(0.022)	(0.000)
7	96.53	0.0560	0.002	-0.004	0.044**	-0.000
			(0.004)	(0.003)	(0.021)	(0.000)
8	86.05	0.0551	-0.001	0.002	0.077***	-0.001***
			(0.003)	(0.004)	(0.020)	(0.000)
9*	75.42	0.0541	0.000	-0.004	0.039*	-0.001
			(0.004)	(0.003)	(0.020)	(0.000)
10	69.42	0.0548	0.002	0.003	0.031	-0.000
			(0.003)	(0.004)	(0.021)	(0.000)
11	61.19	0.0546	-0.002	-0.001	0.039**	-0.000*
			(0.004)	(0.004)	(0.017)	(0.000)
12	54.81	0.0551	-0.002	-0.002	0.039**	-0.000
			(0.003)	(0.004)	(0.018)	(0.000)
Country & year FE	109.82		0.002	-0.002	0.000	-0.000
			(0.003)	(0.003)	(0.023)	(0.000)
Income groups[b]	484.28		0.010***	-0.002	0.033***	-0.001**
			(0.003)	(0.003)	(0.012)	(0.000)

The table reports the value of the objective function and the GFE coefficient for various number of groups. Computation using algorithm 2 with 100 Bootstrap iterations. The * marks the regressions with the minimum BIC value.

[a] GDP per capita (constant 2005 in 1000 USD).

[b] Countries grouped into high income, upper middle, and lower middle income countries.

Table 9: GFE estimates, sugar

Number of groups	Objective function	BIC	Social globalisation	Economic globalisation	GDP per capita[a]	(GDP per capita)^2
1	253.01	0.0889	0.013***	0.000	0.020***	-0.000***
			(0.003)	(0.003)	(0.007)	(0.000)
2	127.51	0.0473	0.008**	0.000	0.015	-0.000
			(0.004)	(0.004)	(0.019)	(0.000)
3	77.13	0.0312	0.007***	-0.001	0.007	-0.000
			(0.002)	(0.003)	(0.014)	(0.000)
4	59.52	0.0263	0.007***	0.003	0.007	-0.000
			(0.002)	(0.003)	(0.011)	(0.000)
5	50.46	0.0242	0.006***	0.003	0.009	-0.000
			(0.002)	(0.003)	(0.011)	(0.000)
6	41.78	0.0223	0.004	0.002	0.015	-0.000
			(0.003)	(0.003)	(0.013)	(0.000)
7	36.14	0.0214	0.004*	0.002	0.015	-0.000
			(0.002)	(0.002)	(0.012)	(0.000)
8	31.83	0.0210	0.004*	0.002	0.017	-0.000
			(0.002)	(0.002)	(0.012)	(0.000)
9*	28.18	0.0208	0.002	0.001	0.022***	-0.000**
			(0.002)	(0.002)	(0.008)	(0.000)
10	25.76	0.0210	0.003	0.002	0.019*	-0.000*
			(0.002)	(0.003)	(0.010)	(0.000)
11	23.77	0.0214	0.003	0.001	0.019**	-0.000*
			(0.002)	(0.002)	(0.008)	(0.000)
12	21.60	0.0217	0.004**	0.000	0.007	-0.000
			(0.002)	(0.002)	(0.009)	(0.000)
Country & year FE	48.08		0.003	0.000	0.002	-0.000
			(0.002)	(0.002)	(0.010)	(0.000)
Income group[b]	230.21		0.010***	-0.002	0.008	-0.000**
			(0.003)	(0.003)	(0.006)	(0.000)

The table reports the value of the objective function and the GFE coefficient for various number of groups. Computation using algorithm 2 with 100 Bootstrap iterations. The * marks the regressions with the minimum BIC value.
[a] GDP per capita (constant 2005 in 1000 USD).
[b] Countries grouped into high income, upper middle, and lower middle income countries.

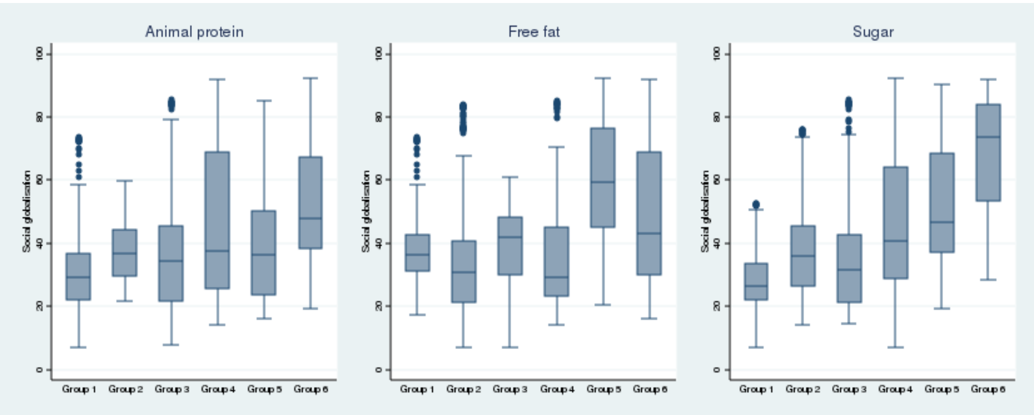

Figure 9: Distribution of social globalisation across groups