JOURNAL OF THE ASIA PACIFIC ECONOMY
2024, VOL. 29, NO. 3, 1239–1256
https://doi.org/10.1080/13547860.2023.2166718

Routledge
Taylor & Francis Group

Check for updates

Food expenditure of the poorest deciles: expected vulnerability and counterintuitive indulgence?

Jan-Jan Soon[a,b], Azira Abdul Adzis[a,b], Shri Dewi Applanaidu[a,b] and Norhaslinda Zainal Abidin[c]

[a]School of Economics, Finance & Banking, Universiti Utara Malaysia (UUM), Sintok, Kedah, Malaysia; [b]Economic & Financial Policy Institute (ECOFI), Universiti Utara Malaysia (UUM), Sintok, Kedah, Malaysia; [c]School of Quantitative Sciences, Universiti Utara Malaysia (UUM), Sintok, Kedah, Malaysia

ABSTRACT

Key findings from our estimation models show that although the poorest households are vulnerable to income and food price shocks, our results also reveal an anomaly: given an increase in income and in food price, the poorest households seem to indulge in non-essential food expenditure, which is counterintuitive. Being the poorest typically conjures images of needing more food, not more food choices. We explain our findings within an intertwined theoretical underpinning, providing empirical verifications to two landmark hypotheses that bridge the economic-psychological frontier. We merge two relatively recent and nationally representative Malaysian household expenditure and price datasets. Our paper is perhaps the first work examining the poorest among poor households in a developing country from an economic-psychological angle, providing insights for more nuanced policy prescriptions. We believe our findings unveil aspects of food and poverty in Malaysia that have yet to be given detailed treatment so far.

ARTICLE HISTORY
Received 30 May 2022
Accepted 5 January 2023

KEYWORDS
Food expenditure; poorest households; pleasure maximisation hypothesis; scarcity mentality hypothesis

JEL CODES
C21; D12

Overview and selected literature

Malaysia is on the cusp of the National Agrofood Policy 2021–2030, which addresses the issues and challenges of maintaining a food supply chain that meets the national food security priorities. Of particular interest to the scope of this paper, is the relevance between this policy and the first two goals of the 2030 United Nations' sustainable development agenda, i.e. (i) to eradicate poverty and, (ii) to end hunger, striving for both food security and better nutrition. Poverty and hunger are intimately intertwined; in fact, as succinctly put by the 2019 Economics Nobel Laureates – the poor are those who have insufficient to eat (Banerjee and Duflo 2011, 2007). Ironically, their empirical works challenge their own definition, as do our subsequent findings here in this current paper. Who are the poor Malaysian households? In the latest round of the Malaysian Household Expenditure Survey 2019 (DOSM 2020), food expenditure takes up 17.3% of total expenditure, second only to housing expenditure

CONTACT Jan-Jan Soon soon@uum.edu.my; soonjanjan@gmail.com
© 2023 Informa UK Limited, trading as Taylor & Francis Group

(23.6%). That same survey also reports an urbanisation rate of 76.2%, i.e. with only slightly less than a quarter of the population still residing in rural areas. It also documents that rural households at the bottom 40th percentile spend an average of 28.8% of their total expenditure on food, compared to their urban counterparts' of 23.6%.

In July 2020, as part of the 11th Malaysian Plan initiatives, the country has revised its national poverty line income or PLI to the RM2,208 ($\approx$ USD520) per month threshold (i.e. monthly total household income), an upward revision from the previous RM980 ($\approx$ USD230) last revised in 2005. Upon revision, more than 400,000 households are now regarded as poor households, i.e. an absolute poverty rate of 5.6%. The previous rate of just 0.4%, with 24,700 poor households, could no longer reflect the current economic conditions and realities. The new PLI threshold has been revised based on changes in methodology that now emphasises optimum healthy eating and quality non-food basic needs (such as clothing, housing, transport, fuel, utilities). The crucial difference between the two threshold calculations lies in the previous threshold using minimum food requirement as the calculation basis, while optimum food requirement is used to obtain the revised PLI. By optimum, it connotes healthy food, based on the Malaysian dietary guidelines and recommended nutritional intake. By minimum, contrastingly, it refers to the minimal caloric requirement, just enough for subsistence. To the extent that the PLI is revised based on food aspects, shows the substantively important binding thread that weaves through poverty, hunger, and food. It also demonstrates the government's commitment in not just poverty eradication, but also the general health and well-being of the society.

In laying the theoretical scaffolding for subsequent analyses and findings' interpretations of this paper, we rely on a collective strand of what we regard as very much related theories and hypotheses: (i) consumers' behaviour theory, treating households as micro-level entities, (ii) Engel's law on food share and household income, (iii) a landmark hypothesis (the 'pleasure maximisation' hypothesis) that the poor, as much as their richer counterparts, do desire for tastier food and not just for more food, empirically proven in the seminal works of Banerjee and Duflo (2011, 2007) and Jensen and Miller (2008), and (iv) a fairly recent hypothesis by Mullainathan and Shafir (2013) on the scarcity mentality of the poor, which bridges the economic-psychological frontier. We recapitulate each briefly.

In standard consumers' behaviour theory, it is a given that preferences dictate behaviour. However, it is actual behaviour that reveals actual preferences, i.e. revealed preference. The revealed preference principle could be easily demonstrated in a simple two-goods scenario as follows: Letting (A_1, A_2) be the actual demanded goods bundle of an optimising consumer, and (B_1, B_2) an arbitrary bundle, we get $p_1A_1 + p_2A_2 \geq p_1B_1 + p_2B_2$, with $p_1A_1 + p_2A_2 = m$, $p_1B_1 + p_2B_2 \leq m$, prices p, and income m. The inequality equation implies $(A_1, A_2) \succ (B_1, B_2)$, i.e. bundle (A_1, A_2) is 'revealed preferred' to (B_1, B_2). In the paper's context, these notations simply mean that the actual observed food expenditure indicates the households' revealed preference of their food choices, i.e. that is why the households chose and actually spent on food combination (A_1, A_2) instead of food combination (B_1, B_2), for instance. That is, revealed preferences indicate that the choices made would divulge all necessary information pertaining to the utility of the actual choice.

Next, the Engel's law is an established empirical regularity which has been proven throughout the decades since its inception in 1857; the law itself is based on inductive observations that the more affluent a household is, the less it spends on food as a proportion of total spending. In the pleasure maximisation hypothesis, the reason why the poor seem to indulge in spending on more palatable but often less-nutritional non-essential food instead of just getting more quantities of essential food, lies in Banerjee and Duflo's theoretical argument of their S-shaped present-future income relationship. They reason that the poor place higher values on today's income than the values of some unguaranteed future income, driving them to seek present pleasure. Similarly, Jensen and Miller (2008) hypothesis on the 'flight of quality' in food consumption suggests that the poorest households' priority lies in getting better-tasting calories, and not just more calories as one would instinctively assume. Lastly, Mullainathan and Shafir's scarcity mentality hypothesis is well-tested in the economic-psychological literature (Shah et al. 2018, Shah, Mullainathan, and Shafir 2012; Mani et al. 2013; Schilbach, Schofield, and Mullainathan 2016). The poor are conjectured to have less mental bandwidth when it comes to making good decisions, which in our case, would be the expenditure decisions on essential and non-essential food choices; that is, poverty erodes good judgement.

This paper seeks to answer three main questions: Who are the poorest among the poor households? How vulnerable are the poorest households to income and price changes? How do they spend on essential and non-essential food? Ironing out these issues would make one wonder if being the poorest and their food choices constitute a problem, in and of itself. This paper would go on to show that although the poorest households are vulnerable to income and food price shocks, our results also reveal an anomaly: given an increase in income and in food price, the poorest households seem to indulge in spending on non-essential food, which is rather counterintuitive. Being the poorest typically conjures images of needing more food, not more food choices. However, if we place our key results within the narratives of the amalgamated theoretical framework explained earlier, we believe our findings unveil aspects of food and poverty in Malaysia that have yet to be given detailed treatment so far.

Studies on food expenditure and consumption patterns of poor households have a long history, dating back to Engel's 1857 seminal work (as cited in Chai and Moneta 2010). Engel's work, which later establishes the Engel's law of food expenditure, examines the food expenditure budgets and consumption patterns of the urban working class in Europe during the first Industrial Revolution in the mid-1800s. Recent worldwide literature on food expenditure and consumption has been increasingly associated with issues of poverty and food security of poor households. Their results find systemic vulnerability to food poverty in Ghana particularly in female-headed households (Addai, Ng'ombe, and Temoso 2022), large food consumption inequalities and almost a quarter of Italy's population is at risk of food poverty (Machetti & Secondi 2022), widespread prevalence of food and nutrition security among agricultural households in Nepal (Kumar et al. 2020), food-poor households in Ireland are likelier to encounter problems with nutritional adequacy, cultural acceptability, and social inclusion (Healy 2019), and that food consumption in Bangladesh are shifting from staple cereals to higher value food items for both the rich and poor households (Mottaleb et al. 2018). This recent

literature strand collectively indicates the importance, urgency, and implications of poor households' food expenditure and consumption.

Insofar when it comes to Malaysian studies on household income and expenditure, published works have been sporadic at best. An established economic think tank in Malaysia published a report on the Malaysian state of household (KRI, 2016), which documents many relatively current aspects of households including food and non-food expenditures, incomes and savings, labour force and age structure. The key takeaways from their findings on food expenditures are that lower-income households can barely afford nutritious food and that food prices are increasing. Tey et al. (2010) examine income and price elasticities of the demand for meat, concluding that there is a preference towards meat while being sensitive to meat price changes. Focusing on just income elasticities of demand for different consumption goods and services ranging from food, health, transport, to entertainment, Yusof and Duasa (2010) find varied consumption patterns across different sociodemographic characteristics. A relatively dated study but nonetheless important Malaysian study, Ishida, Law, and Aita (2003), is an inter-temporal analysis of structural changes in food expenditures; they find accelerated urbanisation rates and economic expansions to be the change catalysts. Kh'ng, Chang, and Hsu (2022) is a notably recent work linking food security, dietary intake, and household food expenditure; they conclude that healthier food choices incur higher food expenditure and are therefore relatively burdensome to poorer households. Though relevant, these works are however, still rather peripheral to the current paper's scope and focus.

This current paper therefore positions itself as an important complement to the existing literature on food expenditure of the poor, not only within the Malaysian context but also in the broader realms of food security, poverty, household expenditure, and the economic-psychological works. We add to the literature pool by specifically linking food expenditure of poor households of a country in this part of the world with two salient psychology-slanting hypotheses, i.e. the pleasure maximisation and the scarcity mentality hypotheses. Readers interested in getting a more comprehensive overview of food demand elasticities are referred to the meta-analyses by Colen et al. (2018), Cornelsen et al. (2015), and Green et al. (2013).

Method

Data

This paper uses two sources of data, i.e. the 2016 Household Expenditure Survey (HES2016) and the 2016 Consumer Price Index (CPI2016) data. In Malaysia, the HES2016 is an authoritatively representative survey conducted by the Malaysian Department of Statistics. It gathers information on household consumption expenditure of 12 main item groups, of which food is one of the main items. Other main item groups include consumption expenditures on housing, home furnishing, health, education, and transportation, among others. Note that consumption expenditures are those spent on acquiring goods and services for private consumption, while non-consumption expenditures are such as income taxes, and social security contributions. This paper focuses on total food expenditure and two of its breakdowns i.e. expenditures on essential, and on non-essential food.

Note that, by food expenditure, we mean food at home (FAH; in main item Group 1). Expenditures on eating-out expenses or also known as food away from home (FAFH; in main item Group 11) are beyond our scope due to the following reasons: (i) the HES2016 dataset lumps all FAFH expenditures in just one 4-digit breakdown; we therefore, do not have specifics on the types of FAFH food consumed, (ii) the CPI2016 dataset only reports prices of beverages sold at restaurants for the sub-items in Group 11, (iii) as we shall see in Table 1, the 40% poorest households spend almost 30% of their total expenditure just on food expenditure (FAH), but only about 10% on FAFH (not reported in Table 1), and (iv) we would not be able to differentiate between eating-out expenses for say a working-class employee eating out during lunch breaks and eating-out expenses for a family dinner.

We use the HES2016 dataset, which details the types of expenditure up to a 4-digit sub-item level. The 4-digit classification follows that of the United Nations' Classification of Individual Consumption According to Purpose (COICOP). The HES2016 surveyed a total of 14,551 households, selected using a multiple stratified random sampling, i.e. from all the states in Malaysia to the district stratum, the rural-urban divide, enumeration blocks, and down to the household level. Trained interviewers would visit the selected households and assist in filling out a questionnaire on sociodemographic, household income, and household private consumption expenditure information on all the aforementioned 12 main consumption item groups. To gain better representation and generalisability, we discard a negligible percentage of households with monthly incomes of more than RM27,000 (≈ USD6,480) (1.01% of the total

Table 1. Summary statistics of sample characteristics.

	Panel A				Panel B			Panel C		
	B40 HH	M40 HH	T20 HH	*p-value*	B40 rural	B40 urban	*p-value*	D10 rural	D10 urban	*p-value*
Y_1: Total food expenditure*	563	767	926	0.000	578	550	0.000	438	390	0.000
Y_2: Essential food exp*	213	261	286	0.000	229	198	0.000	179	149	0.000
Y_3: Non-essential food exp*	78	107	137	0.000	79	78	0.574	62	60	0.366
Food-to-total exp share	0.29	0.22	0.16	0.000	0.32	0.26	0.000	0.35	0.29	0.000
Essential-to-total food share	0.38	0.35	0.31	0.000	0.40	0.36	0.000	0.41	0.37	0.000
Nonessential-to-total food share	0.15	0.14	0.15	0.000	0.14	0.15	0.000	0.14	0.17	0.000
Income**	2541	5722	12542	0.000	2402	2665	0.000	1386	1431	0.009
Age**	48.7	45.5	45.6	0.000	50.1	47.3	0.000	54.2	51.9	0.009
Male	0.79	0.85	0.88	0.000	0.81	0.76	0.000	0.73	0.63	0.000
Married	0.71	0.80	0.85	0.000	0.74	0.68	0.000	0.61	0.55	0.021
Malay ethnic	0.73	0.67	0.59	0.000	0.87	0.61	0.000	0.88	0.57	0.000
Household size**	3.6	4.4	4.7	0.000	3.9	3.4	0.000	3.0	2.6	0.000
House-owner	0.73	0.73	0.80	0.000	0.84	0.64	0.000	0.87	0.59	0.000
Urban	0.53	0.75	0.87	0.000	–	–	–	–	–	–
Degree	0.01	0.09	0.35	0.000	0.005	0.02	0.000	0.002	0.002	0.749
Diploma	0.05	0.15	0.22	0.000	0.03	0.07	0.000	0.01	0.03	0.048
High school	0.37	0.47	0.31	0.000	0.31	0.43	0.000	0.20	0.26	0.014
Public job sector	0.05	0.19	0.25	0.000	0.05	0.06	0.099	0.008	0.008	0.956
Private job sector	0.46	0.51	0.51	0.000	0.38	0.54	0.000	0.27	0.42	0.000
Self-employed	0.30	0.22	0.15	0.000	0.42	0.19	0.000	0.43	0.17	0.000
Professional	0.03	0.15	0.50	0.000	0.02	0.04	0.000	0.01	0.01	0.699
Skilled craftsmen	0.33	0.34	0.25	0.000	0.42	0.25	0.000	0.39	0.18	0.000
Sales & services	0.16	0.18	0.10	0.000	0.13	0.19	0.000	0.09	0.17	0.000
Number of households	5,728	5,733	2,865	–	2,714	3,014	–	824	608	–

Notes: *Denotes monthly expenditure, in Malaysian Ringgit (MYR). **Denotes continuous variables. Y_1, Y_2, Y_3 are the paper's three dependent variables. Total number of households = 14,326. The currency exchange rate stands at USD1.00 = MYR4.16 as of July 3rd, 2021.

14,551 households), and households with monthly total expenditures of more than RM13,000 (≈ USD3,120) (1.12% of 14,551). The final working dataset, with 14,326 households, should be reasonably representative of the Malaysian households' characteristics; this would be our working sample.

We merge our HES2016 working dataset with the 2016 Consumer Price Index dataset (CPI2016) to allow for food price effects on food expenditures. Do note that both the HES2016 and CPI2016 datasets are not readily available publicly, but could be requested from the Malaysian Department of Statistics for academic and research purposes. Although food prices do not vary across households, we still include a vector of selected food prices in our model estimation to take into account some inevitable price variations across different geographical regions and also variations arising from seasonal effects. The CPI2016 dataset comes in price breakdowns by sub-items (row-wise) and by months (column-wise), for each of the geographical states in Malaysia. The price breakdowns are up to the 7-digit sub-item level. However, since we only have expenditures up to only the 4-digit sub-item level from the HES2016 dataset, we need to prepare the CPI2016 dataset in such a way to allow for merging of the two datasets. To do that, we first take the average of the monthly food prices, and collapse the 7-digit prices to their 4-digit equivalents. Upon collapsing, we now have the 4-digit month-averaged prices for the food sub-items. Next, to merge the two datasets, we use geographical states as the identifier variable. In the merged dataset therefore, each row represents a household (i.e. the number of observations), while each column a variable. Therefore, food prices here can be used to account for state effects, i.e. though food prices do not vary by households, they do have some variations by states.

Variables of interest

We have three dependent variables in the paper's model estimation section: (i) total food expenditure, (ii) essential or staple food expenditure, and (iii) non-essential food expenditure. The second and third types of food expenditure are part of total food expenditure. We define essential food expenditures as those spent on rice, eggs, cooking oil, fresh meat, and fresh fish. Non-essential food expenditures are those spent on sugar, coffee, tea/cocoa, biscuit, and pastry, i.e. foods typically bereft of nutrition. We use essential food expenditure to capture how vulnerable and susceptible the rural and urban poorest deciles are in terms of income and price elasticities of food demand, i.e. to see who is poorer among the poorest. Since the Malaysian institutional setting and historical background have seen rural households to be the marginalised group, it prompts our rural-urban analysis. The rural-urban divide is marked by the threshold population of 10,000 inhabitants in a designated area. We use non-essential food expenditure for empirical verification of Banerjee and Duflo (2011) and Mullainathan and Shafir (2013) hypotheses. The model estimations focus on two main explanatory variables of interest, i.e. household income and a vector of food prices.

We focus our attention and scope to estimations of the broader total food expenditure and its two breakdowns (essential and non-essential food expenditures) rather than examining each of the 4-digit food sub-item expenditure individually to allow for more tractable conclusions. Furthermore, it is more important to examine the

effects income and price changes on the more collective food expenditures because such changes would not be realistically isolated in their effects on only a specific sub-item food expenditure. That is, food expenditure is more realistically depicted as a collective basket. The breakdown of total food expenditure into the two essential food and non-essential food expenditure components is a standard procedure in the food demand literature (Subramanian and Deaton 1996).

Households in Malaysia are generally categorised into three relative income groups: (i) the B40 households or those at the bottom 40% of the income distribution, (ii) the middle-class M40 households, and (iii) the T20 households at the top two deciles of the income distribution. Following these relative definitions, we categorise the households in our dataset based on their income percentiles. From the dataset, T20 households are those with a relative total monthly household income threshold of more than RM8,436 (≈ USD2,025), M40 households are those with incomes between RM3,878 and RM8,436, and B40 households are those with less than RM3,878 (≈ USD930). We do a further categorisation among the B40 households, breaking down into four bottom deciles. Focusing on the lowest decile, the D10 households, we regroup them by the rural-urban categories. This way, we get a more nuanced data characterisation in addressing the paper's research questions. We use a vector of selected food prices as the second main explanatory variables of interest. Due to the fact that food prices are only disaggregated up to the state level, we encounter collinearity issues. Therefore, instead of allowing the food price variables to be dropped arbitrarily during estimations, we decide to include a selected vector of 10 food prices (5 each from essential and non-essential food). We select these foods based on our knowledge of the Malaysian institutional, historical, and cultural background pertaining to essential staple foods and non-essential pleasure-maximising foods.

Estimation model specification

We regress the three dependent variables (Y) on household income (X), the vector of selected food prices ($\boldsymbol{P}$), and a vector of controls ($\boldsymbol{W}$), using the ordinary least squares (OLS) models for each Y. We specify our model, $Y = X\beta + \boldsymbol{P\tau} + \boldsymbol{W\delta} + \varepsilon$, as a double-log model to facilitate income and price elasticity interpretations. That is, we take the logarithm of our dependent variables, and the two main explanatory variables of interest. Our coefficients of interest would be the income coefficient β, and the food price coefficients $\boldsymbol{\tau}$. We include socio-demographic, education-related, work-related variables as controls (as listed in Table 1). The control vector also includes the squared terms of age and household size to capture any possible nonlinearities, e.g. the quadratic effects of these continuous variables. For notational clarity, we intentionally drop the intercept and subscript i for the ith household in the model. In a later section, we provide detailed methodological justifications as to why the OLS model estimations are used.

Results and discussion

Results and discussion I: Graphical depictions

Figure 1 shows the distributions of the total food expenditure and household income, for all households in Panel (a), and the subsequent Panels (b) to (d) by the three

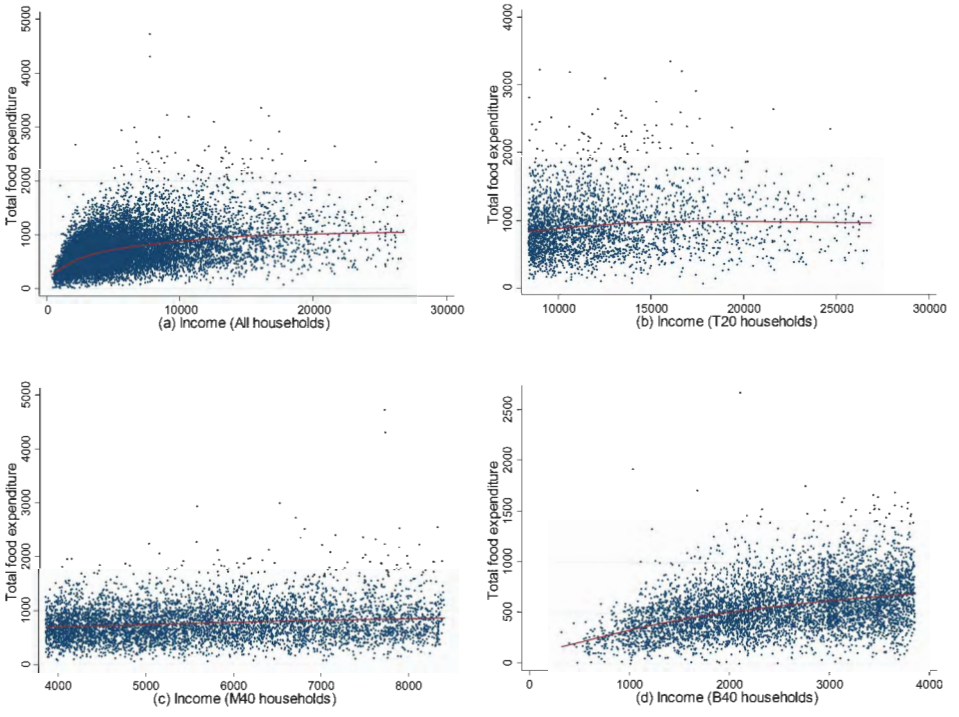


Figure 1. Caption: Total food expenditure-income scatterplots.
A figure depicting 4 scatterplot panels. Panel (a) plots total food expenditure at the Y-axis and income of all households at the X-axis. The remaining 3 panels plot the income of upper-income, middle-income, and low-income households at the X-axis respectively.

major T20, M40, and B40 household income categories. Looking in its entirety, Panel (a) indicates that the higher the income, the more variations there are in the households' total food expenditure. Now, if we break down the graphical analysis by the three income categories, it is obvious that such expenditure variations are largely driven by T20 households at the upper end of the income distribution. The middle class M40 households, on the other hand, seem to exhibit rather constant variations in their food expenditure. Surprisingly, B40 households also show a lot of variations in their total food expenditure, i.e. a scatterplot which seems to mimic that of the T20 households. One would expect that lower-income households to have less food consumption choices and thus less variations in their food expenditure. The rest of the paper delves into this conundrum in more details.

Results and discussion II: Summary statistics

Table 1 reports the summary statistics of our working sample of households' characteristics. The first three rows show the averages of the paper's three dependent variables (in the model estimation section), across different income categories. The next three rows give some ideas on (i) the proportion of food expenditure to the overall total expenditure, i.e. the expenditure in all the 12 main item groups, in which food makes up one of the main groups, (ii) the proportion of essential food expenditure,

and (iii) the proportion of non-essential food to total food expenditure. The remaining rows correspond to the vector of controls used in this paper, with income as one of the main explanatory variables of interest; means are reported for continuous variables and proportions for dummies. The other main explanatory variable of interest, the vector of food prices, is not shown in Table 1 since it is counterintuitive to report mean food prices by income categories.

In Panel B of Table 1, we categorise B40 households by their rural-urban demarcation. To accentuate the behaviour of the poorest, we further break down households at the bottom 40% of the income distribution into 4 deciles and highlight the characteristics of poorest decile (D10), shown in Panel C. In accordance with Engel's law, the share of food to total expenditure would decrease when income increases. Our summary statistics provide empirical support to this law, with B40 households spending about 29% on food from their total expenditure, while the T20 a mere 16%. Such food share proportions are even more pronouncedly higher for the rural poorest decile, whose food expenditure takes up 35% of their total expenditure on all consumption goods and services.

Now, if we focus on essential food expenditure, the rural poorest decile spends slightly over 40% on it from their total food expenditure. The p-value columns report results of either a t-test or an F-test. The low p-values indicate there are indeed statistical differences between the rural and urban poorest deciles for many of the characteristics or variables listed in Table 1. The descriptive analyses so far, seem to be pointing to rural D10 households as the poorest of the poor. Are they poorer than their urban D10 peers? Yes it seems, since the rural D10 has a lower average household income of RM1,386 compared to the urban D10's RM1,431. Both the rural and urban poorest deciles' average household income levels, though slightly higher than the mandated minimum wage of RM1,200 (≈ USD285) per month, are still below the Malaysian absolute poverty line income threshold of RM2,208 (≈ USD520) per month. There are however, many facets to being poor, with vulnerability and susceptibility to changes in income and prices being some of the angles which we will look into, in the following model estimation section.

Results and discussion III: model estimations

Table 2 reports the income and price elasticities of demand of the paper's three dependent variables. For brevity purposes, the estimated coefficients for the vector of controls are unreported here.

On income elasticities of demand

Panel A of Table 2 shows that for the urban poorest decile, when their income increases by 1%, these households tend to increase their total food expenditure by about 0.71%. Now, compare it with the most privileged segment of the society, i.e. the T20 households, which only see about a 0.21% increase in total food expenditure when income increases by 1%. These results are further substantiated in our estimation using all of the households, i.e. as shown in Column 1 of Table 2, the estimated

Table 2. OLS estimation results.

	Household categories							
	All HH	T20	M40	B40	Rural B40	Urban B40	Rural D10	Urban D10
Panel A: Y_1 = total food expenditure								
Income	0.409***	0.209***	0.280***	0.508***	0.506***	0.520***	0.691***	0.711***
P0111_rice	−1.448***	−2.440***	−1.370***	−0.521	−0.731	−0.598	−3.160	−0.667
P0144_egg	0.913***	1.587***	1.099***	−0.053	0.079	−0.073	1.197	−1.677
P0152_oil	−0.101	−0.036	−0.811	2.085	0.083	3.755*	3.591	21.013**
P0121_freshmeat	0.591***	0.680***	0.547***	0.527**	0.897**	0.293	1.293	−0.648
P0131_freshfish	−0.243***	−0.611*	−0.166	−0.311*	−0.779***	0.167	−0.124	0.322
P0181_sugar	0.019	−0.754*	0.034	0.087	−0.226	0.451	−0.446	−1.702
P0101_coffee	−1.127***	−1.342	−1.462*	−0.611	0.258	−1.439	−1.632	−1.348
P0102_teacocoa	3.799***	6.666***	4.718***	−0.564	1.607	−2.181	1.265	−19.028**
P0113_biscuit	−0.215***	−0.303	−0.303*	−0.225	0.024	−0.392*	0.216	−1.255*
P0114_pastry	−0.764***	−1.226***	−0.754***	−0.221	−0.903*	0.342	−0.339	2.469
Urban	−0.055***	–	–	–	–	–	–	–
B40	0.157***	–	–	–	–	–	–	–
M40	0.121***	–	–	–	–	–	–	–
Adjusted R^2	0.355	0.187	0.193	0.339	0.346	0.335	0.283	0.297
F-statistic	179.55	20.50	40.00	68.71	40.54	37.92	10.52	.
Panel B: Y_2 = essential food expenditure								
Income	0.346***	0.190***	0.184***	0.434***	0.460***	0.420***	0.563***	0.735***
P0111_rice	−1.142***	−2.591***	−1.124***	−0.618*	−0.954*	−0.588	−1.998	−3.648**
P0144_egg	−0.398***	0.407	−0.129	−0.896***	−1.094***	−0.737***	−0.784*	−0.281
P0152_oil	1.796***	3.460***	1.256***	1.647***	2.643***	1.333**	3.526***	5.409***
P0121_freshmeat	0.959***	0.652***	0.861***	1.062***	1.262***	0.886***	1.613***	1.353**
P0131_freshfish	−0.732***	−0.313	−0.444***	−1.066***	−1.328***	−0.813***	−1.414***	−0.893*
Urban	−0.091***	–	–	–	–	–	–	–
B40	0.209***	–	–	–	–	–	–	–
M40	0.158***	–	–	–	–	–	–	–
Adjusted R^2	0.275	0.236	0.205	0.305	0.314	0.290	0.265	0.352
F-statistic	135.54	31.90	49.76	61.44	42.50	29.94	12.20	–
Panel C: Y_3 = non-essential food expenditure								
Income	0.393***	0.254***	0.292***	0.475***	0.491***	0.456***	0.528***	0.609***
P0181_sugar	2.769***	2.132***	2.829***	3.614***	4.052***	3.616***	2.988***	3.510***
P0101_coffee	−6.150***	−5.893***	−6.644***	−5.679***	−5.374***	−5.977***	−5.898***	−6.028***
P0102_teacocoa	6.618***	6.067***	7.172***	6.102***	5.751***	6.345***	6.289***	6.131***
P0113_biscuit	−0.232***	−0.490**	−0.388***	0.027	0.318*	−0.211	0.327	0.113
P0114_pastry	0.266**	1.036***	0.440*	−0.527**	−1.183***	−0.166	−0.511	−0.202
Urban	0.021	–	–	–	–	–	–	–
B40	0.072**	–	–	–	–	–	–	–
M40	0.054**	–	–	–	–	–	–	–
Adjusted R^2	0.188	0.068	0.101	0.175	0.177	0.178	0.109	0.151
F-statistic	119.08	10.46	30.08	49.56	26.04	28.20	6.23	11.31

Notes: $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. To facilitate intuitive percentage interpretations, we take the natural logarithm of the dependent variable (Y) and the main explanatory variables of interest, i.e. household income and food prices. Robust standard errors are used in all estimations.

coefficient of 0.209 for the low-income household B40 dummy implies that these households tend to spend 20.9% more than their T20 high-income counterparts. Analogously, the estimated coefficient of 0.158 for the middle-income household M40 dummy suggests that middle-income households tend to spend 15.8% more than the T20 high-income households. Our results here are consistent with those by Wongmonta (2022), who found that low-income households as being more responsive to income changes. What could this finding possibly be implying? As hypothesised, the poorer the households, the more they would be spending on food. As expected, our income elasticities highlight the point that poorer households spend the bulk of any income increases on food. Our income elasticities' results here are also

robust to alternative model specifications, i.e. instead of using total food expenditure as the dependent variable (Y), we change the Y to food share (total food expenditure as a share of the household total expenditure). This robustness check provides us empirical insights that the Engel's law is at play, with the estimations giving us a statistically significant estimated income coefficient of −5.344. The estimated coefficient implies that when income increases by 1%, food share tends to decrease by about 5.3 percentage point.

At this point, one could say that the urban poorest decile seems to be preoccupied with survival rather than enjoying other aspects of life, e.g. spending on other non-food items. Such preoccupations with survival highlight the precarious condition of this decile, vulnerable to any downward income shocks. Our findings however, differ from some recent works, e.g. those by Nsabimana et al. (2020) and Ren et al. (2018) whose findings point to the rural poor being more vulnerable to income shocks.

Taking a closer look at the urban poorest decile, among the types of food breakdowns, these households tend to spend even more on essential food, i.e. with an income elasticity of 0.735 (Panel B). The disparity is even greater if we juxtapose it with the T20's income elasticity of just 0.19. Having said that however, Panel C seems to tell a different story altogether. One would instinctively presume that the bulk of any income increase for the poor would be spent on essential food. For a 1% increase in income, the urban poorest decile's non-essential food expenditure tends to increase by 0.61%. Comparatively, it is still the highest across the different household categories in Table 2. This finding appears to support Banerjee and Duflo (2011) pleasure maximisation hypothesis that the poor do not just want more food, but also more food choices. Non-essential food constitutes wants and choices. This finding is rather anomalous, i.e. given that the poorest households are typically presumed to be the hungriest, it is rather counterintuitive that they seemingly indulge in spending on non-essential food when income increases. However, if viewed through the lens of Mullainathan and Shafir (2013) scarcity mentality hypothesis, this finding lends empirical support to it, i.e. the poorer one is, the worse decision one seems to make. Our finding is also consistent with the empirical work of Spears (2011). He finds a causal impact of poverty on economic decision-making behaviour, i.e. the poorer one is, the more difficult it is to make good choices. To some extent, the scarcity mentality hypothesis help explain our findings on why the poorest deciles seem to be spending more on the less essential non-essential food than their more well-off counterparts. Both the pleasure maximisation and scarcity mentality hypotheses help put our findings into perspectives.

Now, if we compare the income elasticities between the rural-urban B40 and D10 households for essential and non-essential food expenditure, we notice that there are not much income elasticities differences between the rural-urban B40 households. However, for the urban D10 households, they are more sensitive to income changes, i.e. as seen in their higher coefficients (0.735 and 0.609) compared to the rural D10 household (0.563 and 0.528). This is due to higher costs of living in urban areas. Moreover, rural households could typically supplement their food supply, small-scale, by rearing domestic fowls for eggs and meat, or grow their own vegetables – due to relatively abundant land area.

On price elasticities of demand

Panel A shows that the urban poorest decile is most sensitive to price changes in cooking oil and tea/cocoa, though with contrasting effects on their total food expenditure. The urban poorest decile tends to spend a substantially nontrivial 21% more on total food expenditure when the price of cooking oil increases by 1%, but 19% less for a 1% increase in the price of tea/cocoa. Do note that the elasticity coefficients here are not own-price elasticities, which would look at how the quantity demanded for cooking oil change when its own price changes. The increase in the price of cooking oil however, does not have any impact on total food expenditure for the rural poorest decile and the B40 households in general. There appears to be a 'poverty penalty', a term used by Gibson and Kim (2013), associated with being the urban poorest decile; unlike us, they found no empirical support of their hypothesis. In Panel B, when we look at how price changes in cooking oil would affect essential food expenditure, the urban poorest decile tends to increase their spending on essential food by about 5.4%, which is the largest elasticity coefficient across household income categories. To be this sensitive to such price changes connotes vulnerability of the poorest deciles to upward price shocks of essential food like cooking oil and fresh meat, i.e. statistically significant positive price elasticity coefficients. Our findings are also consistent with those found in two other studies of food price shocks on poverty in Mexico (Wood, Nelson, and Nogueira 2012) and on food security in Nigeria (Amolegbe et al. 2021).

The price elasticity coefficients in Panel C suggest that poor households do seem to indulge in spending on non-essential food. For instance, for a 1% increase in sugar price, all categories of poor households tend to spend more on non-essential food than the M40 and T20 households. The narrative is more or less similar for an increase in the price of tea/cocoa, i.e. with both the rural and urban poorest deciles exhibiting slightly higher price elasticities (6.289 and 6.131) than that of the richest T20 households (6.067). Our findings here imply likely similar choices between the richest and the poorest when it comes to non-essential food expenditure. Of course, due to data limitation, we would not be able to differentiate the effects of price changes in, for example, the relatively healthier brown sugar or the nutrient-void white sugar, nor the effects of price changes in relatively pricier brands of tea or the cheaper brands. It does not however preclude the notion that poorer households too, seem to want more choices when it comes to food consumption; they too exhibit optimising behaviour in their revealed preferences as seen in actual expenditures on non-essential food.

Considerations of alternative empirical strategies

Before ultimately deciding on the use of OLS as the estimation workhorse of the paper, we have run through at least three different empirical strategies and estimation models to check for any potential methodological pitfalls with our estimations. The following checks and justifications should help allay concerns over issues of (i) parameter identification of household income, (ii) biased variance of the estimated parameters, and (iii) our dependent variables being corner solution outcomes.

First, our OLS models regress expenditures on household income. Without empirical verifications, we cannot assume its exogeneity. To check for potential endogeneity, we

specify a two-stage least squares (2SLS) model. For this purpose, we require an instrument that fulfils the two conditions of (i) instrument relevance, which can be tested, and (ii) instrument exogeneity, which can only be maintained or argued but not tested. Since we have limitations in terms of data availability, we derive an instrument (Z) from the dataset in hand. By exploiting our institutional background knowledge on the Malaysian education system and labour force regulations, we construct a 'normalised years of work experience' to serve as Z. That is, we define our instrument as $Z = age - years\ of\ education - 7 - 60$. In normalising the Z, necessary for a comparable years of work experience variable, we take the household head's age minus his or her years of education, e.g. minus 6 years for a primary school education, 11 years for a high school education, and 13 years for a pre-university education. We further deduct 7 and 60, where 7 is the age when formal education starts in Malaysia and 60, the retirement age. We argue for instrument exogeneity in that there is no obvious relationship between household expenditure and our normalised years of work experience instrument. Our 2SLS estimations indicate no evidence of weak instrument from the first stage, i.e. $cov(Z,\ income) \neq 0$. However, we find no statistical proof to reject the null hypothesis of exogeneity, therefore negating the need to use 2SLS estimations. The OLS estimator would be more efficient, compared to an instrumental variable estimator.

Second, it is common to estimate different types of expenditure in a multiple-equation framework to exploit cross-equation relationships for more efficient estimations. The seemingly unrelated regression or SUR estimation is a typical set-up. With the three dependent variables, our SUR estimations in fact find evidence of correlated error terms across the three equations, suggesting that the equations should not be estimated independently as in OLS estimations. However, the SUR estimations come with a strong homoscedasticity assumption. From the scatter diagrams in Figure 1, it is obvious that such an assumption is unrealistic. In light of only gaining some trivial improvements in terms of SUR estimates' efficiency (i.e. the SUR and OLS standard errors only start to differ from the fourth and fifth decimal points onwards, which would be practically negligible differences), we proceeded with robust OLS estimations to take into account the heteroscedastic nature of the income-expenditure relationship. It is only realistic for households with different incomes to have varying levels of expenditure, where expenditure variances would likely be higher for households with larger incomes. In other words, when the variance of unobserved factors (in the error term) affecting expenditure increases with income, then heteroscedasticity is present, i.e. estimator of $Var(\hat{\beta})$ would be biased, resulting in invalid t-statistics and therefore, wrong conclusions. We take this consequence as being more serious than any marginally improved efficiency afforded by the SUR estimations.

Third, in modelling expenditures as the dependent or outcome variable Y, it is often the case that the Y is non-negative with a continuous distribution of positive values. As in expenditure, it is not uncommon to have $Y = 0$, i.e. a corner solution outcome. Note that corner solution models are sometimes lumped together as censored or truncated outcome models. In our case, we do not have issues with data censoring/truncation, or data unavailability with our Y variables. Our concern is more of zero expenditure pileups, i.e. households spending nothing on a particular type of expenditure. If this is the case, we would need to resort to using corner solution models to

enable us to capture the characteristics of the observed corner solution outcome, i.e. when the expenditure is zero, but nevertheless still observed. Initial data checking shows that we only have an inconsequentially negligible portion of households with zero expenditure on essential food (only 0.2% of the total number of households) and on non-essential food (also only at 0.2%). As for total food expenditure, all households have a strictly non-zero outcome. We therefore decide against the need for any corner solution models as such estimations would be less efficient than those of an OLS.

Policy implications and conclusion

Combining two relatively recent and nationally representative household expenditure and price datasets, this paper seeks to answer three main questions: Who are the poorest among the poor households? How vulnerable are the poorest households to income and price changes? How do they spend on essential and non-essential food? Within the scopes of our descriptive analyses and model estimations, our key findings are as follows. The descriptive analyses point to the rural D10 households as the poorest of the poor, faring worse than their urban D10 peers. Our estimation models show that the urban poorest households are the most vulnerable to income and food price changes. As expected, our income elasticities highlight the point that poorer households spend the bulk of any income increases on food. Our findings, to a certain extent, also provide empirical evidence in support of the two hypotheses set out at the beginning of the paper. Counterintuitively, our food price elasticities suggest both the rural and urban poorest deciles to seemingly indulge in non-essential food expenditures.

Household income and food prices are not merely two explanatory variables in our estimations of total, essential, and non-essential food expenditures; they can be regarded as fundamental economic variables and crucial policy instruments.

Households' food expenditure behaviour is reflected in their responsiveness towards changes in income and food prices. From our findings, such responsiveness reflects vulnerability to downward income shocks and upward price changes. Our findings can serve as a complementary but informative platform to help inform policy-makers in policy prescriptions related to poverty, income, wages, prices, and food. As what Stevano (2020) points out, using food issue as an example, macro-level broad-brush solutions and approaches are necessary to tackle micro-level issues such as those addressed in our paper. Naturally, the first inkling is to put more cash into the hands of the poorest, either through income increase, price controls, tax and subsidy instrumentations. It is however, not a matter of simply pushing income levels above the PLI threshold, as this would neither be sustainable nor fiscally robust. Radical poverty eradication would require a concerted and multifaceted approach from the government. A broader policy on productivity-led wages would also be a pragmatic way to at least shift the poorest households above the absolute PLI threshold. A stable productivity-led wage level not only provides steady streams of future and put more real income into the hands of the poor, but could also facilitate proper food expenditure planning because there would be less concerns of the availability of future income. There is no longer the need to accord higher values on today's income

than the values of some unguaranteed future income, which pushes the poor to seek present pleasure in the form of non-essential food expenditure.

Our paper contributes to the wider literature by analysing the poorest Malaysian households from an economic-psychological angle, in our effort to have a better understanding and to subsequently provide better forms of assistance. As far as we know, ours is perhaps the first Malaysian study to examine poverty from such an angle. While we cannot entirely preclude the possibilities of data aggregation effects confounding our estimations, we have however, sought to mitigate this potential issue by (i) using the most comprehensible set of controls we can obtain from the data available, (ii) taking steps in meticulously merging the 4-digit sub-item expenditure with 7-digit sub-item prices, (iii) generating graphical depictions, as shown in Figure 1, and (iv) estimating by sub-samples (e.g. rural B40, urban D10) as part of our robustness checks. Though we have taken precautions to ensure rigorous analyses, caveats in data limitation need to be considered when interpreting results. The paper's main limitation lies in the unavailability of a more disaggregated 6 and 7-digit sub-item food expenditure. This inevitably would have us lumped certain foods as one. Future research could address this, because a more granular and more recent dataset would certainly go a long way to help the poorest of the poor.

Acknowledgements

This work was supported by the Malaysian Ministry of Higher Education Fundamental Research Grant Scheme [FRGS/1/2018/SS08/UUM/01/1 & FRGS/1/2016/SS08/UUM/02/9].

Disclosure statement

The authors do not have any competing interests to declare.

Notes on contributors



Dr. Jan-Jan Soon is Associate Professor with the School of Economics, Finance and Banking, Universiti Utara Malaysia. She earned her Phd in economics from the University of Otago, New Zealand. Her areas of interest are in labour economics and applied microeconometrics. She consistently publishes in Scopus-indexed and SSCI-indexed journals.



Dr. Azira Abdul Adzis is Associate Professor with the School of Economics, Finance and Banking, Universiti Utara Malaysia. She earned her doctorate degree from Massey University, New Zealand. Her areas of interest include household behaviour, financial literacy, and e-commerce. She is also an affiliate member of the Asian Institute of Chartered Bankers.



Dr. Shri Dewi Applanaidu is Associate Professor with the School of Economics, Finance and Banking, Universiti Utara Malaysia. She obtained her PhD in Economics from Universiti Putra Malaysia. She has recently been appointed as a Short-Term Consultant with World Bank. Her specialisation areas are in food security, agricultural econometric modelling, and development economics.



Dr. Norhaslinda Zainal Abidin is Associate Professor with the School of Quantitative Sciences, Universiti Utara Malaysia. She received her PhD from the University of Salford, United Kingdom. Her main research interests are in the application of system dynamics simulation models to issues in health, agriculture, transportation manufacturing, and public policies.

ORCID

Jan-Jan Soon http://orcid.org/0000-0003-0647-8833

Data availability statement

The data that support the findings of this study are available from the Department of Statistics Malaysia, but restrictions apply to the availability of these data, which were used under licence for the current study, and are not publicly available. The data are however, available from the main author upon reasonable request and with permission from the Department of Statistics Malaysia.

References

Addai, K. N., J. N. Ng'ombe, and O. Temoso. 2022. "Food Poverty, Vulnerability, and Food Consumption Inequality among Smallholder Households in Ghana: A Gender-Based Perspective." *Social Indicators Research* 163 (2): 661–689. doi:10.1007/s11205-022-02913-w.

Amolegbe, K. B., J. Upton, E. Bageant, and S. Blom. 2021. "Food Price Volatility and Household Food Security: Evidene from Nigeria." *Food Policy,*.102: 102061. doi:10.1016/j.foodpol.2021.102061.

Banerjee, A. V., and E. Duflo. 2007. "The Economic Lives of the Poor." *The Journal of Economic Perspectives : a Journal of the American Economic Association* 21 (1): 141–167. doi:10.1257/jep.21.1.141.

Banerjee, A. V., and E. Duflo. 2011. *Poor Economics: A Radical Rethinking of the Way to Fight Global Poverty*. New York, Public Affairs.

Chai, A., and A. Moneta. 2010. "Retrospectives Engel Curves." *Journal of Economic Perspectives* 24 (1): 225–240. doi:10.1257/jep.24.1.225.

Colen, L., P. C. Melo, Y. Abdul-Salam, D. Roberts, S. Mary, and S. G. Y. Paloma. 2018. "Income Elasticities for Food, Calories and Nutrients across Africa: A Meta-Analysis." *Food Policy.*77: 116–132. doi:10.1016/j.foodpol.2018.04.002.

Cornelsen, L., R. Green, R. Turner, A. D. Dangour, B. Shankar, M. Mazzocchi, and R. D. Smith. 2015. "What Happens to Patterns of Food Consumption When Food Prices Change?? Evidence from a Systematic Review and Meta-Analysis of Food Price Elasticities Globally." *Health Economics* 24 (12): 1548–1559. doi:10.1002/hec.3107.

DOSM 2020. *Household Expenditure Survey Report 2019*. Putrajaya: Department of Statistics Malaysia (DOSM).
Gibson, J., and B. Kim. 2013. "Do the Urban Poor Face Higher Food Prices? Evidence from Vietnam." *Food Policy*.41: 193–203. doi:10.1016/j.foodpol.2013.05.003.
Green, R., L. Cornelsen, A. D. Dangour, R. Turner, B. Shankar, M. Mazzocchi, and R. D. Smith. 2013. "The Effect of Rising Food Prices on Food Consumption: Systematic Review with Meta-Regression." *BMJ (Clinical Research ed.)* 346: f3703. doi:10.1136/bmj.f3703.
Healy, A. E. 2019. "Measuring Food Poverty in Ireland: The Importance of Including Exclusion." *Irish Journal of Sociology* 27 (2): 105–127. doi:10.1177/0791603519828313.
Ishida, A., S. H. Law, and Y. Aita. 2003. "Changes in Food Consumption Expenditure in Malaysia." *Agribusiness* 19 (1): 61–76. doi:10.1002/agr.10038.
Jensen, R. T., and N. H. Miller. 2008. "Giffen Behavior and Subsistence Consumption." *The American Economic Review* 98 (4): 1553–1577. doi:10.1257/aer.98.4.1553.
Kh'ng, K., C. C. Chang, and S. H. Hsu. 2022. "Implications of Food and Nutrition Security on Household Food Expenditure: The Case of Malaysia." *Agriculture & Food Security* 11 (1): 30. doi:10.1186/s40066-022-00367-4.
KRI 2016. *The State of Households II*. Kuala Lumpur: Khazanah Research Institute (KRI).
Kumar, A., G. Thapa, A. K. Mishra, and P. K. Joshi. 2020. "Assessing Food and Nutrition Security in Nepal: evidence from Diet Diversity and Food Expenditure Patterns." *Food Security* 12 (2): 327–354. doi:10.1007/s12571-019-01004-y.
Mani, A., S. Mullainathan, E. Shafir, and J. Zhao. 2013. "Poverty Impedes Cognitive Function." *Science (New York, N.Y.)* 341 (6149): 976–980. doi:10.1126/science.1238041.
Marchetti, S., and L. Secondi. 2022. "The Economic Perspective of Food Poverty and (in)Security: An Analytical Approach to Measuring and Estimation in Italy." *Social Indicators Research* 162 (3): 995–1020. doi:10.1007/s11205-021-02875-5.
Mottaleb, K. A., D. B. Rahut, G. Kruseman, and O. Erenstein. 2018. "Changing Food Consumption of Households in Developing Countries: A Bangladesh Case." *Journal of International Food & Agribusiness Marketing* 30 (2): 156–174. doi:10.1080/08974438.2017.1402727.
Mullainathan, S., and E. Shafir. 2013. *Scarcity: Why Having Too Little Means so Much*. New York: Times Books.
Nsabimana, A., R. B. Swain, Y. Surry, and J. C. Ngabitsinze. 2020. "Income and Food Engel Curves in Rwanda: A Household Microdata Analysis." *Agricultural and Food Economics* 8 (1): 1–20. doi:10.1186/s40100-020-00154-4.
Ren, Y., Y. Zhang, J. Loy, and T. Glauben. 2018. "Food Consumption among Income Classes and Its Response to Changes in Income Distribution in Rural China." *China Agricultural Economic Review* 10 (3): 406–424. doi:10.1108/CAER-08-2014-0079.
Schilbach, F., H. Schofield, and S. Mullainathan. 2016. "The Psychological Loves of the Poor." *American Economic Review* 106 (5): 435–440. doi:10.1257/aer.p20161101.
Shah, A. K., S. Mullainathan, and E. Shafir. 2012. "Some Consequences of Having Too Little." *Science (New York, N.Y.)* 338 (6107): 682–685. doi:10.1126/science.1222426.
Shah, A. K., J. Zhao, S. Mullainathan, and E. Shafir. 2018. "Money in the Mental Lives of the Poor." *Social Cognition* 36 (1): 4–19. doi:10.1521/soco.2018.36.1.4.
Spears, D. 2011. "Economic Decision-Making in Poverty Depletes Behavioural Control." *The B.E. Journal of Economic Analysis & Policy* 11 (1). doi:10.2202/1935-1682.2973.
Stevano, S. 2020. "Small Development Questions Are Important, but They Require Big Answers." *World Development* 127: 104826. doi:10.1016/j.worlddev.2019.104826.
Subramanian, S., and A. Deaton. 1996. "The Demand for Food and Calories." *Journal of Political Economy* 104 (1): 133–162. doi:10.1086/262020.
Tey, Y. S., M. N. Shamsudin, Z. Mohamed, A. M. Abdullah, and A. Radam. 2010. "Demand Analysis of Meat in Malaysia." *Journal of Food Products Marketing* 16 (2): 199–211.
Wongmonta, S. 2022. "An Assessment of Household Food Consumption Patterns in Thailand." *Journal of the Asia Pacific Economy* 27 (2): 289–309. doi:10.1080/13547860.2020.1811191.

Wood, B. D. K., C. H. Nelson, and L. Nogueira. 2012. "Poverty Effects of Food Price Escalation: The Importance of Substitution Effects in Mexican Households." *Food Policy*.37 (1): 77–85. doi:10.1016/j.foodpol.2011.11.005.

Yusof, S. A., and J. Duasa. 2010. "Consumption Patterns and Income Elasticities in Malaysia." *Malaysian Journal of Economic Studies* 47 (2): 91–106.