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DEMOGRAPHIC TRENDS AND ENGEL'S LAW ACROSS THE DEVELOPMENT SPECTRUM

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Demographic Trends and Engel's Law across the Development Spectrum

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Abstract

Economic progress brings with it two key patterns. Firstly, we observe the progressive change in the demographic structure of the population. Secondly, as nations advance economically, the portion of food in total expenditures tends to decrease. Using household-level consumption data from 20 countries, this work document that as the age of household members increases, the proportion of total household expenditures dedicated to food also increases. This finding suggests that an ageing population will result in a higher overall food share of total expenditures. I test this hypothesis by constructing a quantitative, demand side model and document that the demographic evolution slows down the shift away from food consumption in almost every country in the sample. The correlation between income and the demographic transition implies that not accounting for demography leads to an underestimation of the income effect by up to 20%.

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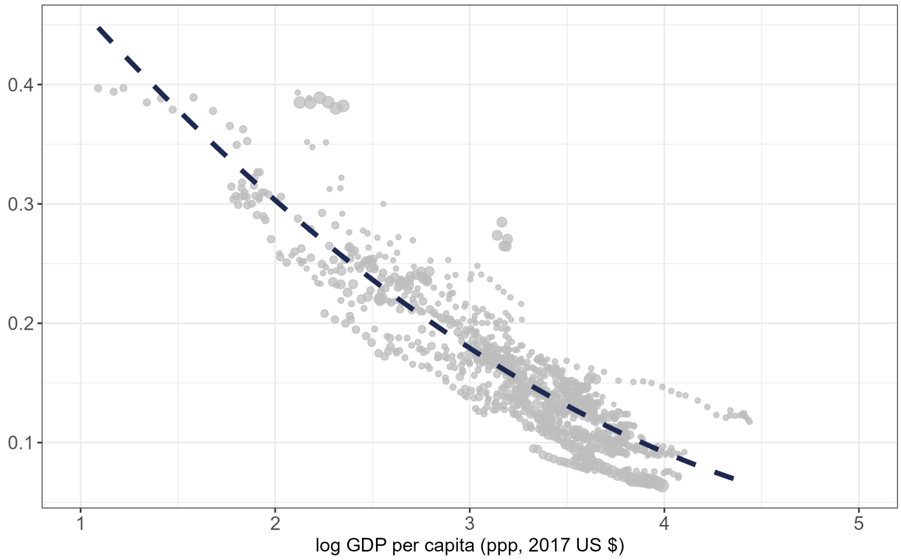
1 Introduction

Economic progress brings with it two key patterns. Firstly, we observe a movement from a demographic regime marked by high mortality and high fertility rates to one characterized by low mortality and low fertility rates. Referred to as the demographic transition, it portends a slow and gradual aging of society, as well as other shifts in demographic composition. Secondly, as nations advance economically, the portion of food in total expenditures tends to decrease. This latter trend is but one aspect of the larger structural transformation, wherein expenditures, output, and employment are reallocated across broad economic sectors, from agriculture to manufacturing and then to services. In this work, I shall delve into the interplay between these two phenomena. If demographic factors such as age and gender impact food expenditure decisions, then the shifting demographic trends brought on by the demographic transition ought to shape the sectoral distribution of total expenditures. Is the demographic transition a driving force behind the shift away from food expenditures in the structural transformation?

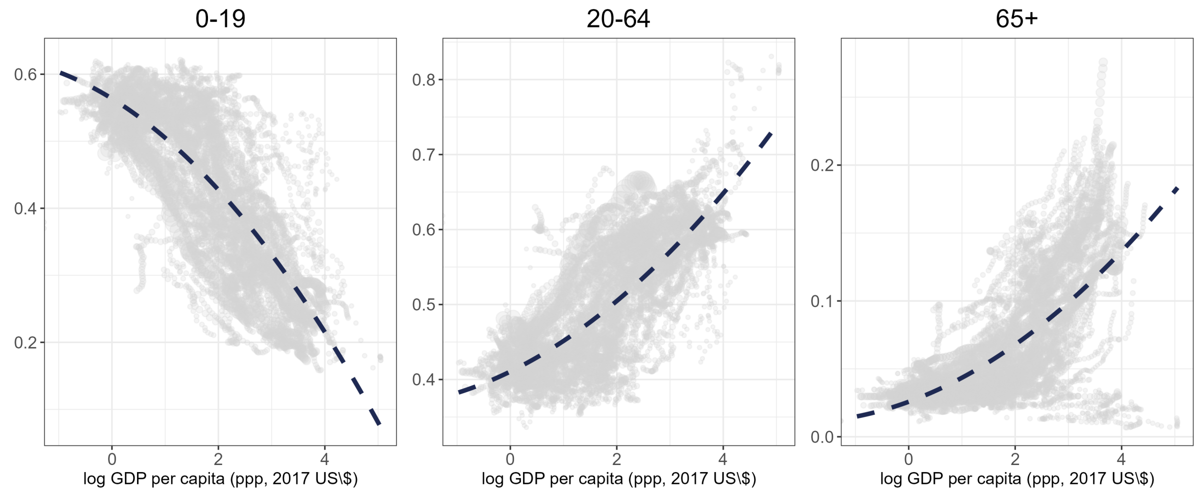


This figure shows the relationship between the food (at home) share of total expenditures and GDP per capita at purchasing power parity for 41 countries in the period 1959-2018. The blue line represents a quadratic fit. The source of the expenditure data is the OECD's "Final consumption expenditures of households". Expenditure categories are defined according to to use ("Classification of individual consumption by purpose", COICOP) and food (at home) refers to "01 - food and non-alcoholic beverages". Notice that expenditure on food away from home belongs to "11 - Restaurants and hotels". The source of GDP data is the World Bank.

Figure 1: Food as share of total expenditure and GDP per capita

The reduction in the food share of final consumption and demographic transition are both highly correlated to the rise of real income, the methonym for economic development (see figure 1). The relationship between income and sectoral demand - among the earliest and more persistent contributions in econometrics - goes by the name of Engel's Law: "the poorer is a family, the greater is the proportion of the total [family expenditures] which must be used for food" (Engel, 1895[1]). The idea is simple: once basic needs like food are met, households have more money to spend on non-essential items like manufactured goods and services. This kind of evidence, observed at the household level, has major implications for the larger macroeconomic structure. Recent research argues that this income effect is a

[1]As quoted by Zimmerman (1932), p. 80.



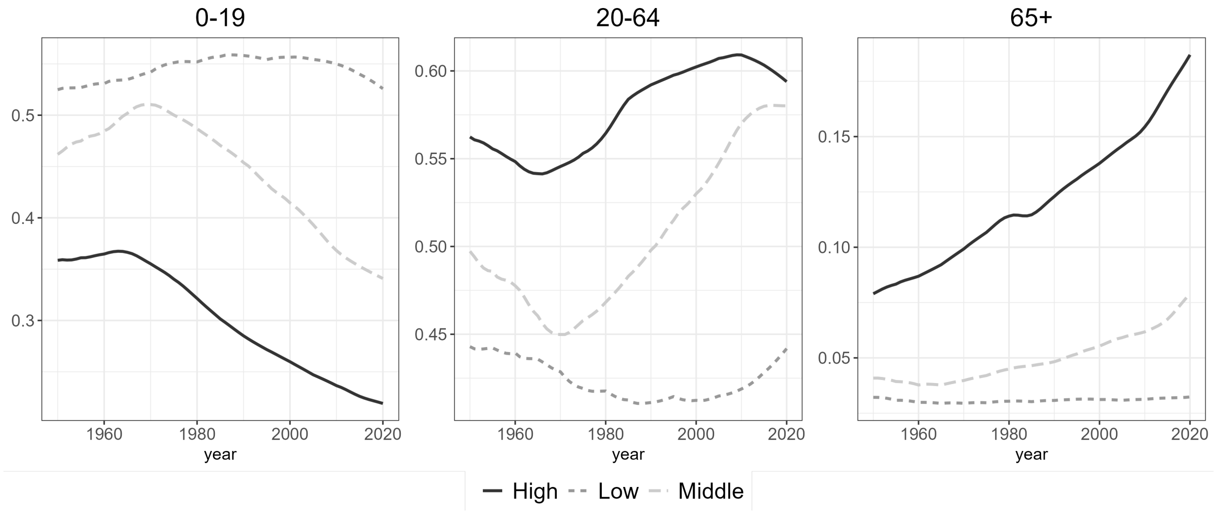
This figure shows the relationship between age structure (across three age groups) and GDP per capita at purchasing power parity. The blue lines represent a quadratic fit. The outlier at the bottom-right of panel "60+" are oil-rich Gulf Countries: their GDP per capita is higher than their socio-demographic structure would predict. The source of the demographic data is the World Population Prospects by the United Nations, while the source of GDP data is the World Bank.

Figure 2: Age groups shares of total population

key driver of long-term structural transformation (Herrendorf et al., 2013, Boppart, 2014, Comin et al., 2021, Alder et al., 2022).

The connection between income and demography is a matter that has captured the attention of scholars for centuries, dating back at least to Malthus (1798). Recently, Doepke et al., 2022 conducted a comprehensive review of the literature on this topic. For the purposes of this work, we note that fertility and mortality rates tend to be lower in richer countries than in developing ones (see, for example Delventhal et al., 2021). As both fertility and mortality decline, populations tend to age, resulting in a higher median age in wealthier societies. This relationship is illustrated in Figure 2, where we observe a strong negative correlation between GDP per capita and the share of younger individuals, and a positive correlation with the share of older individuals. However, the underlying shift in demographic structure is not monotonic. As we can see in Figure 3, the proportion of adults under the age of 20 initially increases before declining as development progresses. The opposite is true for the proportion of working-age individuals, which initially declines before increasing. Finally, the proportion of elderly individuals increases steadily over time and development. The cause of this non-monotonicity lies in the asymmetrical timing of the decline in fertility and mortality: if mortality, and particularly infant mortality, declines before fertility does, then a "baby boom" may occur (i.e., an increase in the proportion of younger individuals in the total population). This is what happened in many developed countries in the 1950s and is currently happening in some African countries (Delventhal et al., 2021). From the non-monotonicity of the changes in demographic structure it follows that the impact of demographic preferences may vary dramatically across the development spectrum.

The observed co-movement of demographic trends, structural change, and income presents a confounding factor to the impact of income on food expenditures at the aggregate level. We already know that income has an influence on both demographic changes and expenditures. However, if demographics affect expenditures through a means unrelated to income, the income effect we observe is actually a mix of two distinct forces - the "demographic effect" and the "true income effect". This leads us to a new question:



This figure shows the evolution over time of age structure across three age groups and three income groups. Countries are grouped by income according to World Bank's classification: income-group level shares are computed using population to weight country-level observations.The source of the demographic data is the World Population Prospects by the United Nations.

Figure 3: Age groups shares of total population

to what extent can we attribute the observed (gross) income effect to the demographic transition?

The research questions presented so far hinge on the key assumption that demographic characteristics affect food expenditures choices. The first contribution of this work is to document that this is indeed the case: aggregate data suggest that age is a significant predictor of higher expenditures shares in food consumption. Countries with higher median age spend a larger share of their aggregate expenditures in food *for home consumption*, after controlling for total expenditures. This seem to hold also at the household level: Using data from 20 countries across the development spectrum, I document a strong relationship between individual age characteristics and household's food expenditure shares. In particular, food expenditure share of household total expenditures are increasing in the age of individual members. Furthermore, I also document that in some country (notably, from a development perspective, Ivory Coast, Vietnam and Mexico) an additional adult female household member increases the food (at home) share more than a similarly aged male would. This observation does not hold across all countries. In particular, the differences between male and female consumption patterns in developed countries is negligible. These finding are aligned to Aguiar and Hurst (2013)'s hypothesis that expenditures over the life cycle (including food consumption) are a consequence of time opportunity cost: the sex component might reflect the traditional role - shared across many countries in the sample - of females as the household's cooks. More directly, this papers's finding are aligned with the results of Foster (2015) and Mao and Xu (2014): using household-level data from the US and China respectively, they observe that expenditures in food for home consumption are increasing with the age of the household head and *individual* household members.

The finding that older individuals - and in particular older females in some countries - drive higher household expenditures in food consumption suggests that the demographic trends might be a slowing force upon structural change out of food consumption. To quantify the size of this mechanism, I build a demand-side, quantitative model centered around the PIGL demand system (Boppart, 2014), a natural choice due to aggregability properties and the ability to capture all key drivers of structural change. Calibrated using the same microdata from the empirical exploration, the model confirms that the evolution of age-sex composition in the economy has been a significant slowing down force upon structural change. A counterfactual exercise reveals that shutting down the demographic channel would decrease the change rate of food share of aggregated expenditure by between 0.1 to 0.5 percentage yearly for most countries. That is, demographic trends in age and sex are a sizable force upon structural change. Finally, a counterfactual exercise documents that estimating the income effect without taking into account the demographic trends leads to an under-estimation of the income effect by up to 20%.

This work joins the body of literature that explores the impact of long-run demographic trends on the macro-economy. For example, Aksoy et al. (2019) explores the impact of demographic trends upon key macroeconomic indicators such as investment, savings and hours worked per capita; Jones (2022) inquires on the (potentially abysmal) consequences upon the economic growth of taking the demographic transition to its logical extreme. Closely related to this paper, Brembilla (2018) and Cravino et al. (2022) explore the impact of aging upon structural transformation into services in the US. This work expands on this literature in three different directions: I allow for a broader definition of demographic trends by adding the sex dimension and focus on a separate but concomitant facet of structural change - namely, food expenditures. Finally, I consider a large set countries and document cross-country heterogeneity. However, what sets this work apart from Cravino et al. (2022)'s - a work that shares the methodology used here - is outcome: while they observe that aging drives structural change toward services, I observe that aging hinders structural change out of food expenditures. These results are not conflictual, and highlight a complex relationship between the evolution of demographic characteristics and sectorial demand.

2 Cross-country evidences

Let's start by presenting some evidences of the relationship between demographic characteristics and sectoral expenditures. In particular, I focus on food expenditures, defined as food purchased for home consumption. First of all, I use country-level data to present some suggestive evidences that a larger share of elderly population is correlated with a larger food share of total expenditures, after controlling for the usual drivers such as income and prices. To further explore this phenomenon at the household level and across the development spectrum, I use microdata from a variety of countries. This data will allow me to explore further dimensions of the demographic transition, and thus I will use it to document that elderly women imply a larger share of the household budget allocated to food consumption.

2.1 Country-level evidence

In this section I've used country-level data to evaluate the correlation between demographic structure and the sectorial consumption. For this purpose, I've employed "Final consumption expenditures of households" data from the OECD, covering 41 countries for the period 1959-2018. Price data comes from the same source, while demographic variables are obtained from the UN Population Division.

To explore the relationship between food expenditures and demographic structure, I estimated the following model

$$\omega^j_{i,t} = \alpha_i + \beta^j_1 \text{Share\_65}_{i,t} + \beta^j_2 \log(\text{Exp\_tot}_{i,t}) + \beta^j_3 \log(\text{Exp\_tot})^2 + \beta^j_4 \text{Rel\_price}_j + \epsilon^j_{i,t}. \quad (1)$$

In this equation, $\omega^j_{i,t}$ represents the share of total expenditures allocated to sector j in country i at time t. Exp_tot is the level of private expenditures per capita at purchasing power parity (2017 US$). α_i is a country fixed effect. Finally, Rel_price is the ratio between the consumer price index for sector j and the one of the complement sector nj:

$$\text{Rel\_price} \equiv \frac{p^j_{i,t}}{p^{nj}_{i,t}} = \frac{p^j_{i,t}(1-\omega^j_{i,t})}{p^{tot}_{i,j} - \omega^j_{i,t} \cdot p^j_{i,t}}$$

The equality on the right hand side follow naturally from

$$p^{tot}_{i,j} \equiv \omega^j_{i,t} \cdot p^j_{i,t} + \omega^{nj}_{i,t} \cdot p^{nj}_{i,t}.$$

Table 1 presents the results of estimating equation 1 for food consumption. Consistent with Engel's Law, we can observe a negative and statistically significant relationship between food consumption shares and total expenditures. Notably, this relationship exhibits strong nonlinearity. We can also examine the impact of relative prices on food consumption and find that higher relative prices are associated with greater expenditures on food. This outcome aligns with expectations based on the gross complementarity of these broad expenditure categories.

Dependent Variable:	Food Share			
Model:	(1)	(2)	(3)	(4)
Variables				
Share of pop. 65+	-0.8812*** (0.3035)	-0.9238*** (0.1972)	0.2258** (0.0894)	0.1771*** (0.0631)
log(Tot. Exp.)		-0.0306** (0.0116)	-0.2404*** (0.0145)	-0.2200*** (0.0172)
log(Tot. Exp.) square			0.0243*** (0.0016)	0.0222*** (0.0018)
Relative food price				0.0577*** (0.0191)
Fixed-effects				
Country	Yes	Yes	Yes	Yes
Fit statistics				
Observations	1,123	1,114	1,114	1,064
R^2	0.82337	0.87962	0.97025	0.97079
Within R^2	0.29442	0.52591	0.88284	0.83027

Clustered (Country) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 1

Of particular interest, this analysis reveals that countries with a larger proportion of elderly individuals tend to allocate a greater share of their income to food consumption. This result remains robust even after controlling for expenditure levels and relative prices. It is worth noting, however, that prior to controlling for expenditure levels, the unconditional relationship between food shares and age is negative, likely reflecting the fact that richer countries tend to have older populations.

Dependent Variable:	Services Share			
Model:	(1)	(2)	(3)	(4)
Variables				
Share of pop. 65+	1.507*** (0.4291)	1.616*** (0.2076)	0.7192*** (0.1804)	0.6124*** (0.1793)
log(Tot. Exp.)		0.0430*** (0.0100)	0.2072*** (0.0215)	0.0138*** (0.0044)
log(Tot. Exp.) square			-0.0190*** (0.0023)	
Relative serv. price				0.1682*** (0.0463)
Fixed-effects				
Country	Yes	Yes	Yes	Yes
Fit statistics				
Observations	1,043	1,035	1,035	661
R^2	0.81064	0.88200	0.91752	0.94951
Within R^2	0.41015	0.63607	0.74563	0.64215

Clustered (Country) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 2

Table 1 shows the result of estimating equation 1 for services. Again, we observe that countries with a larger share of elder individuals are also the countries that spend a larger share of their income into services. The impact of total expenditures and relative prices are aligned with our priors. This result is consistent with the main finding of CLR.

CLR's cross-country analysis reveals a negative relationship between the share of population aged 65 or older and food consumption, controlling for GDP per capita. While I maintain that total expenditures provide a superior control for the allocation of total expenditure shares across sectors, I have replicated their analysis using GDP data from Maddison in Table 3. The left columns contain estimates using data up to 2007, consistent with CLR's approach, while the other columns utilize the full sample.

Dependent Variable:	food_share					
Sample	Reduced			Full		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Share of pop. 65+	-1.255	-0.0557	0.0080	-0.8812***	0.0500	0.0405
	(0.8047)	(0.0766)	(0.0474)	(0.3035)	(0.0514)	(0.0347)
log(GDP per capita)		-0.4247***	-1.380***		-0.5762***	-0.7067***
		(0.1218)	(0.2107)		(0.0576)	(0.1192)
log(GDP per capita) square		0.0156**	0.0630***		0.0241***	0.0309***
		(0.0066)	(0.0107)		(0.0029)	(0.0057)
Relative food price			0.0959***			0.0716***
			(0.0139)			(0.0158)
Fixed-effects						
Country	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	316	316	301	1,123	1,123	1,073
R^2	0.67526	0.96890	0.97322	0.82337	0.96427	0.96774
Within R^2	0.28286	0.93132	0.94309	0.29442	0.85726	0.80846

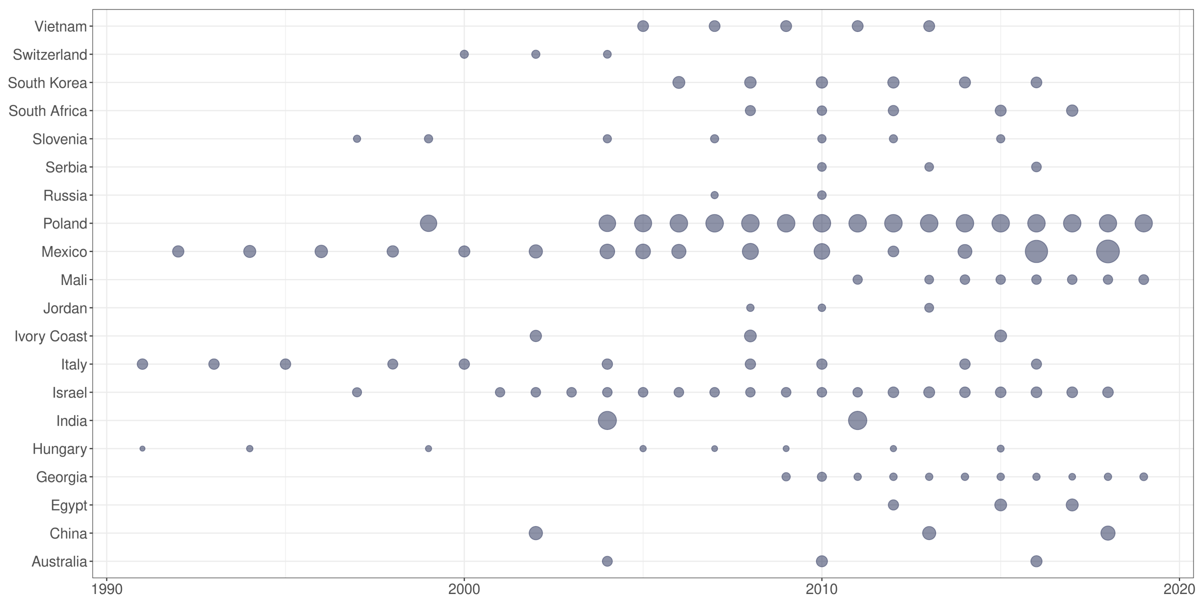
Clustered (Country) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 3

The results obtained from the reduced sample align with those of CLR, while the full sample produces a positive, albeit non-significant, relationship between the share of population aged 65 or older and food consumption. This finding suggests that the relationship between population age and food expenditures may be highly susceptible to changes in the sample due to country-level heterogeneity. Nonetheless, I interpret the results of this section as providing tentative support for one of the main empirical claims of this study, namely that aging increases food consumption. In the next section, I will use cross-country microdata at the household level to confirm this claim.

2.2 Household-level evidence

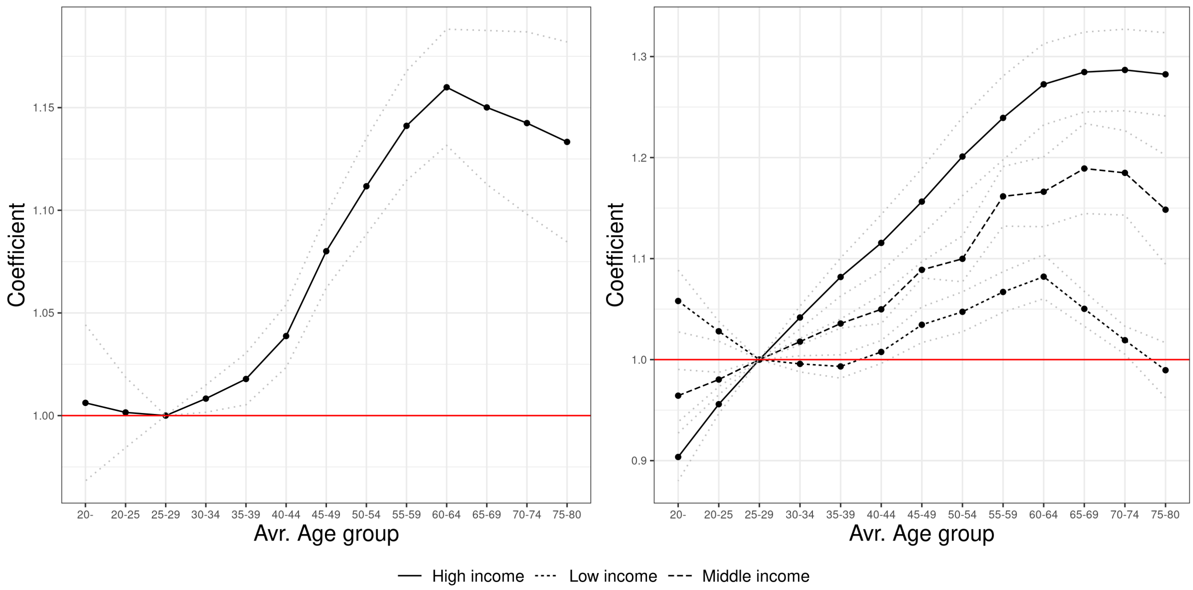
This section employs cross-sectional household-level data from the Luxembourg Income Survey (LIS), a large harmonized database that collects and synthesizes data from diverse national surveys, such as the CPS (United States) and the German Socio-Economic Panel. Spanning five decades and covering about 50 countries, the LIS database is one of the largest harmonized databases worldwide, focusing on income data but also providing a range of expenditure variables, including total and food expenditures according to the COICOP classification, the same used in OECD expenditure data. Notably, a well-assorted subset of 20 countries report these expenditure variables, covering the entire development spectrum from Mali to Switzerland. The distribution of the surveyed countries and waves is depicted in Figure 4, and summary statistics of the relevant variables can be found in appendix 4.1



The figure shows the country-waves of the Luxembourg Income Survey (LIS) that report food expenditure data. The size of the dots represent the number of observations: the larger, the more observations are reported.

Figure 4: LIS - Data coverage

In this empirical analysis, households with strictly positive food consumption (and therefore positive total consumption) and non-negative income are included, and sample weights are applied. These weights are based on the country's total population and enable cross-country comparisons.



This figure plots the estimated values for $\exp(D_h^{\text{Avr Age}})$ from equation 2. The right-hand panel shows the value estimated across all countries, while the left-hand one represent the value with the sample split across World Bank income classification. Notice that Upper and Lower-middle income have been merged into "Middle income", to ensure a sufficient number of observations.

Figure 5: Estimated value of $\exp(D_h^{\text{Avr Age}})$ by income group.

Two different baseline models are estimated in this section. The first model, inspired by Aguiar and Bils (2015) and Cravino et al. (2022), is estimated as follows:

$$log(\omega_h^f) = \alpha_{c,t} + \log(D_h^{\text{Avr Age}}) + \beta \cdot \log(\text{Income}_h) + \gamma \mathbf{X}_h + \epsilon_h \tag{2}$$

Here, ω_h^f represents the food share of total expenditures for household h, and $\alpha_{c,t}$ denotes the country-year fixed effects. The demographic controls $\mathbf{X}$ in this study include the number of household members, household type (e.g., single individual, couple, couple with children, couple living with parents), and number of earners. Unlike CLR, income is not grouped into income categories, which allows for income to be instrumented with total expenditures to account for measurement errors (Aguiar and Hurst, 2013). Time indexes are absent due to the cross-sectional nature of the LIS dataset, where each household is observed only once. The logarithmic shape of Equation 2 follows from the typical log-linear shape of the Marshallian demand and thus the sectoral shares implied by commonly used utility functions. This is the case for the PIGL preferences that will be used in section (...). The log-linear formulation allows for easy interpretation of the D_h^{m} coefficients: they represent the ratio between the consumption shares of a household with an average age = m and the consumption shares of an omitted reference age group, in this case the age group $25-29$.

Figure 5 shows the OLS estimates for the age coefficients from equation 2.The left-hand panel shows that older households tend to consume a higher share of their total expenditures on food. For example, households with an average age between 60 and 64 consume on average 15% more than households aged between 25 and 29, even after controlling for income and other demographic factors.

The right-hand panel of figure 5 reveals that this effect holds true across different levels of development, but appears to be stronger in richer countries. To confirm this heterogeneity, I estimate equation 2 for each country and present the results in Figure 6. While most countries show a similar pattern to Figure 5, some exceptions include India and South Africa. Nonetheless, the effect remains consistently strong for the large majority of countries across the development spectrum.

2.3 Accounting for household demographic structure - a structural approach

The analysis presented so far is well suited to enquire of the impact of some household-level characteristic (in this case, average age) upon food expenditure shares. However, if we wish to investigate the impact of the exact demographic structure, a different approach is necessary. This is because the mapping between individual and household behavior introduces several complications, such as intra-household bargaining and the presence of public goods, that require more detailed consumption data than what is available in the LIS dataset[2]. To address these issues, I will employ a structural model that aggregates individual preferences rather than expenditures. Under this model, the household behaves as a single representative agent and allocates expenditures across goods based on preferences that reflect the exact composition of the household. To accomplish this, I will use the PIGL class of preferences (Muellbauer, 1975), which have a long history as the basis for empirical work[3]. This class of preferences has been applied to the context of structural change by Boppart (2014), and possesses appealing aggregability properties that will be useful when exploring the impact of demographic trends on the aggregate allocation of food expenditures. Additionally, PIGL preferences are non-homothetic, which makes them capable of capturing the dynamics of the Engel Law.

2.3.1 Model

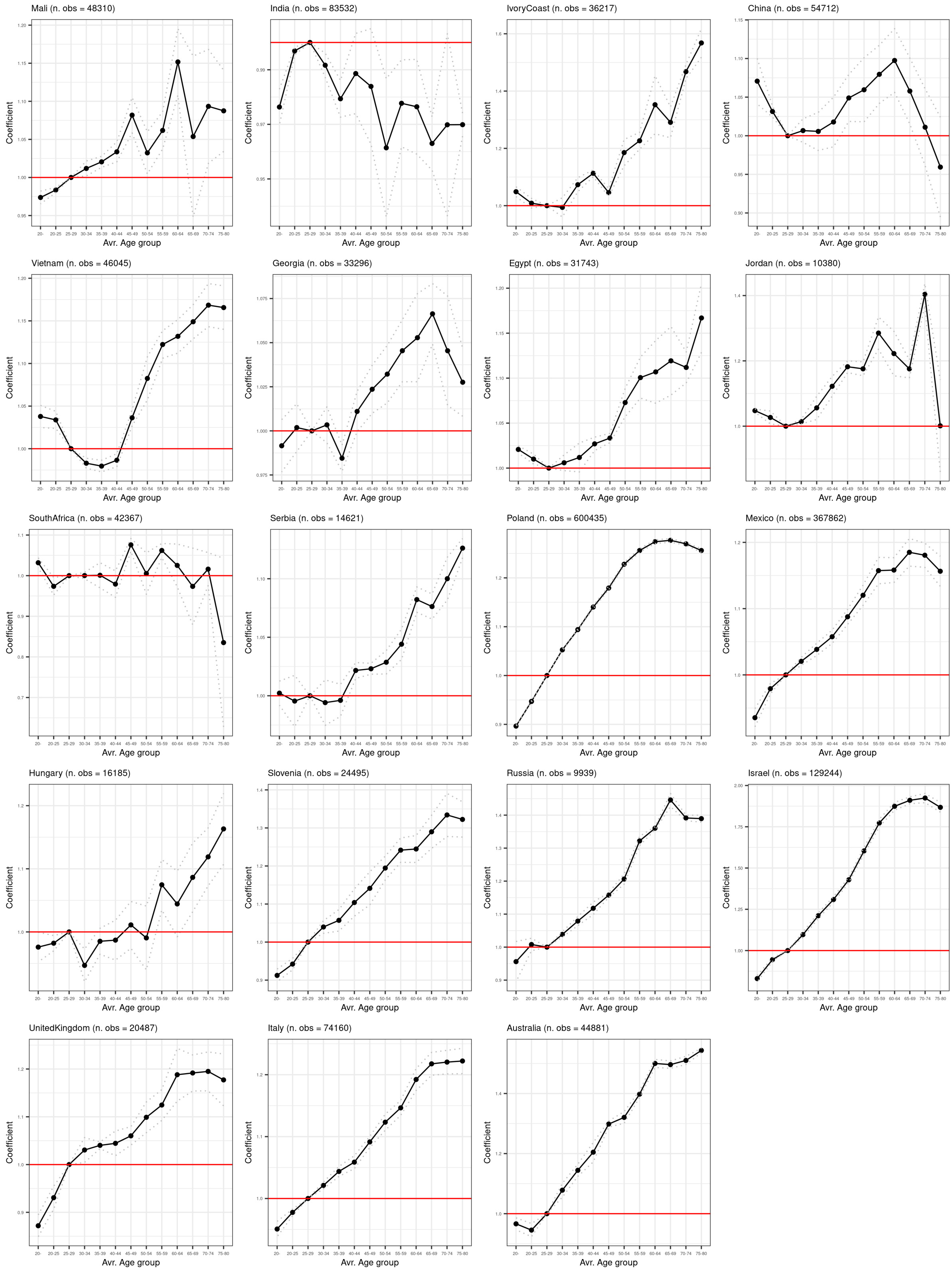
The economy there are two goods: food ("f") and non-food ("n"). Household h's demographic structure, specifically the distribution of members across M demographic groups, is exogenously given. Based on the price vector $\mathbf{P}$, the household allocates its consumption across the two sectors. Preferences follow a PIGL (Boppart, 2014) functional form:

$$\mathcal{V}^h(\mathbf{P}, E_{h,t}) = \frac{1}{\epsilon}\left[\frac{E_t^h}{P_t^n}\right]^{\epsilon} - \frac{\nu_t^h}{\gamma}\left[\frac{P_t^f}{P_t^n}\right]^{\gamma} - \frac{1}{\epsilon} + \frac{\nu_t^h}{\gamma}$$

The parameters can be interpreted as follow: ϵ is the real expenditures elasticity, while γ represent the marginal impact of a change in relative prices. Finally, ν_t^h is a household-specific taste-shifter. To see its role the allocation of expenditures across sectors, notice that from Roy's identity we can derive

[2]For example, Browning et al. (2013) and Lechene et al. (2019) have proposed approaches for empirically decomposing intra-household expenditure allocation, but these require more detailed data

[3]The Almost Ideal Demand System is derived from the logarithmic form of PIGL, known as PIGLOG.



This figure plots the estimated values for $D_h^{\text{Avr Age}}$ from equation 2 for each country in the LIS dataset.

Figure 6: Estimated value of $D_h^{\text{Avr Age}}$ by country.

household's h food share of total expenditures:

$$\omega_h^f = \left(\frac{E_{h,t}}{P_t^n}\right)^{-\epsilon} \cdot \left(\frac{P_t^f}{P_t^n}\right)^{\gamma} \cdot \nu_t^h \tag{3}$$

A higher taste-shifter ν_t^h implies a higher food share of total expenditures, given prices and expenditure levels.

In contrast to Cravino et al. (2022), I have defined the complement of the sector that I am interested in (i.e., the non-food) as the "reference sector". This reference sector serves as the denominator in the indirect utility function. My argument is simple: as shown in equation 3, it allows us to obtain log-linear shares of total expenditures for the sector that we are interested in. On the other hand, the reference sector's shares are the complement, which is not log-linear. This approach allows for a clearer interpretation of the parameters, as they directly refer to the relevant sector.Additionally, it simplifies the math. For example, we can derive equation 8 directly, while in Boppart (2014) and Cravino et al. (2022) it can be only approximated using two Taylor expansions. As shown in appendix (4.2), which sector is used as a reference does affect the outcome[4].

I assume that each household could be represented by a single agent. However, we know that households are made up of diverse individuals with their own preferences and varying abilities to impact the allocation of the household budget. To account for this, I propose using a geometric average of individual members' preferences as the household taste-shifter. That is:

$$\nu_t^h \equiv \left(\prod_i^{N_h} \nu_t^i(m)\right)^{\frac{1}{N_h}} \tag{4}$$

In addition to its useful mathematical properties, the choice of using a geometric mean aggregator for household taste-shifter has strong economic intuition. Let's start that by noticing that a generalized mean is both intuitively and mathematically equivalent to a CES aggregator (de La Grandville and Solow, 2016). In turn, the geometric mean is to generalized means what a Cobb-Douglas aggregator is to CES. Specifically, equation 4 can be seen as a Cobb-Douglas aggregator of individual taste-shifters. Therefore, by using a geometric mean aggregator I assume imperfect substitution between individual preferences within the household[5]. This suggests that the household care about the distribution of welfare across their members, and that they view all members as equally important. These assumptions are reasonable and make sense in the context of household decision-making.

Following Cravino et al. (2022), the individual[6] taste-shifter takes the form:

$$\nu_t^i(m) = \nu_t \cdot \delta^m \cdot \mu_t^h,$$

[4]Since the approach by Cravino et al. (2022) require use of approximations, the numerical outcomes are slightly different but qualitatively equivalent.

[5]If the household were to maximize any linear combination of member's utility, then we would have perfect substitution across individuals

[6]In Cravino et al. (2022) this is the shape of the *household-level* taste-shifter.

That is, the taste-shifter of individual i of household h, belonging to the demographic group m, can be decomposed into an aggregate component (ν_t), a demographic component (δ^m) and, finally, a household-level idiosyncratic one (μ_t^h). Therefore, the household-level taste-shifter can be written as

$$\nu_t^h = \nu_t \cdot \mu_t^h \cdot \underbrace{\exp\left[\sum_m^M s_m^h \cdot \log(\delta^m)\right]}_{\equiv \delta_t^h} \equiv \nu_t \cdot \mu_t^h \cdot \delta_t^h$$

where $s_m^h \equiv N_m/N$ is the share of household members belonging to demographic group m. That is, the demographic component of the preferences of household h is the log-linear aggregation of individual member preferences. This structure allows us to incorporate the detailed structure of the household such as number and demographic characteristics of individual members.

2.3.2 Empirical estimation

The food share of total expenditures for a generic household h can be written as3 yields

$$\omega_h^f = \left(\frac{E_{h,t}}{P_t^n}\right)^{-\epsilon} \cdot \left(\frac{P_t^f}{P_t^n}\right)^{\gamma} \cdot \exp\left[\sum_m^M s_m^h \cdot \log(\delta^m)\right] \cdot \nu_t \cdot \mu_t^h \tag{5}$$

After taking logs, this equation can be estimated empirically by OLS using the data from the previous section. The model that will be fitted is

$$\log(\omega_h^f) = \epsilon \cdot \left(\frac{P_t^n}{E_{h,t}}\right) + \gamma \cdot \left(\frac{P_t^f}{P_t^n}\right) + \sum_m^M s_m^h \cdot \text{DUMMY}_m + \alpha_c + \epsilon_h \tag{6}$$

where α_c is a region-level fixed effect which captures potential local differences in relative prices.

I will start by defining the M demographic groups according to age. Specifically, I classify all individual household members according to 9 10-year groups. Therefore, s_{0-9}^h represent the shares of household members aged between 0 and 9. Table 4 shows the output. As expected, the coefficient ϵ, ruling the income effect, is positive - i.e. food expenditures shares decline with total expenditures. This result is consistent with Engel's Law.

	Log(food share)									
Country		CHN	CIV	EGY	GEO	IND	JOR	MLI	VNM	ZAF
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ϵ	0.395***	0.325***	0.116***	0.389***	0.234***	0.460***	0.165***	0.154***	0.456***	0.374***
	(0.012)	(0.009)	(0.022)	(0.012)	(0.023)	(0.014)	(0.029)	(0.019)	(0.008)	(0.007)
γ	0.562***	0.465***	1.71***	-0.021	0.287	0.485***	-1.56***	-0.983***	1.04***	-0.074
	(0.036)	(0.048)	(0.477)	(0.099)	(0.234)	(0.119)	(0.368)	(0.262)	(0.055)	(0.168)
Observations	1,658,667	53,686	34,291	31,980	33,457	82,029	10,435	46,401	46,445	41,096
R^2	0.45810	0.37270	0.19098	0.40288	0.09546	0.52983	0.13268	0.48618	0.48458	0.38166
Within R^2	0.32431	0.33707	0.06550	0.34000	0.08076	0.50115	0.10941	0.17415	0.44874	0.35602
Reg. fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

	Log(food share)								
Country	AUS	GBR	HUN	ISR	ITA	MEX	POL	RUS	SRB
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ϵ	0.566^{***}	0.536^{***}	0.212^{***}	0.546^{***}	0.416^{***}	0.527^{***}	0.571^{***}	0.270^{***}	0.354^{***}
	(0.009)	(0.014)	(0.013)	(0.008)	(0.015)	(0.013)	(0.007)	(0.023)	(0.017)
γ	0.872^{***}	0.655^{***}	-0.077	0.230^{***}	0.152	-0.387^{***}	0.170^{***}	-0.163	1.72^{**}
	(0.155)	(0.159)	(0.121)	(0.075)	(0.175)	(0.132)	(0.052)	(0.218)	(0.450)
Observations	26,508	21,393	10,859	127,458	78,436	367,640	613,680	6,897	15,401
R^2	0.31840	0.36767	0.09367	0.33276	0.27232	0.39741	0.49504	0.23133	0.35499
Within R^2	0.31762	0.36477	0.08522	0.29523	0.25304	0.35956	0.48537	0.21683	0.32953
Reg. fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓

Table 4

Figure 7 displays the estimated values for δ^m using the entire LIS dataset. To understand the figure, consider two households, each with two members. The only difference between these households is the age of one of their members. In the first household, the member is 62 years old, while in the second household, the member is 12 years old. The figure shows that their respective δ values are approximately 0.85 and 1.25. Since δ is a multiplier in equation 5, the consumption shares of each household must be multiplied by $\sqrt{0.85}$ and $\sqrt{1.25}$ respectively. Note that the square root represents the weight of the individual within a two-individual household. Therefore, the household with the 62-year-old member will consume 20%[7] more on food than the household with the 12-year-old member. Since the impact of an additional household member upon food expenditure shares is weighted by the size of the household, interpreting the numerical implications of the coefficients may be difficult. However, higher coefficients necessarily imply higher food expenditure shares *ceteris paribus*. This section's results confirm the previous section's findings that households with higher average age spend relatively more on food. Furthermore, this section suggests that even at the individual level (while accounting for household structure), higher age implies higher food expenditures.

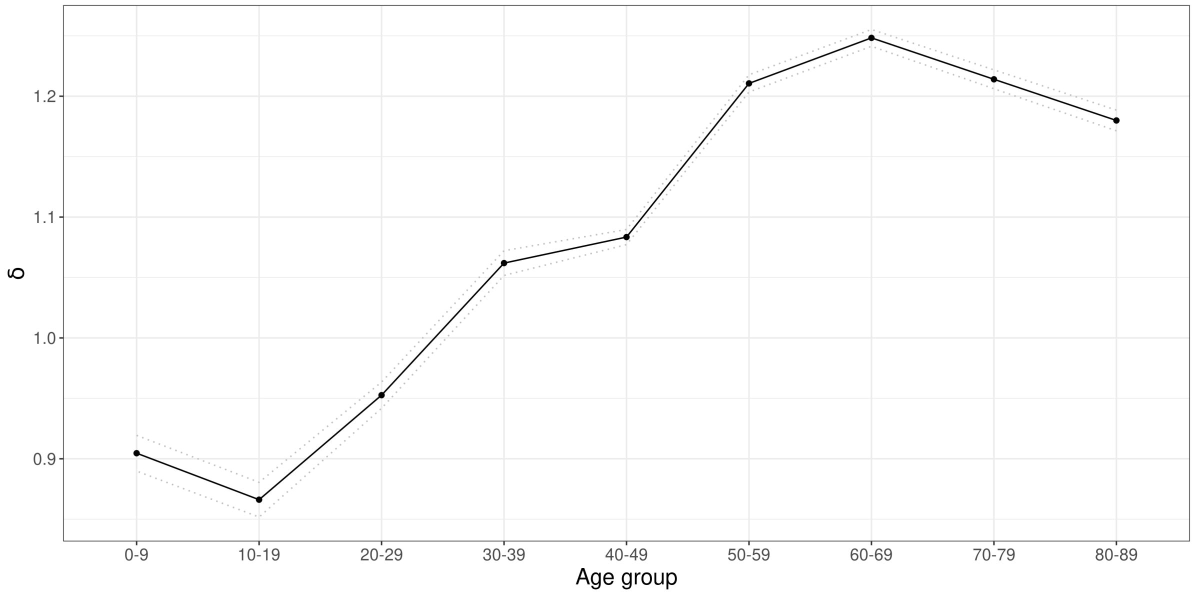


Figure 7: Estimated value of δ^m for the entire LIS sample

[7] $\sqrt{1.25}/\sqrt{0.85} \approx 1.2$. Since we assume that the household are symmetric, then the remaining part of equation 5 are the same, and thus cancel over.

Figure 9 shows the results obtained by estimating equation 6 for each individual county in the LIS dataset. All countries show an upward trend for the coefficients of elderly individuals. However, there is significant heterogeneity across countries in the impact of younger individuals on the household's budget allocation. Even countries that previously showed no evidence of a correlation between average age and food expenditure shares, such as India and South Africa, now demonstrate a convincing relationship between individual age and food expenditure shares. This finding suggests that household composition may have played a significant role in the results from the previous section.

The next step is to expand the definition of the demographic groups to include sex. Figure 8 shows the coefficients for the same sample. As you can see, after the age group 20 – 29 the coefficient are higher for females compared to males of same age. While the difference is small, the coefficients are statistically different from each other. This result suggests that elderly females imply a larger food share of total expenditures.

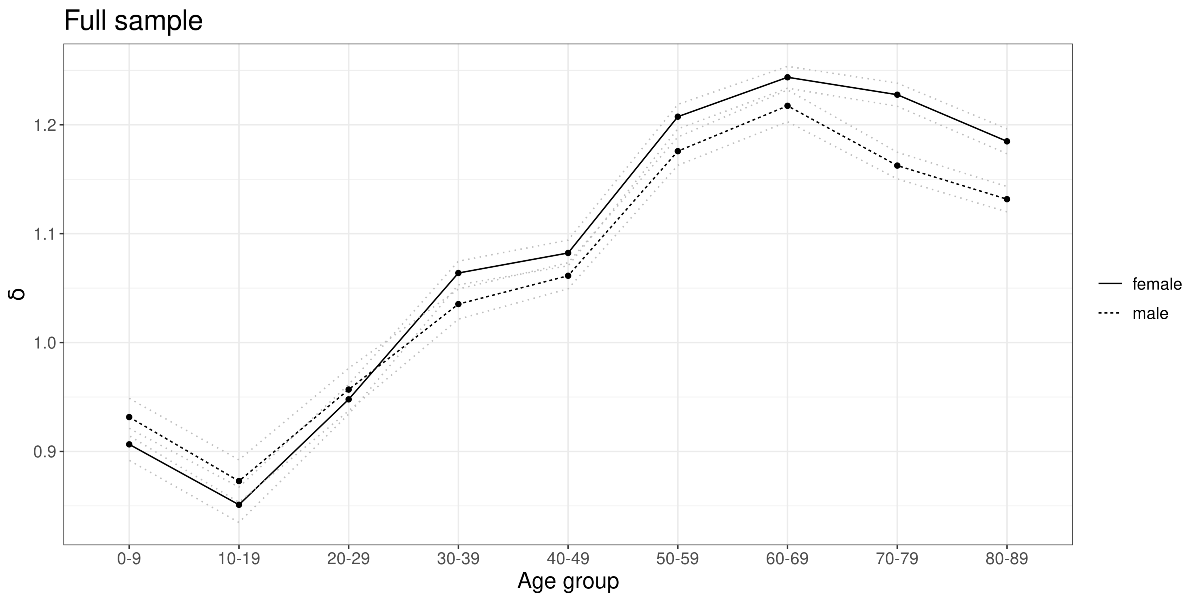


Figure 8: Estimated value of δ^m for the entire LIS sample (age and sex)

By estimating the model for each individual country as depicted in Figure 10, we can observe a substantial cross-country heterogeneity. The gender differences in developed countries are negligible, whereas in some countries the gap appears to be considerably significant, especially in Egypt and Ivory Coast for middle-aged individuals. Remarkably, Mexico stands out among the countries experiencing the stronger difference. These findings are particularly noteworthy, as these countries are currently undergoing the ”working-age population explosion” phase of their demographic transition. The results demonstrate a significant heterogeneity across countries, and the effect in the affected ones seems to be significant enough to imply a non-insignificant impact on structural change. Overall, I argue that these findings provide compelling evidence to support the importance of including gender as a potential driver of structural change out of food consumption, albeit without presumption of cross-country generality.

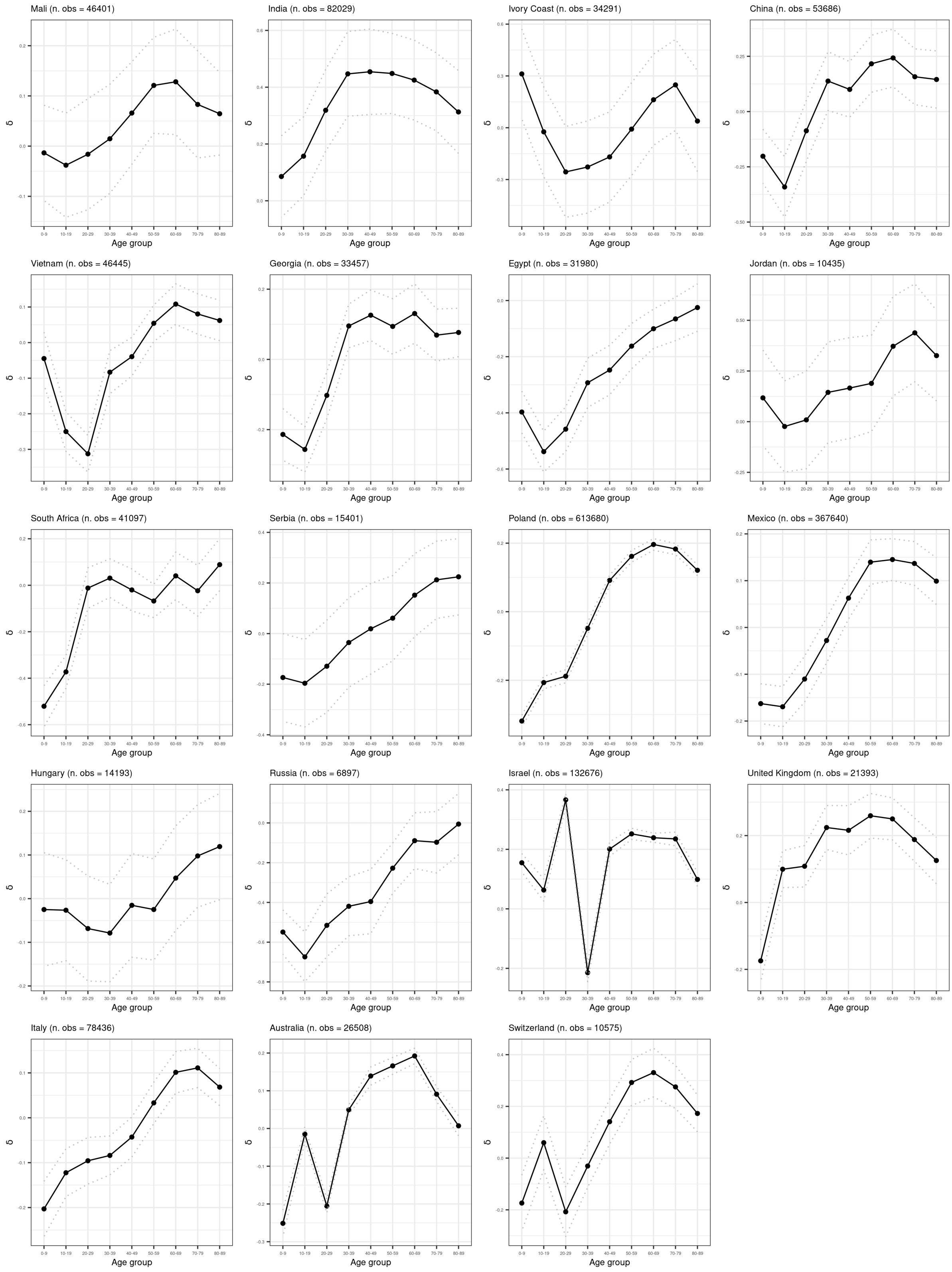


Figure 9: Estimated value of δ^m by country.

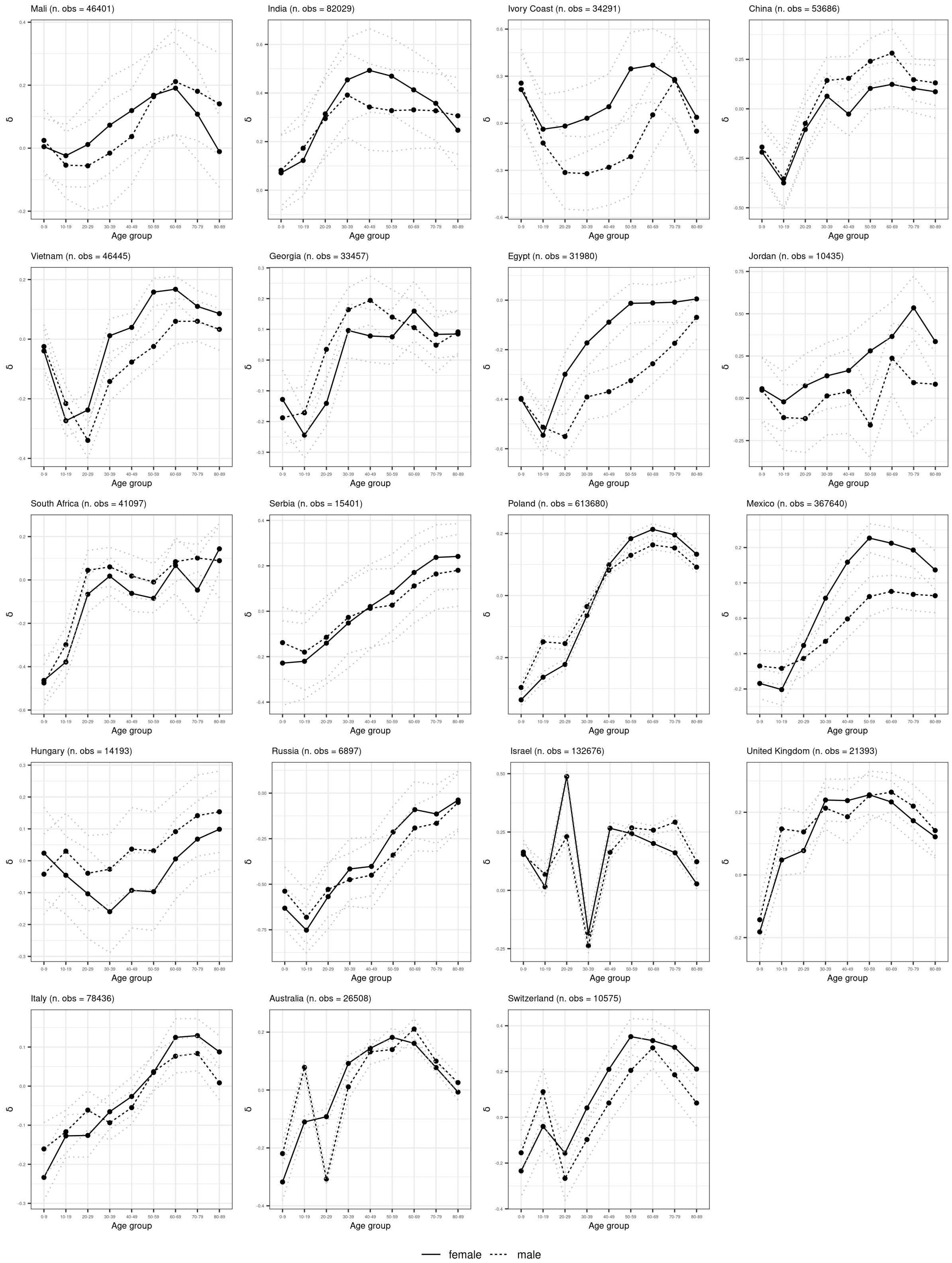


Figure 10: Estimated value of δ^m by country (age and sex).

2.4 Accounting for the impact of demographic transition upon aggregated food consumption

One key properties of PIGL preferences is that they allow for tractable aggregation. In particular, the aggregated food share of total consumption can be written as

$$\Omega_{\mathrm{f}} \equiv \frac{\sum_h^H E_h^f}{\sum_h E_h} = \left(\frac{P_t^n}{E_t}\right)^{\epsilon} \left(\frac{P_t^f}{P_t^n}\right)^{\gamma} \bar{\delta}_t \cdot \theta_t \cdot \nu_t, \tag{7}$$

where

$$E_t \equiv \frac{1}{H}\sum_h E_{h,t} \qquad \text{(Average expenditures)}$$

$$\bar{\delta}_t \equiv \frac{1}{H}\sum_h^H \frac{E_{h,t}}{E_t} \cdot \delta_t^h \qquad \text{(Expenditure-weighted average of HH demographic shifters)}$$

$$\theta_t \equiv \frac{1}{H}\sum_h^H \frac{\delta_t^h}{\bar{\delta}_t} \cdot \left[\frac{e_h}{E}\right]^{1-\epsilon} \qquad \text{(Preference-weighted expenditure inequality)}$$

As in Boppart (2014), taking a log change of aggregated share of food consumption from a reference period τ allows us to decompose the different drivers of a change in aggregate food consumption:

$$\hat{\Omega}_t^f = \underbrace{\epsilon(\hat{\mathbf{P}}_t - \hat{E}_t)}_{\text{Income}} + \underbrace{\overbrace{(\gamma - \epsilon\Omega_t^f)}^{\text{Rel. Price elasticity}} \quad (\hat{P}_t^f - \hat{P}_t^n)}_{\text{Substitution}} + \underbrace{\hat{\bar{\delta}}_t}_{\text{Demography}} + \underbrace{\hat{\theta}_t + \hat{\nu}_t}_{\text{Residual}}, \tag{8}$$

where

$$\hat{x}_t \equiv \ln x_t - \ln x_\tau \quad \forall x \qquad \text{(cumulative log change)}$$

$$\hat{\mathbf{P}}_t \equiv (1 - \Omega_t^f)\hat{P}_t^n + \Omega_t^f \hat{P}_t^f \qquad \text{(log change in the aggregate price index)}$$

The concept behind equation 8 is easy to understand: the income effect is defined as the effect of a change in *real* expenditures ($\hat{\mathbf{P}}_t - \hat{E}_t$). The substitution effect is the elasticity of substitution between food and non-food multiplied by the change in relative prices. Finally, the demographic effect is the change in the expenditure-weighted average demographic taste-shifters.

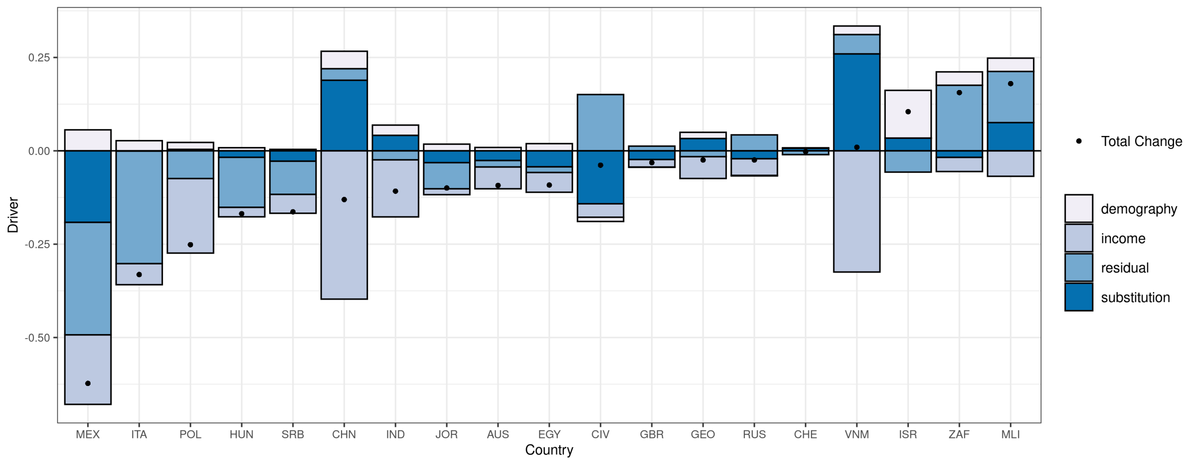
All parameters in equation 8 can be estimated using OLS and the LIS microdata. In fact, we have already estimated the coefficients shown in figure 8 in the previous section. Table 5 displays the estimated values for the coefficients ϵ and γ.

Country		CHN	CIV	EGY	GEO	IND	JOR	MLI	VNM	ZAF
	Log(food share)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ϵ	0.395***	0.325***	0.116***	0.389***	0.234***	0.460***	0.165***	0.154***	0.456***	0.374***
	(0.012)	(0.009)	(0.022)	(0.012)	(0.023)	(0.014)	(0.029)	(0.019)	(0.008)	(0.007)
γ	0.562***	0.465***	1.71***	-0.021	0.287	0.485***	-1.56***	-0.983***	1.04***	-0.074
	(0.036)	(0.048)	(0.477)	(0.099)	(0.234)	(0.119)	(0.368)	(0.262)	(0.055)	(0.168)
Observations	1,658,667	53,686	34,291	31,980	33,457	82,029	10,435	46,401	46,445	41,096
R^2	0.45810	0.37270	0.19098	0.40288	0.09546	0.52983	0.13268	0.48618	0.48458	0.38166
Within R^2	0.32431	0.33707	0.06550	0.34000	0.08076	0.50115	0.10941	0.17415	0.44874	0.35602
Reg. fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Country	AUS	GBR	HUN	ISR	ITA	MEX	POL	RUS	SRB
	Log(food share)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ϵ	0.566***	0.536***	0.212***	0.546***	0.416***	0.527***	0.571***	0.270***	0.354***
	(0.009)	(0.014)	(0.013)	(0.008)	(0.015)	(0.013)	(0.007)	(0.023)	(0.017)
γ	0.872***	0.655***	-0.077	0.230***	0.152	-0.387***	0.170***	-0.163	1.72**
	(0.155)	(0.159)	(0.121)	(0.075)	(0.175)	(0.132)	(0.052)	(0.218)	(0.450)
Observations	26,508	21,393	10,859	127,458	78,436	367,640	613,680	6,897	15,401
R^2	0.31840	0.36767	0.09367	0.33276	0.27232	0.39741	0.49504	0.23133	0.35499
Within R^2	0.31762	0.36477	0.08522	0.29523	0.25304	0.35956	0.48537	0.21683	0.32953
Reg. fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓

Table 5

Figure 11 illustrates the breakdown of the different drivers for all countries in the sample. As we can see, the Income effect is a critical mechanism that reduces the aggregate food expenditure shares. This is consistent with Engel's Law and unsurprising. However, the most interesting finding is the effect of changes in demographic structure. As shown, demographic changes have led to a positive driver of food consumption in all countries except Ivory Coast, where the change in demography resulted in a decline in the food shares of total consumption. Interestingly, a few countries observed an increase in aggregate food consumption: Mali, South Africa, Vietnam, and Israel. In all these countries, the demographic and substitution effects offset the Income effect.



This figure shows the value of the different drivers from equation 8. Countries are observed over a different time span (see table 6) and the total change over said period is shown by the black dot. Values represent log-changes of aggregated food expenditures.

Figure 11: Estimated value of the different drive of food expenditures

To quantify the impact of the demography upon food consumption, I conducted a counterfactual exercise. Table 6 demonstrates the observed change in food consumption shares ($\Delta\Omega_f$ in percentile points) and the implied compounded change rate over the observed time period (in % points). The following two columns show how the food consumption would be if we shut down the demographic effect and the compounded change rate. Finally, the last two columns display the difference between the baseline and the observed and the counterfactual. Changes in demographic structure may significantly affect the annual growth rates. For example, we observed that food consumption in Mali increased by 2.28% annually in the period 2011-2018, of which 0.46 percentage points ($\approx$ 20%) can be imputed to the demographic transition. However, there is strong cross-country heterogeneity: most high-income countries observe a small impact, while some countries such as Switzerland report no effect whatsoever.

Country	Interval	$\Delta\Omega_f$	$\Delta\Omega_f$ (CAGR)	$\Delta\Omega_f$ (counterfactual)	$\Delta\Omega_f$ (counterfactual, CAGR)	Δ	Δ (yearly)
Mali	2011-2019	10.73	2.28	8.45	1.82	2.28	0.46
Ivory Coast	2002-2015	-1.66	-0.30	-1.18	-0.21	-0.48	-0.09
India	2004-2011	-4.54	-1.53	-5.61	-1.92	1.07	0.39
Vietnam	2005-2013	0.37	0.12	-0.50	-0.17	0.87	0.29
Jordan	2008-2013	-3.83	-1.97	-4.48	-2.32	0.65	0.35
Egypt	2012-2017	-3.79	-1.82	-4.54	-2.19	0.75	0.37
South Africa	2008-2017	3.61	1.75	2.73	1.34	0.88	0.41
Georgia	2009-2019	-0.87	-0.24	-1.44	-0.41	0.57	0.17
China	2002-2018	-3.95	-0.81	-5.24	-1.10	1.29	0.29
Serbia	2010-2016	-6.20	-2.69	-6.33	-2.75	0.13	0.06
Mexico	1992-2018	-22.35	-2.37	-23.76	-2.58	1.41	0.21
Russia	2007-2010	-0.83	-0.81	-0.79	-0.77	-0.04	-0.04
Hungary	1991-2015	-6.73	-0.70	-7.04	-0.73	0.31	0.03
Poland	1999-2019	-7.46	-1.25	-7.93	-1.34	0.47	0.09
Israel	1997-2018	1.74	0.50	-0.35	-0.11	2.09	0.61
Italy	1991-2016	-11.69	-1.32	-12.49	-1.42	0.80	0.10
United Kingdom	1991-1993	-0.62	-1.57	-0.61	-1.54	-0.01	-0.03
Australia	2004-2016	-1.24	-0.77	-1.36	-0.84	0.12	0.07
Switzerland	2000-2004	-0.03	-0.05	-0.03	-0.05	0.00	0.00

Table 6

So far I have documented that both income - proxied by total expenditures - and demography affect food consumption. At the aggregated level, income growth decreases food consumption, while the demographic transition leads to an increase. However, as I argued in the introduction, demographic transition and income are strongly correlated, namely a richer country is usually ahead in the demographic transition. Therefore, estimating the income effect alone without considering demographic trends would underestimate the income effect, as the estimation would incorporate the negative demographic component.

To test this hypothesis, I conducted another counterfactual exercise where I estimated an equation without demographic controls. Specifically, I estimated equation

$$\log(\omega_h^f) = \epsilon \cdot \left(\frac{P_t^n}{E_{h,t}}\right) + \gamma \cdot \left(\frac{P_t^f}{P_t^n}\right) + \alpha_c + \epsilon_h \tag{9}$$

That is, equation 9 without demographic controls. This allow me to estimate the income effect from equation 8 without taking into account the demographic driver. Figure 12 the ratio between the income effect without and with taking into account the demographic structure. As you can see, for almost all countries, accounting for the demographic transition leads to an increase in the magnitude of the income effect. That is, accounting for the demographic transition increases the observed impact of income growth upon food consumption.

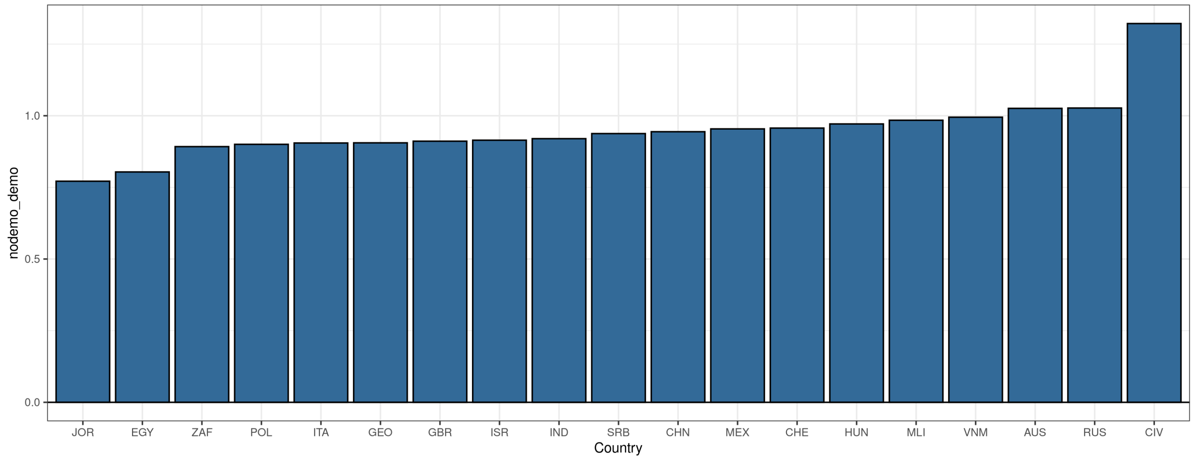


Figure 12: Ratio between the income effect without and with demographic controls.

3 Conclusion

This study contributes to the literature by highlighting the significant impact of demographic trends, particularly age and sex, on food consumption expenditure. Using both aggregate and household level data from 20 countries across different levels of development, this study establishes a positive relationship between individual age characteristics and food expenditure shares. In particular, the empirical reveals that, after controlling for total expenditures, countries with higher median age spend a larger share of their aggregate expenditures on food for home consumption. Additionally, it finds that the food expenditure share of household total expenditures increases with the age of individual members. Notably, the study also documents that in some countries, such as Ivory Coast, Vietnam, and Mexico, an additional adult female household member increases the food share more than a similarly aged male.

This research implies that demographic trends, particularly older individuals and females in some countries, are slowing the decline in food consumption. To quantify the size of this mechanism, a demand-side, quantitative model based on the PIGL demand system is built and calibrated using the same microdata from the empirical exploration. The results confirm that the evolution of age-sex composition in the economy has been a significant force slowing down structural change. A counterfactual exercise shows that shutting down the demographic channel would decrease the change rate of the food share of aggregated expenditure by between 0.1 to 0.5 percentage yearly for most countries. In other words, demographic trends in age and sex have a considerable impact on structural change. Finally, the study documents that estimating the income effect without taking into account the demographic trends leads to an underestimation of the income effect by up to 20%.

References

Mark Aguiar and Mark Bils. Has consumption inequality mirrored income inequality? *American Economic Review*, 105(9):2725–56, 2015.

Mark Aguiar and Erik Hurst. Deconstructing life cycle expenditure. *Journal of Political Economy*, 121(3): 437–492, 2013.

Yunus Aksoy, Henrique S Basso, Ron P Smith, and Tobias Grasl. Demographic structure and macroeconomic trends. *American Economic Journal: Macroeconomics*, 11(1):193–222, 2019.

Simon Alder, Timo Boppart, and Andreas Muller. A theory of structural change that can fit the data. *American Economic Journal: Macroeconomics*, 14(2):160–206, 2022.

Timo Boppart. Structural change and the kaldor facts in a growth model with relative price effects and non-gorman preferences. *Econometrica*, 82(6):2167–2196, 2014.

Laurent Brembilla. The demographics of structural change. In *24th Conference of the Society of Computational Economics and Finance*, 2018.

Martin Browning, Pierre-Andre Chiappori, and Arthur Lewbel. Estimating consumption economies of scale, adult equivalence scales, and household bargaining power. *Review of Economic Studies*, 80(4): 1267–1303, 2013.

Diego Comin, Danial Lashkari, and Martí Mestieri. Structural change with long-run income and price effects. *Econometrica*, 89(1):311–374, 2021.

Javier Cravino, Andrei A Levchenko, and Marco Rojas. Population aging and structural transformation. Technical report, National Bureau of Economic Research, 2022.

Olivier de La Grandville and Robert Solow. *The CES production function as a general mean (in collaboration with Robert M. Solow)*, page 92–113. Cambridge University Press, 2 edition, 2016. doi: 10.1017/9781316335703.009.

Matthew J Delventhal, Jesús Fernández-Villaverde, and Nezih Guner. Demographic transitions across time and space. Technical report, National Bureau of Economic Research, 2021.

Matthias Doepke, Anne Hannusch, Fabian Kindermann, and Michèle Tertilt. The economics of fertility: A new era. Technical report, National Bureau of Economic Research, 2022.

E Engel. Die productions-und consumtionsverhältnisse des königreichs sachsen (1857). wiederabgedr. *Derselbe, Die Lebenskosten belgischer Arbeiter-Familien früher und jetzt. Ermittelt aus Familien-Haushaltrechnungen und vergleichend zusammengestellt. Dresden*, 1895.

AC Foster. Consumer expenditures vary by age. beyond the numbers: Prices and spending, 4 (14). us bureau of labor statistics, 2015. URL https://www.bls.gov/opub/btn/volume-4/consumer-expenditures-vary-by-age.htm.

Berthold Herrendorf, Richard Rogerson, and Akos Valentinyi. Two perspectives on preferences and structural transformation. *American Economic Review*, 103(7):2752–89, 2013.

Charles I Jones. The end of economic growth? unintended consequences of a declining population. *American Economic Review*, 112(11):3489–3527, 2022.

Valérie Lechene, Krishna Pendakur, and Alex Wolf. Ols estimation of the intra-household distribution of consumption. Technical report, IFS Working Papers, 2019.

Thomas Malthus. An essay on the principle of population. printed for j. johnson. *St. Paul's church-yard, London*, pages 1–126, 1798.

Rui Mao and Jianwei Xu. Population aging, consumption budget allocation and sectoral growth. *China Economic Review*, 30:44–65, 2014.

John Muellbauer. Aggregation, income distribution and consumer demand. *The Review of Economic Studies*, 42(4):525–543, 1975.

Carle C Zimmerman. Ernst engel's law of expenditures for food. *The Quarterly Journal of Economics*, 47 (1):78–101, 1932.

4 Appendix

4.1 LIS - Summary Statistics

cname	year	nobs	mean	median	sd	cname	year	nobs	mean	median	sd
Australia	2004	6, 896	36.970	31.157	26.156	Italy	1991	8, 165	25.323	21.905	14.449
Australia	2010	9, 680	41.067	34.326	30.079	Italy	1993	8, 056	24.606	20.717	14.459
Australia	2016	9, 932	42.929	35.480	34.933	Italy	1995	8, 081	22.819	21.493	11.614
China	2002	16, 967	4.281	3.132	3.893	Italy	1998	7, 050	21.261	19.023	13.476
China	2013	16, 419	10.859	8.334	9.671	Italy	2000	7, 972	21.928	21.469	11.821
China	2018	20, 300	15.382	12.128	12.749	Italy	2004	7, 977	23.032	20.424	12.505
Egypt	2012	7, 525	13.111	11.210	8.715	Italy	2008	7, 901	22.483	20.597	11.364
Egypt	2015	11, 977	15.208	12.640	12.626	Italy	2010	7, 869	22.897	20.131	12.141
Egypt	2017	12, 478	14.179	12.099	10.384	Italy	2014	8, 070	22.663	20.555	12.352
Georgia	2009	3, 857	8.108	6.231	6.890	Italy	2016	7, 295	22.712	19.525	14.849
Georgia	2010	5, 267	8.493	6.434	17.149	Ivory Coast	2002	10, 483	8.938	5.609	17.675
Georgia	2011	2, 701	8.498	6.790	6.781	Ivory Coast	2008	11, 920	8.773	6.300	8.598
Georgia	2012	2, 840	8.885	7.048	7.147	Ivory Coast	2015	11, 888	6.824	4.882	7.732
Georgia	2013	2, 707	10.055	8.075	8.094	Jordan	2008	2, 746	28.256	23.476	20.486
Georgia	2014	2, 763	10.645	8.637	8.196	Jordan	2010	2, 841	31.496	25.588	35.668
Georgia	2015	2, 726	10.180	8.201	7.544	Jordan	2013	4, 848	27.834	23.704	16.975
Georgia	2016	2, 605	10.326	8.273	7.954	Mali	2011	5, 590	10.266	7.284	12.110
Georgia	2017	2, 113	10.237	8.227	8.487	Mali	2013	4, 630	10.160	7.755	9.451
Georgia	2018	2, 706	9.880	8.350	7.009	Mali	2014	6, 057	8.685	6.904	8.877
Georgia	2019	3, 172	10.218	8.396	8.035	Mali	2015	5, 841	8.286	6.565	7.514
Hungary	1991	1, 466	12.780	10.830	9.782	Mali	2016	5, 915	8.035	6.226	9.359
Hungary	1994	1, 868	11.896	10.428	7.148	Mali	2017	6, 081	8.654	6.948	6.322
Hungary	1999	1, 732	11.520	9.692	8.306	Mali	2018	5, 674	10.108	8.056	7.770
Hungary	2005	1, 820	13.129	11.446	8.037	Mali	2019	6, 613	9.965	7.771	8.275
Hungary	2007	1, 616	11.492	10.132	6.433	Mexico	1992	10, 446	12.883	9.075	13.961
Hungary	2009	1, 659	11.335	10.142	6.114	Mexico	1994	12, 768	12.778	8.934	14.123
Hungary	2012	1, 775	10.691	9.504	6.230	Mexico	1996	13, 954	10.417	7.625	10.437
Hungary	2015	2, 257	11.461	10.210	6.448	Mexico	1998	10, 679	12.780	8.835	14.407
India	2004	40, 508	6.361	4.797	5.810	Mexico	2000	9, 867	14.538	9.839	18.660
India	2011	41, 521	8.292	6.247	8.042	Mexico	2002	16, 890	13.811	9.681	14.790
Israel	1997	5, 218	38.307	30.125	32.943	Mexico	2004	22, 235	14.367	10.155	15.777
Israel	2001	5, 734	29.461	24.564	21.680	Mexico	2005	22, 725	14.115	9.791	17.807
Israel	2002	6, 119	28.008	23.143	20.495	Mexico	2006	20, 434	15.762	11.160	18.224
Israel	2003	6, 124	28.149	23.507	21.223	Mexico	2008	29, 049	13.757	10.229	15.702
Israel	2004	6, 060	29.165	24.082	22.190	Mexico	2010	27, 189	13.123	9.657	13.776
Israel	2005	6, 201	29.897	24.785	22.664	Mexico	2012	8, 859	13.382	9.741	13.375
Israel	2006	6, 203	30.460	25.118	23.477	Mexico	2014	19, 273	12.715	9.194	14.279
Israel	2007	6, 101	31.230	26.053	23.733	Mexico	2016	69, 457	13.029	9.864	12.623
Israel	2008	5, 904	31.523	26.460	22.997	Mexico	2018	73, 815	13.292	10.125	14.753
Israel	2009	6, 209	31.741	26.268	23.708	Poland	1999	31, 272	15.994	13.616	11.384
Israel	2010	6, 102	31.738	26.654	24.413	Poland	2004	32, 088	15.430	12.706	12.158
Israel	2011	5, 964	31.870	26.936	24.487	Poland	2005	34, 585	15.089	12.438	11.673
Israel	2012	8, 588	32.193	27.362	22.820	Poland	2006	37, 287	16.051	13.266	12.039
Israel	2013	9, 372	33.013	27.457	28.324	Poland	2007	37, 144	17.064	13.979	13.691
Israel	2014	8, 368	33.559	28.171	23.458	Poland	2008	37, 115	18.275	14.953	15.001
Israel	2015	8, 446	34.657	28.990	25.533	Poland	2009	37, 037	18.592	15.304	14.573
Israel	2016	8, 733	36.004	29.638	26.984	Poland	2010	37, 217	18.723	15.528	14.069
Israel	2017	8, 736	37.207	31.098	27.305	Poland	2011	37, 130	18.438	15.371	13.738
Israel	2018	8, 494	37.384	31.400	27.797	Poland	2012	37, 179	18.318	15.386	13.372

Table 7

cname	year	nobs	mean	median	sd
Poland	2013	36, 959	18.432	15.470	13.647
Poland	2014	36, 976	18.707	15.802	13.803
Poland	2015	36, 898	19.039	16.012	13.712
Poland	2016	36, 633	19.861	16.784	13.862
Poland	2017	36, 457	20.245	17.065	14.241
Poland	2018	35, 967	20.044	16.612	17.594
Poland	2019	35, 736	20.718	17.301	19.977
Russia	2007	2, 551	14.728	10.261	16.884
Russia	2010	4, 346	17.443	13.209	17.945
Serbia	2010	4, 556	14.438	12.097	9.926
Serbia	2013	4, 458	14.026	11.934	9.063
Serbia	2016	6, 387	15.351	13.030	10.556
Slovenia	1997	2, 577	31.477	26.995	22.115
Slovenia	1999	3, 859	28.832	24.966	18.519
Slovenia	2004	3, 716	28.596	24.153	19.734
Slovenia	2007	3, 691	30.448	26.191	19.153
Slovenia	2010	3, 921	30.671	26.487	19.145
Slovenia	2012	3, 652	29.197	25.421	18.496
Slovenia	2015	3, 749	29.187	25.527	18.172
South Africa	2008	7, 284	12.929	4.689	25.944
South Africa	2010	5, 928	11.242	4.442	19.873
South Africa	2012	7, 858	10.286	4.623	16.263
South Africa	2015	9, 454	10.655	4.775	17.911
South Africa	2017	10, 573	11.846	5.069	22.844
South Korea	2006	12, 359	27.247	24.552	16.870
South Korea	2008	10, 938	26.898	24.277	16.641
South Korea	2010	10, 576	27.485	25.204	16.997
South Korea	2012	10, 322	27.846	25.753	17.097
South Korea	2014	9, 840	27.767	24.912	17.882
South Korea	2016	8, 878	26.790	23.403	17.785
Switzerland	2000	3, 628	40.832	35.026	31.547
Switzerland	2002	3, 705	40.353	34.665	28.185
Switzerland	2004	3, 242	40.353	34.532	27.057
Vietnam	2005	9, 125	8.027	6.086	7.846
Vietnam	2007	9, 178	10.085	7.590	11.033
Vietnam	2009	9, 386	11.712	8.940	12.206
Vietnam	2011	9, 379	14.600	11.777	11.691
Vietnam	2013	9, 377	14.954	11.759	15.447

Table 8

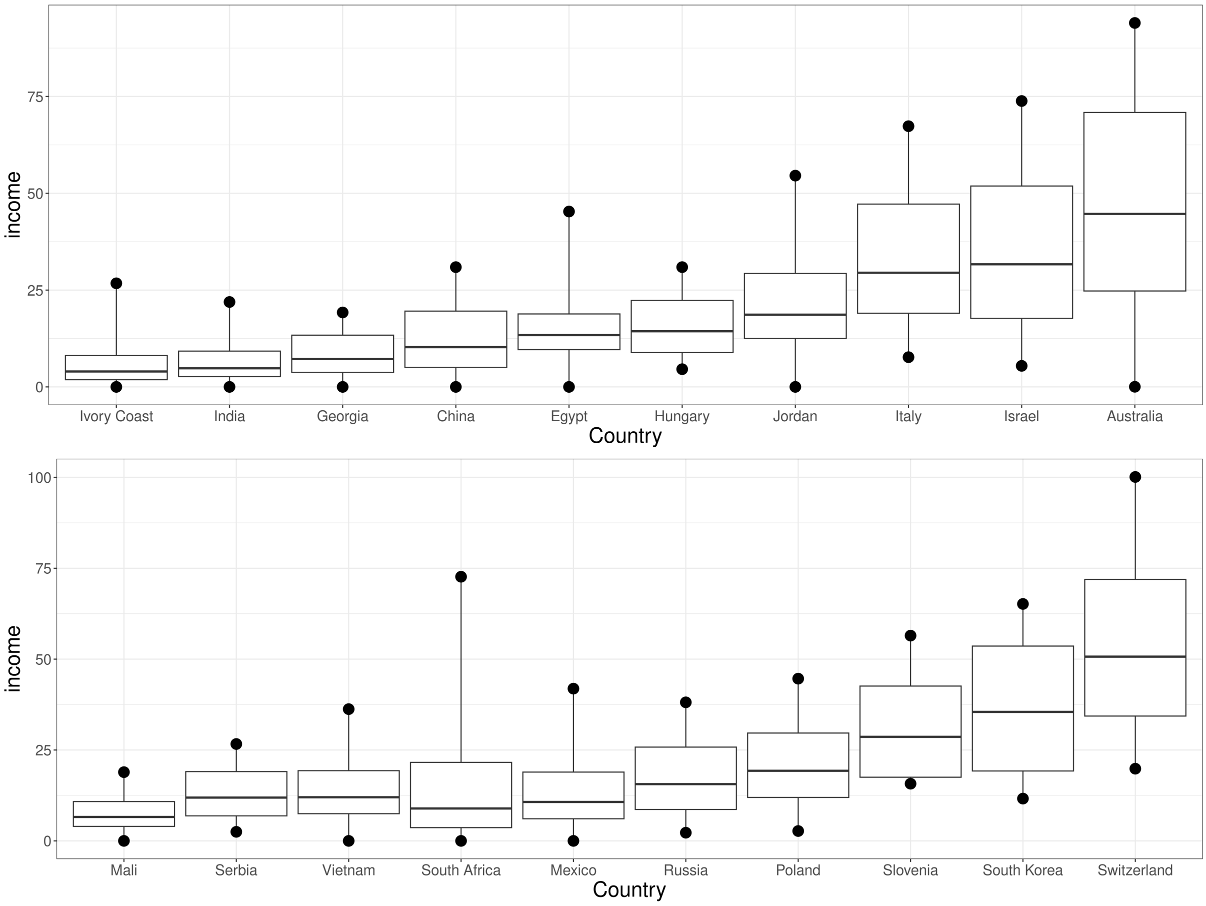


Figure 13: Average Household Income (.000 0f 2017 US$)

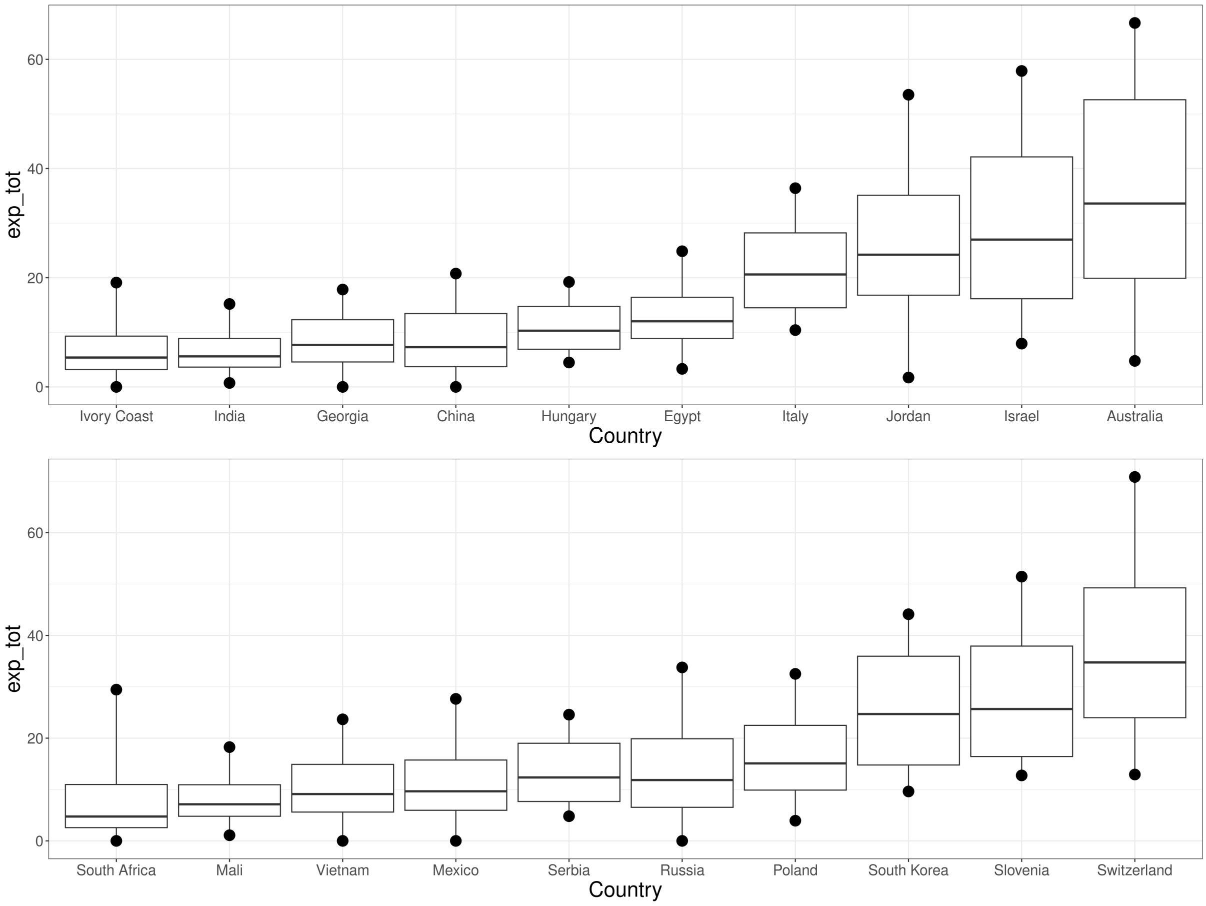


Figure 14: Average Household Total Expenditures (.000 0f 2017 US$)

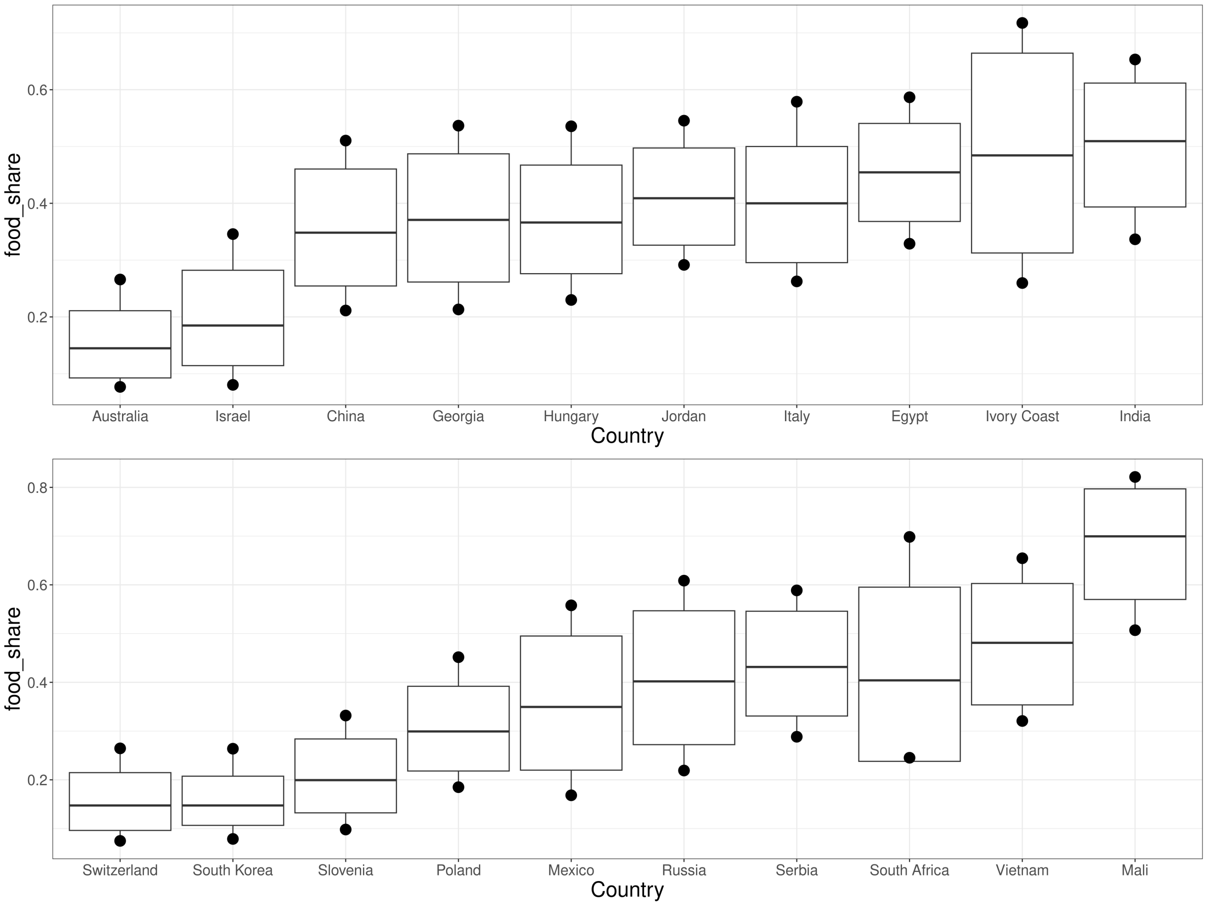


Figure 15: Average Food Share of Total Expenditures

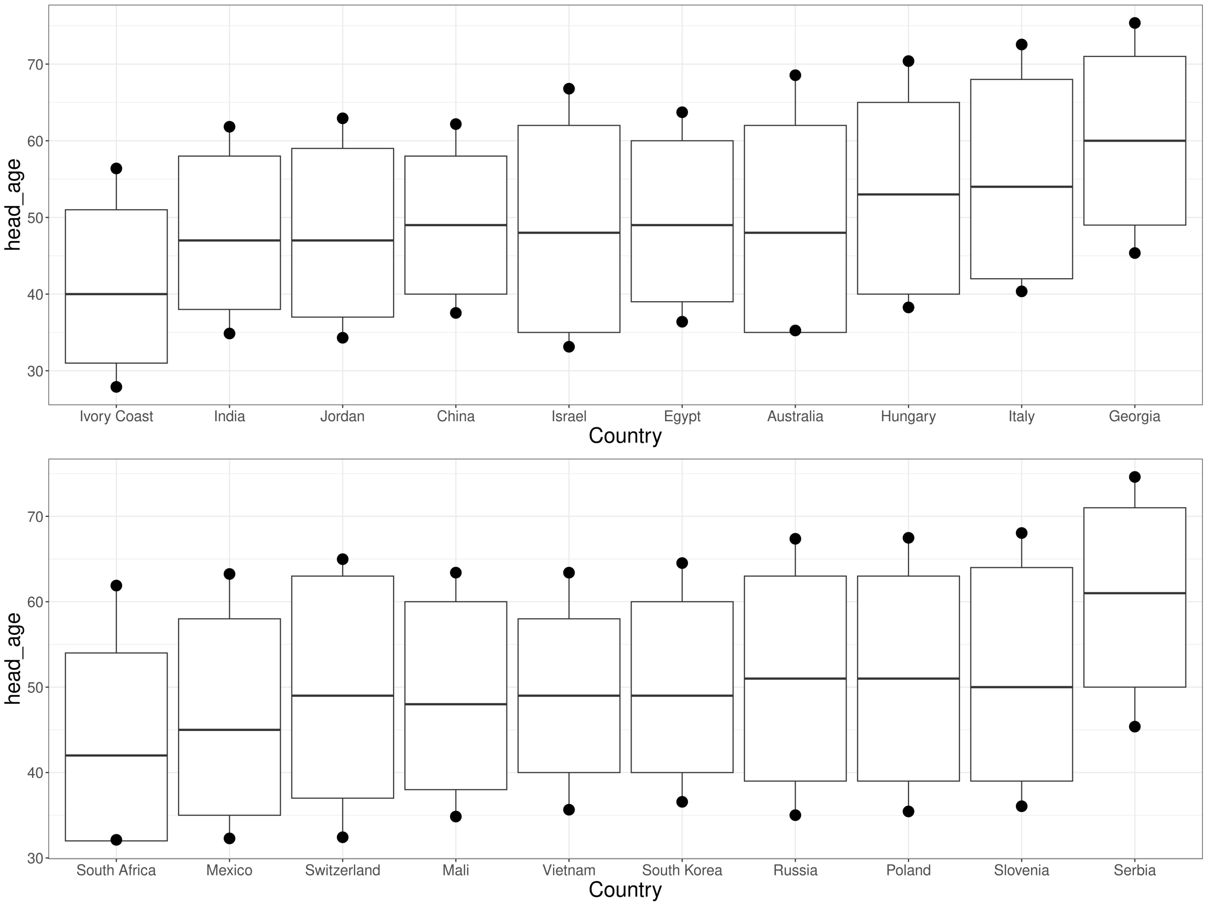


Figure 16: Average Household Head Age

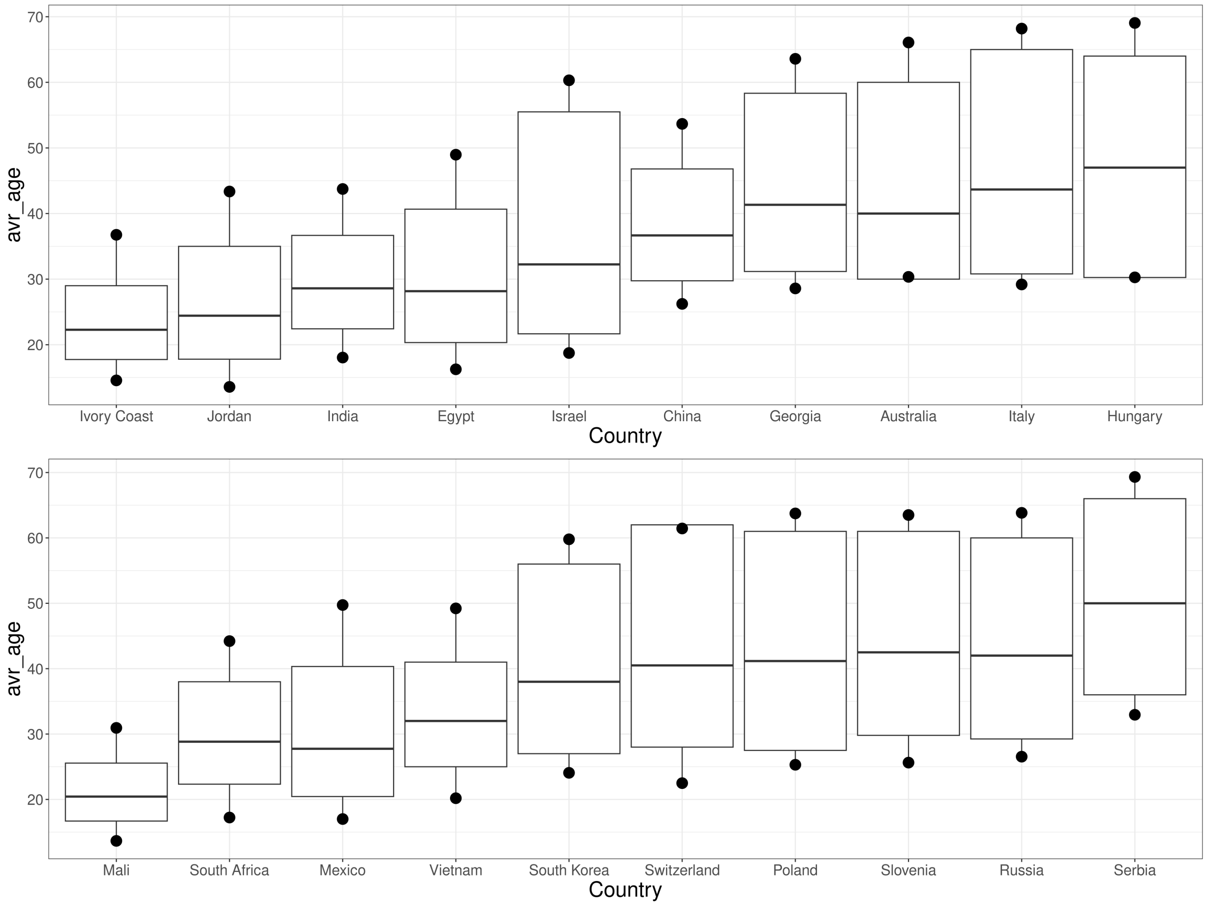


Figure 17: Household Average Age

4.2 Impact of a change in the reference sector

Assume that the preferences take the form

$$\mathcal{V}^h(\mathbf{P}, E_{h,t}) = \frac{1}{\epsilon}\left[\frac{E_t^h}{P_t^f}\right]^{\epsilon} - \frac{\nu_t^h}{\gamma}\left[\frac{P_t^n}{P_t^f}\right]^{\gamma} - \frac{1}{\epsilon} + \frac{\nu_t^h}{\gamma}$$

that is, we used the food price (P_t^f) as the reference sector. Then the food share of total consumption is

$$\omega_t^f = 1 - \underbrace{\left(\frac{E_{h,t}}{P_t^f}\right)^{-\epsilon} \cdot \left(\frac{P_t^n}{P_t^f}\right)^{\gamma} \cdot \nu_t^h}_{\equiv \omega_t^n} \tag{10}$$

Notice that equation 10 is non-log-linear, and thus cannot be estimated directly by OLS. However we can log-linearize the *non-food shares* ω_t^n. That is, under the same assumptions as in the main model,

$$\log(\omega_t^n) = \epsilon \cdot \left(\frac{P_t^f}{E_{h,t}}\right) + \gamma \cdot \left(\frac{P_t^n}{P_t^f}\right) + \sum_m^M s_m^h \cdot \mathrm{DUMMY}_m + \alpha_c + \epsilon_t \tag{11}$$

Notice that compared to 6 the parameters γ, ϵ and the demographic dummy δ_m have different values and interpretation as they refer to the complement sector. Again, following Boppart (2014), we can aggregate consumption:

$$\Omega_t^n \equiv \frac{\sum_t^H E_t^n}{\sum_t E_t} = \left(\frac{P_t^f}{E_t}\right)^{\epsilon}\left(\frac{P_t^n}{P_t^f}\right)^{\gamma} \bar{\delta}_t \cdot \theta_t \cdot \nu_t, \tag{12}$$

Since $\Omega_t^f = 1 - \Omega_t^n$, the log difference between time t and T is:

$$\hat{\Omega}_t^n \equiv \log \Omega_t^n - \log \Omega_T^n = \epsilon(\hat{P}_t^f - \hat{E}_t) + \gamma(\hat{P}_t^n - \hat{P}_t^f) + \hat{\bar{\delta}}_t + \hat{\theta}_t + \hat{\nu}_t$$

$$\hat{\Omega}_t^f \equiv \log \Omega_t^f - \log \Omega_T^f = \log(1 - \Omega_t^n) - \log(1 - \Omega_T^n)$$

First order Taylor approximation around time T

$$\log \Omega_t^f \equiv \log(1 - \Omega_t^n) \approx \log(1 - \Omega_T^n) - \frac{1}{1 - \Omega_T^n}(\Omega_t^n - \Omega_T^n) = \log(\Omega_T^f) - \frac{1}{\Omega_T^f}(\Omega_t^n - \Omega_T^n)$$

and

$$\log \Omega_t^n \approx \log \Omega_T^n + \frac{1}{\Omega_T^n}(\Omega_t^n - \Omega_T^n) = \log \Omega_T^n - \left(1 - \frac{\Omega_t^n}{\Omega_T^n}\right)$$

substituting yields

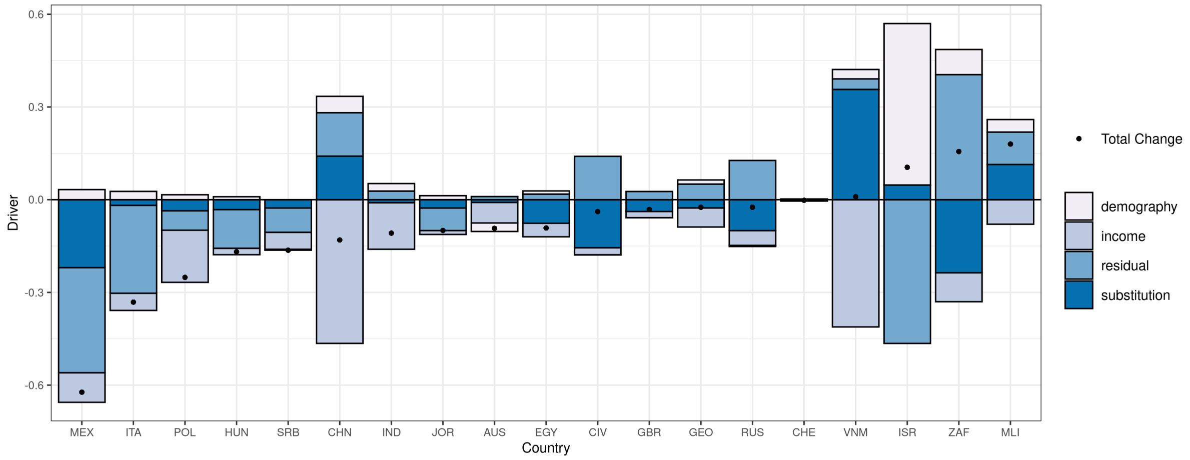
$$\hat{\Omega}_t^f \approx -\frac{\Omega_T^n}{\Omega_T^f}\left(1 - \frac{\Omega_t^n}{\Omega_T^n}\right) \tag{13}$$

$$\hat{\Omega}_t^n \approx \left(1 - \frac{\Omega_t^n}{\Omega_T^n}\right) \tag{14}$$

Therefore

$$\hat{\Omega}_t^f \approx -\frac{\Omega_T^n}{\Omega_T^f} \cdot \hat{\Omega}_t^n = -\frac{\Omega_T^n}{\Omega_T^f} \left[\underbrace{\epsilon(\hat{P}_t^f - \hat{E}_t)}_{income} + \underbrace{\gamma(\hat{P}_t^n - \hat{P}_t^f)}_{substitution} + \underbrace{\hat{\hat{\delta}}_t}_{demography} + \underbrace{\hat{\theta}_t + \hat{\nu}_t}_{residual} \right] \tag{15}$$

Estimating equation 11 by OLS and replacing the parameters into the equation above yield a driver decomposition shown in figure 18. The result is qualitative equivalent by the one shown in figure 11. The main differences are an increase in the demographic effect in Israel and an increase in the substitution and income effects in South Africa. All differences are compensated by a concomitant increase in the residual.



This figure shows the value of the different drivers from equation 15. Countries are observed over a different time span (see table 6) and the total change over said period is shown by the black dot. Values represent log-changes of aggregated food expenditures.

Figure 18: Estimated value of the different drive of food expenditures (Different reference price)