UNIVERSIDADE DE SÃO PAULO
FACULDADE DE ECONOMIA, ADMINISTRAÇÃO E CONTABILIDADE
DEPARTAMENTO DE ECONOMIA
PROGRAMA DE PÓS-GRADUAÇÃO EM ECONOMIA

Peer effects in consumption: a spatial demand system estimation using data from Brazil

Efeitos de pares no consumo: estimação de um sistema de demanda espacial usando dados do Brasil

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São Paulo
2021

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Tese apresentada ao Programa de Pós-graduação em Economia do Departamento de Economia da Faculdade de Economia, Administração e Contabilidade da Universidade de São Paulo, como requisito parcial para a obtenção do título de Doutora em Ciências.

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Versão corrigida
(versão original disponível na Biblioteca da Faculdade de Economia, Administração e Contabilidade)

São Paulo

2021

Catalogação na Publicação (CIP)
Ficha Catalográfica com dados inseridos pelo autor

Li, Denise Leyi.
Peer effects in consumption: a spatial demand system estimation using data from Brazil / Denise Leyi Li. - São Paulo, 2021.
170 p.

Tese (Doutorado) - Universidade de São Paulo, 2021.
Orientador: André Luis Squarize Chagas.

1. Consumo. 2. Efeitos de pares. 3. Sistema de demanda. 4. Elasticidade da demanda. I. Universidade de São Paulo. Faculdade de Economia, Administração e Contabilidade. II. Título.

AGRADECIMENTOS

Aos meus pais e irmãos, pela compreensão e torcida de sempre. Esse último ano me mostrou ainda mais a importância de ter o apoio e acolhimento de vocês.

Ao Luiz, meu noivo, pelos momentos de felicidade que passamos juntos e também por estar ao meu lado nos momentos mais difíceis sempre me ouvindo, apoiando e motivando. Sua paciência, seu humor e amor foram essenciais para mim.

Aos meus colegas e amigos da pós. Adriano, Alex, Bruno, Edu, Elias, Frotinha e Gabriel agradeço pelas conversas e pelo companheirismo desde o mestrado. Keyi e Renata, obrigada pela companhia, pelos conselhos e trocas. E claro, o grupo dos "meus" fiéis: Duda, Dudu, Eduardo, Karina, Liz, Lúcia, Pedro, Rapha e Tainá, mais que o apoio nos estudos, vocês trouxeram muita alegria e leveza para os meus dias. Um obrigada especial ao Rapha, por ser tão companheiro e por ter unido um grupo de amigos tão especiais. Construí memórias simples, mas marcantes dos nossos momentos tomando cafezinhos, bandejando, lanchando bolo na Eca, viajando para congressos e das nossas conversas virtuais do último ano. Com certeza meu doutorado não teria sido o mesmo sem vocês!

Aos meus amigos de longa data Bispo, Clara, Sofia e Tef. A vida nos levou para diferentes cantos, mas sei que vocês sempre estão na torcida e à disposição para me apoiarem.

Ao André, meu orientador, pelo aprendizado acadêmico, pelas trocas de experiências e pela motivação e paciência desde o mestrado. Aos professores Azzoni, Ariaster, Haddad e Lucinda pelos ensinamentos e contribuições durante os seminários e bancas de avaliação. Aos demais membros do Nereus pelas conversas e aprendizados trocados.

À equipe da secretaria da pós, Dri, Pinho, Leka e toda equipe da secretaria de pós-graduação da FEA 5.

À Fundação Instituto de Pesquisas Econômicas (Fipe) por conceder o acesso aos dados utilizados na pesquisa e pelo apoio das equipes do SIT e do IPC. Um agradecimento especial ao Jackson e ao Marcelo.

Por fim, ao Conselho Nacional de Desenvolvimento Científico e Tecnológico (CNPq) pelo apoio financeiro durante o doutorado.

RESUMO

O consumo das famílias é tradicionalmente modelado sem levar em conta a influência dos pares (*peer effects*). Estudar os efeitos dos pares no consumo é relevante, pois a presença deles pode afetar a decisão de consumo intratemporal e intertemporal dos domicílios levando a distorções no bem-estar social. Além disso, podem haver impactos no planejamento e avaliação de políticas de consumo, tais como programas de transferência de renda e políticas tributárias. A literatura sobre interações sociais é notoriamente desafiadora em termos teóricos e empíricos, sendo a disponibilidade de dados uma das principais restrições. Poucos estudos da área investigam o consumo desagregado e quase nenhum foca no cálculo e análise das elasticidades de demanda. Dado que *spillover* espaciais e os efeitos de *feedback* podem ser relevantes, os impactos dos preços e da renda na demanda podem ser influenciados pelas interações sociais entre os domicílios. São duas as principais contribuições desta tese: desenvolver um sistema de demanda espacial teoricamente e empiricamente bem especificado com o objetivo de estimar os efeitos dos pares no consumo desagregado; e fornecer elasticidades de demanda específicas para impactos diretos, indiretos e totais. O efeito dos pares na composição das despesas dos domicílios foi investigado com base em dados de consumo de domicílios da cidade de São Paulo, Brasil, coletados entre 2008 e 2013. Informações dos endereços exatos de todos os domicílios foram disponibilizados e utilizados para definir com maior precisão os grupos de referência de cada domicílio pelo critério de proximidade geográfica. O modelo de sistema de demanda espacial é uma adaptação do Sistema de Demanda Quase Ideal. Também foi considerado um sistema de demanda de dois estágios orçamentários, no qual os domicílios primeiro escolhem como gastar sua renda em grupos amplos de produtos, que inclui o grupo de alimentos, e na segunda fase, a despesa alocada para o grupo de alimentos é então distribuída entre as subcategorias alimentares. Os resultados da investigação empírica revelam que vizinhos causam um efeito significante, ainda que pequeno, no comportamento de consumo de um domicílio e, consequentemente, as elasticidades derivadas do modelo com interações sociais diferem daquelas calculadas a partir de um modelo de demanda tradicional.

Palavras-chave: Consumo, Efeitos de pares, Sistema de demanda, Elasticidade da demanda

ABSTRACT

Household consumption is traditionally modeled without considering the influence of peers. Studying peer effects in consumption is relevant, as its presence can affect the intratemporal and intertemporal consumption decisions of households leading to distortions in social welfare. Additionally, there may be impacts on the planning and evaluation of policies involving consumption, such as income transfer programs and tax policies. The literature of social effects is theoretically and empirically challenging, with data availability being one of the main constraints. Few studies focus on disaggregated consumption, and almost none take a further step to analyze the resulting elasticities. Given that the spillover and feedback effects are relevant, price and income effects on demand can now be influenced by the social interactions between households. This thesis's main contribution is twofold: it develops a theoretically and empirically well-specified spatial demand system to estimate peer effects in disaggregated consumption, and it provides elasticity of demand specific to direct, indirect, and total impacts. This thesis investigates the peer effects in the composition of household expenditure using disaggregated consumption data of households from the city of São Paulo, Brazil, surveyed by Fipe between 2008 and 2013. Data about the exact addresses of all households were available and used to define household's reference groups characterized by geographical proximity with more precision. The spatial simultaneous demand model is an adaptation of the classic Almost Ideal Demand System. In addition, a two-stage budgeting system is considered, where consumers first choose how to spend their income among broad groups of products, which include food, and in the second stage, expenditure allocated to the food group is then distributed among food subcategories. The results of the empirical investigation suggest that neighbors cause a small but not negligible effect on a household's consumption behaviors. Consequently, the elasticities derived from the model with social interactions differ from those calculated from the traditional demand model.

Keywords: Consumption, Peer effects, Demand system, Elasticity of demand

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1 INTRODUCTION

Household consumption is traditionally modeled without considering the influence of peers. Classic models of consumer demand such as those proposed by Deaton and Muellbauer (1980a) and Banks et al. (1997) do not consider that when making the consumption decision, the individual is influenced by the consumption behavior of his peer. However, the existence of this peer effect is discussed since Veblen (1899), which emphasizes the utility gain when one observes their consumption higher than of their peers. According to Duesenberry et al. (1949), the strength of any family's desire to increase their consumption expenditure is a function of a weighted average consumption of those with whom they have had contact.

Studying the peer or neighbor's effect on consumption is considered crucial in the context of underdeveloped countries (Roychowdhury, 2019) and is relevant for at least two reasons (De Giorgi et al., 2016). The first concerns the distortions in social welfare observed in intratemporal and intertemporal household consumption decision context. If a neighbor's effect is relevant, in a behavior known in the literature as *keeping up with the Joneses*, a household may be sparing sub-optimal or even borrowing excessively to keep pace with an increase in the consumption of the neighbor. An intratemporal distortion can also occur due to the mechanism known as the conspicuous consumption case (Veblen, 1899). In this case, in pursuit of social status, the consumption of more conspicuous goods, usually luxury goods, causes excessive weight on the family budget.

The second reason is related to the planning and evaluation of policies involving consumption, such as income transfer programs and tax policies. If the existence and magnitude of the peer or neighborhood effects are not considered, the policy's social effect would be imprecise since the indirect effects of overflow may not be negligible in addition to the direct effects. Thus, depending on the character and degree of connection between social groups, policies targeting certain groups' may cause not foreseen impacts to others.

The literature on social effects is notoriously challenging. From the theoretical point of view, different mechanisms can be consistent with the presence of social effects. Few studies have taken further steps to identify the underlying channel through which a given estimated social effect operates, given that it can be a near-impossible task when accessible data are limited (Sacerdote, 2011). From the empirical point of view, two main problems have to be addressed for identifying causal social effects: the definition of the relevant social interactions and the endogeneity of the social effects.

The theory does not provide guidance for the correct measurement of groups, and data availability is the primary constraint. The reference groups have been defined chiefly based on geographical proximity such as agents from the same city, census strata (Ravina, 2019; Alvarez-Cuadrado et al., 2016; Verhelst and Van den Poel, 2014) or narrower spatial units (Grinblatt et al., 2008; Kuhn et al., 2011; Boneva, 2014) and based on similarity in socio-demographic characteristics (Maurer and Meier, 2008). Different approaches can be taken when rich data on individual's networks are available as in De Giorgi et al. (2020) that exploits the households' social network at the family and firm levels.

Another great challenge of studying the peer effect is isolating it. The observation of similar behavior (e.g., related to consumption) between a household and its peers or neighbors is not sufficient to identify the peer effect. The reason is the potential simultaneous presence of three effects first listed by Manski (1993): 1) endogenous effect; 2) exogenous or contextual effect, and 3) correlation effect. The first effect arises when the peers act according to the behavior of the group/neighborhood. The second effect represents the influence of the peers' or neighbor's exogenous characteristics on the behavior of the individual or household. Finally, the latter effect arises when common factors among individuals belonging to the same group cause them to behave in the same way.

The most popular strategy adopted by recent literature to separate the effects mentioned above involves an instrumental instrument approach using income shocks of families (Roychowdhury, 2019) or exogenous income variations such as those generated by some transfer programs (Boneva, 2014; Angelucci et al., 2017). Due to data limitations, this thesis strategy does not separate all three effects. This thesis aims to understand the peer effect on household expenditure composition using disaggregated and geo-referenced consumption data from households in the city of São Paulo surveyed by the *Fundação Instituto de Pesquisa Econômica* (Fipe - "Institute of Economic Research Foundation") between 2008 and 2013. The access to geographically referenced locations of the households allows the construction of peer reference groups. By adopting the spatial autoregressive model strategy proposed by Bramoullé et al. (2009), I investigate whether changes in the composition of the neighbor's expenses lead to one household changing its expenditure composition as well.

The majority of the literature on social interactions in consumption focus on aggregated consumption of households. However, understanding specifically the peer effects in the composition of expenditures is relevant to differentiate the income effect from the neighborhood effect (Boneva, 2014). The income effect stems from risk-sharing behavior among neighbors. Investigating only the total consumption expenditure of households or the specific expenditure on some isolated goods does not differentiate these effects.

This thesis's main contribution is twofold: it develops a theoretically and empirically well-specified spatial demand system to estimate peer effects in disaggregated consumption, and it provides elasticity of demand specific to direct, indirect, and total impacts. Most of the literature on peer effects in consumption is focused on investigating the importance of peer effects and understanding its mechanisms. Few studies consider disaggregated consumption, and only one takes a further step to analyze the resulting elasticities (Verhelst and Van den Poel, 2014). However, due to the spillover effects and feedback effects, price and income effects on demand are now influenced by the social interactions between households.

The spatial demand system is an adaptation of the Almost Ideal Demand System first proposed by Deaton and Muellbauer (1980a). A two-stage budgeting structure based on the weak separability of preference hypothesis was constructed. In the first stage, households chose to expend their income among broad groups of products (habitation, food, transportation, personal expenses, health, clothing, and education). In the second stage, each group's level of expenditure from the first stage is allocated to the products within that group. The focus was subcategories from the food group.

In the demand estimation procedure, censoring and price variable construction are important issues to attend to, especially when using household survey data. The zero values in the estimation process are treated by applying a generalization of the two-stage Heckman procedure proposed by Heien and Wesseils (1990). For the first-stage estimation, Fipe's Consumer Price Index was used to construct price indices for each broad category. For the demand estimation for food subcategories, the unit value with quality-adjusted price correction and imputation approach proposed by Cox and Wohlgenant (1986) was considered.

The empirical investigation results present evidence that neighbors cause a small but not negligible effect on a household's consumption behaviors. Peer effects were found to be more relevant for the 2011-2013 sample and for demand for food as a broad category and when considering demand for its subcategories. Several robustness exercises were considered to evaluate if the spatial effect found significant is, in fact, peer effects, that is, if a household's expenditure decision is affected by their neighbor's demand. One of the robustness tests was estimating a spatial demand system in which the neighbors' demographics are also considered as explanatory variables for demand. The test results reveal that while neighbors' demographics do not affect demand, the influence of neighbor's demand is still persistent. The computed elasticities are only broadly comparable to the literature on demand estimation due to differences in data (most of the studies are based on national data from different periods), demand function applied, and definition of product categories. Still, overall the elasticities found are at the same range as the values found by the literature.

The outline of the thesis is as follows. Chapter 2 is dedicated to present the demand theory and estimation framework of the study. I briefly overview the neoclassical demand theory and describe the traditional Almost Ideal Demand System and its adaptations. The chapter also presents a review of the main empirical results on the demand estimation for food products. Chapter 3 presents the literature on the social interaction effects in consumption and the spatial demand system model that incorporates social interaction to the almost ideal demand system. Chapter 4 presents details of the empirical investigation adopted with information on the data and econometric setup (empirical specification, estimation, and identification). Chapter 5 provides and compares the main results from the traditional and spatial demand estimations. Also, I evaluate the robustness of the main findings with further estimation exercises. Finally, Chapter 6 concludes the thesis with final considerations.

2 DEMAND THEORY AND ESTIMATION

This chapter is dedicated to present and discuss the demand theory and estimation framework of the thesis. The outline of the chapter is as follows. First, the neoclassical demand theory is introduced, where the consumer preferences, the theory of utility maximization, the duality in consumer demand theory, and the demand properties are briefly reviewed. Next, the focus is the Almost Ideal Demand System specification. The demand model derivation and extensions are presented. Lastly, the main results on demand estimation for the food category are presented.

2.1 The Neoclassical Demand Theory

In the neoclassical demand theory preferences can be represented by an utility function $U(\boldsymbol{x})$ given by the vector or bundle $\boldsymbol{x}$ of goods consumed. The existence of utility functions that represents consumer preferences ordering relies on the following axioms of choice (Deaton and Muellbauer, 1980b):

Axiom 1. *Reflexivity.* For any bundle $\boldsymbol{x}$, $\boldsymbol{x} \succeq \boldsymbol{x}$ ($\boldsymbol{x}$ is “at least as good as” itself).

Axiom 2. *Completeness.* For any two bundles in the choice set $\boldsymbol{x^1}$, $\boldsymbol{x^2}$, either $\boldsymbol{x^1} \succeq \boldsymbol{x^2}$, or $\boldsymbol{x^2} \succeq \boldsymbol{x^1}$, or $\boldsymbol{x^2} \sim \boldsymbol{x^1}$ ($\boldsymbol{x^1}$ “is indifferent to” $\boldsymbol{x^2}$). That is, any two bundles of goods are comparable.

Axiom 3. *Transitivity or Consistency.* If $\boldsymbol{x^1} \succeq \boldsymbol{x^2}$ and $\boldsymbol{x^2} \succeq \boldsymbol{x^3}$, then $\boldsymbol{x^2} \succeq \boldsymbol{x^3}$.

Axiom 4. *Continuity.* For any bundle $\boldsymbol{x^1}$, the set of bundles “at least as good as” $\boldsymbol{x^1}$ and the set of bundles “no better than” $\boldsymbol{x^1}$ contain their own boundaries.

Considering the Axioms 1 to 4, $U(\boldsymbol{x^1}) \geq U(\boldsymbol{x^2})$ and $\boldsymbol{x^1} \succeq \boldsymbol{x^1}$ are equivalent statements. This means that when the utility is maximized, the most preferred bundle is chosen. The choice of bundle is, however, restricted by the total of goods available in the economy (G) and by the consumers total wealth disposable for expenditure. The individuals choice set is therefore given by the budget set:

$$B(\boldsymbol{p}, w) = \left\{ \boldsymbol{x} \in \mathbb{R}^G_+ : \boldsymbol{p'x} = \textstyle\sum_{k=1}^{G} p_k x_k \leq w \right\} \tag{2.1}$$

where $\boldsymbol{x}$ is the $G \times 1$ non-negative vector of goods, $\boldsymbol{p}$ is the $G \times 1$ corresponding non-negative vector of prices, and w is the individual’s “nominal income” or total expenditure on goods.

2.1.1 The Utility Maximization Problem and Marshallian demands

The Consumer Utility Maximization Problem consists of choosing the bundle of goods $\boldsymbol{x} \in B(\boldsymbol{p}, w)$ that is most preferred or, equivalently, that maximizes it's utility:

$$\max_{\boldsymbol{x} \in B(\boldsymbol{p}, w)} U(\boldsymbol{x}) \tag{2.2}$$

If $\boldsymbol{p} >> 0$, $w > 0$ and U is continuous, then the solution of the consumer problem exists and is obtained by solving the Kuhn-Tucker first order conditions (admits $x_k = 0$):

$$\begin{aligned} &\frac{\partial U(\boldsymbol{x})}{\partial x_k} \leq \lambda p_k \quad \forall k = 1, ..., G, \\ &\sum_{k=1}^{G} p_k x_k = w \end{aligned} \tag{2.3}$$

where λ is the Lagrange multiplier. The solution for the utility optimization problem are demand functions known as the *Marshallian, Walrasian* or *Uncompensated demands*:

$$\boldsymbol{x}^* = \boldsymbol{x}(\boldsymbol{p}, w) \tag{2.4}$$

The following additional axioms for preference are necessary for the Marshallian demand to meet important properties discussed in sequence.

Axiom 5. *Non-satiation.* A preference relation $\succeq$ is locally non-satiated if, for any bundle $\boldsymbol{x^1}$, there exists some $\boldsymbol{x^2}$ close enough to $\boldsymbol{x^1}$, such that $\boldsymbol{x^2} \succeq \boldsymbol{x^1}$.

Axiom 6. *Strict convexity.* If $\boldsymbol{x^1} \succeq \boldsymbol{x^2}$, then for $0 \leqslant \lambda \leqslant 1$, $\lambda \boldsymbol{x^2} + (1-\lambda)\boldsymbol{x^1} \succ \boldsymbol{x^1}$. Which means that indifference curves are convex to the origin.

Now to the properties:

Property 1. *Uniqueness.* If preferences are strictly convex, then the consumer optimum $\boldsymbol{x}^*$ is always unique.

Property 2. *Adding-up or the Walras' Law.* If preferences are locally non-satiated, then for any pair of (p, w) and $\boldsymbol{x}^* \in \boldsymbol{x}(\boldsymbol{p}, w)$, the entire budget is consumed:

$$\boldsymbol{p'x} = \sum_{k=1}^{G} p_k x_k = w \tag{2.5}$$

Property 3. *Homogeneity.* Marshallian demand is homogeneous of degree zero in $(\boldsymbol{p}, w)$:

$$\boldsymbol{x}(\alpha \boldsymbol{p}, \alpha w) = \boldsymbol{x}(\boldsymbol{p}, w), \quad \forall \boldsymbol{p}, w, \alpha > 0 \tag{2.6}$$

That is, if prices and income changes in the same proportion, the purchase pattern will not be altered ("absence of money illusion").

From the Marshallian demands and its properties comes other important definitions and relations. The expenditure share of a good i is defined by

$$s_i = \frac{p_i x_i(\boldsymbol{p}, w)}{w} \tag{2.7}$$

and are the fractions of total expenditure going to each good. Naturally, $\sum_{i=1}^{G} s_i = 1$. The elasticity measures comes from the logarithmic derivatives of the Marshallian demands. The income elasticity of demand, $\epsilon_{iw}(\boldsymbol{p}, w)$, for $i = 1, ...G$, is given by

$$\epsilon_{iw} = \frac{\partial ln(x_i(\boldsymbol{p}, w))}{\partial ln(w)} = \frac{\partial x_i(\boldsymbol{p}, w)}{\partial w} \frac{w}{x_i(\boldsymbol{p}, w)} \tag{2.8}$$

If $\epsilon_{iw}(\boldsymbol{p}, w) > 0$, the ith good is classified as normal at $(\boldsymbol{p}, w)$, and as inferior if $\epsilon_{iw}(\boldsymbol{p}, w) < 0$. Also, if $\epsilon_{iw}(\boldsymbol{p}, w) > 1$, the ith good is classified as a luxury, and as a necessity, if $\epsilon_{iw}(\boldsymbol{p}, w) < 1$.

The uncompensated (Cournot) price elasticities, $\epsilon_{ij}(\boldsymbol{p}, w)$, for $i, j = 1, ...G$, are given by

$$\epsilon_{ij} = \frac{\partial ln(x_i(\boldsymbol{p}, w))}{\partial ln(p_j)} = \frac{\partial x_i(\boldsymbol{p}, w)}{\partial p_j} \frac{p_j}{x_i(\boldsymbol{p}, w)} \tag{2.9}$$

If $\epsilon_{ij}(\boldsymbol{p}, w) > 0$, the goods are Cournot gross substitutes. If $\epsilon_{ij}(\boldsymbol{p}, w) < 0$, they are gross complements; and if $\epsilon_{ij}(\boldsymbol{p}, w) = 0$, they are independent.

The Engel and Cournot aggregations are relations obtained by derivatives of the *Adding-up* property (Equation 2.5) for, respectively, total expenditure and price. They show how changes in w or p_i cause rearrangements in purchases so that the budget restriction are still satisfied. The Engel aggregation is given by

$$\sum_{k=1}^{G} p_k \frac{\partial x_k(\boldsymbol{p}, w)}{\partial w} = 1 \quad \text{or} \quad \sum_{k=1}^{G} s_k \epsilon_{kw} = 1 \tag{2.10}$$

which implies that a change in income or total expenditure will be redistributed between the purchases of each good k by the proportion $p_k \frac{\partial x_k(\boldsymbol{p}, w)}{\partial w}$. The Cournot aggregation is given by

$$\sum_{k=1}^{G} p_k \frac{\partial x_k(\boldsymbol{p}, w)}{\partial p_i} + x_i(\boldsymbol{p}, w) = 0 \quad \text{or} \quad \sum_{k=1}^{G} s_k \epsilon_{ik} + s_i = 0 \quad \forall i, k = 1, ..., G \tag{2.11}$$

which means that price changes do not affect the total expenditure once the sum of the direct and indirect effects of the price change on demand cancels out.

Another important result from the utility maximization problem is the *indirect utility function*, which is the maximum level of utility at given prices and income. It's obtained by considering the Marshallian demand functions (Equation 2.4) in the utility function $U(\boldsymbol{x})$ (the objective function),

$$v(\boldsymbol{p}, w) = U(\boldsymbol{x}^*(\boldsymbol{p}, w)) \tag{2.12}$$

The function is homogeneous of degree zero and continuous in $(\boldsymbol{p}, w)$, strictly increasing in w, not decreasing in $\boldsymbol{p}$ and quasi convex.

With the indirect utility, the demand system can be derived in a relation called *Roy's Identity*,

$$x_i(\boldsymbol{p}, w) = -\frac{\partial v(\boldsymbol{p}, w)/\partial p_i}{\partial v(\boldsymbol{p}, w)/\partial w} \quad \forall \quad i = 1, ..., G \tag{2.13}$$

2.1.2 The Dual problem and Hicksian demands

The consumer's utility maximization problem can be reformulated as a problem of minimizing the cost or expenditure necessary to obtain a fixed level of utility, u, given market prices, $\boldsymbol{p}$,

$$\min_{\boldsymbol{x}} \boldsymbol{p}'\boldsymbol{x} \quad \text{subject to} \quad U(\boldsymbol{x}) \geq u \tag{2.14}$$

The solution of the Expenditure Minimization Problem are known as the *Hicksian* or *Compensated* demands,

$$\boldsymbol{h}^* = \boldsymbol{h}(\boldsymbol{p}, u) \tag{2.15}$$

They show how the demands are affected by prices when utility is held constant, hence the name "compensated". The indirect cost function are the minimum expenditure obtained by considering the Hicksian demand functions (Equation 2.14) in the expenditure function (the objective function),

$$e(\boldsymbol{p}, u) = \boldsymbol{p}'\boldsymbol{h}^* \tag{2.16}$$

The indirect cost function is homogeneous of degree one and concave in $\boldsymbol{p}$, strictly increasing in u, not decreasing in p and continuous in $\boldsymbol{p}$ and u.

With the indirect cost, the demand system can be derived in a relation called *Sheppard's Lemma*,

$$h_i(u, \boldsymbol{p}) = \frac{\partial e(\boldsymbol{p}, u)}{\partial p_i} \quad \forall \quad i = 1, ...G \tag{2.17}$$

The Expenditure Minimization Problem is considered the Utility Maximization Problem's dual problem. While the last finds a level of maximum utility u given exogenous variables $(\boldsymbol{p}, w)$, the first selects the minimum cost to achieve the level of utility u. The following relations summarizes the duality between the two problems

$$\max_{\boldsymbol{x}} v(x) = U(\boldsymbol{x}) \quad \text{subject to} \quad \boldsymbol{p'x} = w \quad \equiv \quad \min_{\boldsymbol{x}} w = \boldsymbol{p'x} \quad \text{subject to} \quad U(\boldsymbol{x}) = v(x) \tag{2.18}$$

$$v(\boldsymbol{p}, e(\boldsymbol{p}, u)) = u \tag{2.19}$$

$$\boldsymbol{h}(\boldsymbol{p}, u) = \boldsymbol{h}(\boldsymbol{p}, v(\boldsymbol{p}, w)) = \boldsymbol{x}(\boldsymbol{p}, w) \tag{2.20}$$

$$\boldsymbol{x}(\boldsymbol{p}, w) = \boldsymbol{x}(\boldsymbol{p}, e(\boldsymbol{p}, u)) = \boldsymbol{h}(u, \boldsymbol{p}) \tag{2.21}$$

$$\frac{\partial h_i(\mathbf{p}, u)}{\partial p_j} = \frac{\partial x_i(\mathbf{p}, w)}{\partial p_j} + \frac{\partial x_i(\mathbf{p}, w)}{\partial w} x_j(\mathbf{p}, w) \quad \forall \quad (\mathbf{p}, u) \text{ and } u = v(\mathbf{p}, w) \tag{2.22}$$

The last equation is known as the *Slutsky's Equation*. With the dual problem, the Marshallian demands can be reached from the Hicksian demand and the indirect utility function (inverse of the cost function) using the Shephard's Lemma (Equation 2.17) and the Roy's Identity (Equation 2.13).

2.1.3 Desirable demand properties, Separability and Aggregation

Now the four general properties of the Marshallian and Hicksian demand functions can be highlighted. They are desirable properties of a "theoretically plausible" demand system. As shown in the following sections, these properties will usually be constraints to the demand models to be tested empirically.

Property 1. *Adding-up*. The total value of both Marshallian and Hicksian demands exhausts the total expenditure.

$$\boldsymbol{p'x} = \boldsymbol{p'h} = w$$

The demand alters only with changes in relative prices.

Property 2. *Homogeneity*. The Hicksians demands are homogeneous of degree zero in prices, and the Marshallians demands in total expenditure and prices. Given a scalar $\alpha > 0$,

$$\boldsymbol{h}(\alpha\mathbf{p}, u) = \boldsymbol{h}(\mathbf{p}, u) = \boldsymbol{x}(\alpha\mathbf{p}, \alpha w) = \boldsymbol{x}(\mathbf{p}, w)$$

Property 3. *Symmetry*. The cross-price derivatives of the Hicksian demands are symmetric, that is, for all $i \neq j = 1, ..., G$,

$$\frac{\partial h_i(\mathbf{p}, u)}{\partial p_j} = \frac{\partial h_j(\mathbf{p}, u)}{\partial p_i}$$

Property 4. *Negativity*. The matrix formed by the derivatives $\nabla_p h(\mathbf{p}, u)$ is negative semidefinite.

$$\nabla_p h(\mathbf{p}, u) = \begin{bmatrix} \partial h_1/\partial p_1 & ... & \partial h_1/\partial p_G \\ \vdots & ... & \vdots \\ \partial h_G/\partial p_1 & ... & \partial h_G/\partial p_G \end{bmatrix}$$

The last two properties are direct consequences of the axioms of choice. With them, the Slutsky substitution matrix

$$S(\mathbf{p}, w) = \begin{bmatrix} s_{11} & ... & s_{1G} \\ \vdots & ... & \vdots \\ s_{G1} & & s_{GG} \end{bmatrix} \quad \text{with} \quad s_{ij} = \frac{\partial h_i(\mathbf{p}, u)}{\partial p_j} = \frac{\partial x_i(\mathbf{p}, w)}{\partial w} x_j(\mathbf{p}, w) + \frac{\partial x_i(\mathbf{p}, w)}{\partial p_j}$$

is negative semi-definite, symmetric and $S(\mathbf{p}, w).\mathbf{p} = \mathbf{0}$ must hold. The diagonal elements of S must be non-positive, for all i, $s_{ii} \leq 0$. That means that an increase in price with utility held constant won't cause an increase in the demand for the good, which is known as the "Law of Demand".

For the practical application of the demand theory, the estimation of the demands for all goods together can be impossible due to lack of complete micro data on consumer consumption and computational limitations. Most empirical models will rely on the hypothesis of *weak separability of the utility* developed by Blackorby et al. (1978)[1].

If all goods $\boldsymbol{x}$ can be classified into N categories so that preference ordering on goods within the category is independent to the consumption outside the category, then the preferences are weakly separable. Separate preferences can be represented by a utility function of the form

$$u = f[u_1(\mathbf{x}^1), ..., u_N(\mathbf{x}^N)] \tag{2.23}$$

[1]See Chapter 5 of Deaton and Muellbauer (1980b) for a complete review of the separability concept.

where $u_n(x_n)$ is the subutility function for the category n and f is a function increasing in all its arguments. Each category has a subutility functions and the sum of the values of these results in the total utility.

Weak separability places restrictions on the degree of substitution between goods in different groups. Because a price change alters the allocation of expenditure between categories, the demand for a good will be affected by the price changes of goods from other categories. In fact, the impact of a change in the price of one good on the demands of goods within its own category is the same on goods of other categories.

The weak separability is both necessary and sufficient for the second stage of the two-stage budgeting process. The two-stage budgeting behavior considers that the consumer allocates total expenditure in two stages. In the first stage, expenditure is allocated to broad categories of goods, while in the second stage, category expenditures are allocated to individual goods. At each stage, only the information related to its own stage is required; that is, the consumption within the category can always be written as a function of group total expenditure and prices within the group alone. This implies that the decision at each stage is correspondent to a utility maximization problem as its own, which separates and simplifies the demand estimation[2].

Another frequent challenge of the empirical demand estimation is the aggregation problem. Again, it is common for only aggregate consumption data to be available. In most cases, the aggregate demand functions should share some or all of the properties of individual demand functions. *Exact aggregation* occurs when aggregate consumer behavior is equivalent to the outcome of the decisions of a single maximization consumer. The conditions under which the aggregated model is accepted will be discussed case by case in the following sections when relevant[3].

2.2 The Almost Ideal Demand System - AIDS

As briefly reviewed in the previous subsection, the economic theory reveals that under certain conditions, the existence of consumer preferences implies the existence of a utility function (and expenditure function), which through maximization (minimization) leads to a demand function. The theory does not indicate specific functional forms for the demand and only outlines the particular restrictions that it should hold. In fact, one of the main challenges for a demand analysis model to be consistent with the demand theory of consumers' utility maximization is the definition of a convenient functional form.

[2] Decoster et al. (1998) presents an evaluation of the empirical performance of three popular models (Rotterdam, AIDS, and QUAIDS) when two-stage budgeting based on weak separability is applied.

[3] See Chapter 6 of Deaton and Muellbauer (1980b) and Clements et al. (1996) for general conditions of the aggregation theory.

There are essentially two different approaches to the derivation of theoretically plausible demand systems. One approach starts from a particular specification of the utility function that satisfies certain axioms of choice. The demand system is consequently obtained from the optimization process of the utility function. The second approach starts directly from an arbitrary demand function and then imposes restrictions on the demand system. The restrictions usually consist of conditions for the desirable properties that all theoretically plausible demand systems should hold, as explained in the previous subsection.

The Locally flexible demand models are based on functional forms with the property of having enough parameters to approximate any elasticities at a particular set of prices. The locally flexible functional form is a second-order local approximation to an arbitrary function (Barnett, 1983). Three of the most important models are the Linear Expenditure System, The Translog model, and the Almost Ideal Demand System.

The Almost Ideal Demand System (AIDS) model was introduced in Deaton and Muellbauer (1980a) and to this day is one of the most popular models used for empirical demand analysis. Its use is often justified by its flexibility, aggregation properties, and practicality to test and impose most of the properties for a theoretical well behaved demand model. The original derivation of the demand system can be outlined by the following steps[4]:

1. Consider an expenditure function that represents a specific class of preferences known as *Price independent generalized logarithmic* (PIGLOG).

2. Define the functional forms for the components of the expenditure function.

3. Find the compensated or Hicksian demand by applying the Shephard's Lemma.

4. Find the indirect utility function.

5. Find the uncompensated or Marshallian demand functions using the indirect utility function.

The AIDS model derivation starts from an expenditure function representing a specific class of preferences known as *Price independent generalized logarithmic* (PIGLOG). Muellbauer (1975) proposed the *Price independent generalized linearity* (PIGL) and the PIGLOG models in order to establish the most general possible solution to the problem of consistent aggregation across consumers. By the theorems presented in the paper, this class permits exact aggregation over consumers; that is, the aggregate consumer behavior can be treated as if it were the outcome of a single maximizing consumer. The representative PIGL minimum cost of reaching utility u at prices $\mathbf{p}$ is given by

[4]Given the duality of the demand theory, an equivalent derivation of the AIDS model starts with a PIGLOG indirect utility function and applies the Roy's Identity.

$$c(u, \mathbf{p}) = [(1-u)a(\mathbf{p})^{\alpha} + u \log b(\mathbf{p})^{\alpha}]^{1/\alpha} \tag{2.24}$$

where parameter α defines the non-linearity of the Engel curves and therefore, dictates the relation between the representative expenditure and the mean expenditure. When $\alpha = 1$, the expenditure and Engel curves are linear, while when $\alpha = -1$ the Engel curves are quadratic. Finally, when $\alpha \to 0$, the PIGLOG model expenditure is derived and given by[5]

$$\log c(u, \mathbf{p}) = (1-u) \log a(\mathbf{p}) + u \log b(\mathbf{p}) \tag{2.25}$$

By assuming the PIGLOG model, Deaton and Muellbauer (1980a) considers that in the aggregated demand, the mean expenditure level of each good is independent of prices and depends only on the distribution of expenditures in the economy. With normalization, the utility index u ranges between $0 \leq u \leq 1$ and $a(\mathbf{p})$ and $b(\mathbf{p})$ are positive linearly homogeneous price functions that can be considered, respectively, as the subsistence cost (when $u = 0$) and the cost of maximum utility (when $u = 1$).

In the second step, a Translog price index specification is chosen for $\log a(\mathbf{p})$ and $\log b(\mathbf{p})$ is given by $\log a(\mathbf{p})$ plus a Cobb-Douglas function as follows

$$\log a(\mathbf{p}) = \alpha_0 + \sum_i \alpha_i \log(p_i) + \frac{1}{2} \sum_i \sum_j \gamma_{ij}^* \log(p_i) log(p_j) \tag{2.26}$$

and

$$\log b(\mathbf{p}) = \log a(\mathbf{p}) + \beta_0 \prod_i p_i^{\beta_i} \tag{2.27}$$

where $i, j = 1, ..., G$ are the goods available for consumption and α_i, β_i and γ_{ij}^* are parameters. The functional forms were chosen based on two criteria (Chalfant, 1987): to attend a flexible functional form and to result in a system of demand functions with desirable properties. For $\log a(\mathbf{p})$, a sufficient number of parameters was needed so as to obtain a locally flexible functional form for the cost function, that is, for any single point, the gradient and Hessian matrix must represent any arbitrary cost function[6].

By replacing Equations 2.26 and 2.27 in Equation 2.25 the AIDS cost function is written

$$\log c(u, \mathbf{p}) = \alpha_0 + \sum_i \alpha_i \log(p_i) + \frac{1}{2} \sum_i \sum_j \gamma_{ij}^* \log(p_i) \log(p_j) + u\beta_0 \prod_i p_i^{\beta_i} \tag{2.28}$$

[5]By rewriting the cost function as $c(u, \mathbf{p})^{\alpha} = (1-u)a(\mathbf{p})^{\alpha} + u \log b(\mathbf{p})^{\alpha}$ and considering $\lim_{\alpha \to 0} \frac{x^{\alpha}-1}{\alpha} = \log x$.

[6]At any single point its derivatives $\frac{\partial c}{\partial p_i}$, $\frac{\partial c}{\partial u}$, $\frac{\partial^2 c}{\partial p_i \partial p_j}$, $\frac{\partial^2 c}{\partial u \partial p_i}$, and $\frac{\partial^2 c}{\partial u^2}$ can be set equal to those of an arbitrary cost function (Deaton and Muellbauer, 1980a).

The third step is to apply the Shephard's Lemma from which follows the relation

$$\frac{\partial \log c(u,\mathbf{p})}{\partial \log(p_i)} = \frac{p_i}{c(u,\mathbf{p})}\frac{\partial c(u,\mathbf{p})}{\partial p_i} = \frac{p_i q_i(u,\mathbf{p}))}{c(u,\mathbf{p})} = s_i(u,\mathbf{p}) \quad \forall i = 1,...,G \tag{2.29}$$

where $q_i(u,\mathbf{p})$ is the Hicksian demand for good i and $s_i(u,\mathbf{p})$ denotes the share of expenditure with good i in total expenditure. Now, partially deviating Equation 2.28 in terms of $\log(p_i)$ followed by some manipulations results in

$$s_i(u,\mathbf{p}) = \alpha_i + \sum_j \gamma_{ij}\log(p_j) + \beta_i u \beta_0 \prod_i p_i^{\beta_i} \quad \forall i = 1,...,G \tag{2.30}$$

where $\gamma_{ij} = \frac{\gamma^*_{ij}+\gamma^*_{ji}}{2}$.

For continuous and locally non satiable preferences, the duality of the maximization and minimization problems assures that at the optimum $c(v(\mathbf{p},w),\mathbf{p}) = w$, where w is the total expenditure and $v(\mathbf{p},w)$ the indirect utility function. By replacing $c(u,\mathbf{p})$ with w in Equation 2.25 and isolating the utility, the following indirect utility function is obtained

$$v(\mathbf{p},w) = \frac{\log(w) - \log a(\mathbf{p})}{\log b(\mathbf{p}) - \log a(\mathbf{p})} = \frac{\log(w) - \alpha_0 - \sum_i \alpha_i \log(p_i) - \frac{1}{2}\sum_i\sum_j \gamma^*_{ij}\log(p_i)\log(p_j)}{\beta_0 \prod_i p_i^{\beta_i}} \tag{2.31}$$

Finally, the last step is to replace u in Equation 2.30 with $v(\mathbf{p},w)$ as in Equation 2.31. The Marshallian AIDS demand system in budget shares format is

$$s_i = \alpha_i + \sum_j \gamma_{ij}\log(p_j) + \beta_i \log\left(\frac{w}{g(\mathbf{p})}\right) \quad \forall i = 1,...,G \tag{2.32}$$

where $g(\mathbf{p})$ is a Translog price index defined by

$$\log g(\mathbf{p}) = \alpha_0 + \sum_i \alpha_i \log(p_i) + \frac{1}{2}\sum_i\sum_j \gamma_{ij}\log(p_i)\log(p_j) \tag{2.33}$$

As reviewed in the previous subsection, for the demand system to be consistent with the consumer theory, it must attend to the adding-up, homogeneity, symmetry, and negativity properties. One of the highlights of the AIDS model is that the theoretical adequacy of the system can *almost* be attended by considering restrictions upon the parameters of the model. Except for the negativity property, the remaining can be applied with linear restrictions that involve only the model parameters and can therefore be imposed globally. The following restrictions can be imposed and/or tested

a) Adding-up restrictions:

$$\sum_i \alpha_i = 1, \quad \sum_i \beta_i = 0 \quad \text{and} \quad \sum_i \gamma_{ij} = 0 \quad \forall j$$

b) Homogeneity restrictions:

$$\sum_j \gamma_{ij} = 0 \quad \forall i$$

c) Symmetry restrictions:

$$\gamma_{ij} = \gamma_{ji} \quad \forall i, j$$

The derivation of the restrictions can be found in Appendix I - Constraints for AIDS. It is also shown that the negativity property depends on each point separately and cannot be ensured by any restrictions on the parameters alone.

Given the regularity properties, the parameters of the AIDS model have intuitive interpretations. The shares will be constant if relative prices and real income are unchanged and the intercept α_i represents the average budget share of the i^{th} good when the expenditure is at the subsistence level (when all logarithmic prices and real expenditures are equal to one). The coefficient γ_{ij} can be interpreted as the effect of a percentage change in the j^{th} price on the i^{th} budget share with real income held constant. The coefficient β_i captures the change in the i^{th} budget share with respect to a percentage change in the real income with prices held constant, where $\beta_i > 0$ implies a luxury good and $\beta_i < 0$ implies a necessity.

2.2.1 Linear Approximations

The AIDS is also almost linear except for the income's price deflator $\log g(\mathbf{p})$. To simplify estimation, studies have proposed and applied linear approximations of the AIDS models. The model commonly known as the linear approximation of the AIDS (LA-AIDS) was proposed by Deaton and Muellbauer (1980a) themselves[7] and approximates the original Translog price index by the Stone's log-linear price index weighted by the expenditure shares (Stone, 1954):

$$s_i = \alpha_i + \sum_j \gamma_{ij} \log p_j + \beta_i \log\left(\frac{w}{P^s}\right) \tag{2.34}$$

where

[7] Barnett and Seck (2008) notes that in the original literature on this model, the model was not called AIDS until after linearization.

$$\log P^s = \sum_i s_j \log(p_i) \tag{2.35}$$

Simplifying the empirical estimation of the AIDS with its linear approximation introduces several shortcomings. Although Deaton and Muellbauer (1980a)'s argued that if prices are closely collinear, any price index is an adequate approximation to the actual translog price index, Buse (1994) proved the argument untrue. The approximation of the exact price index necessarily leads to an approximation error that can be seen as an omitted variable problem (Pashardes, 1993) or an error-in-variables problem (Buse, 1994).

Because budget weights are present in both sides of the LA-AIDS demand share equation, another issue is the potential for simultaneity bias of the estimation. The straightforward solution is to use price indexes that does not depend on current expenditure shares such as the lagged Stone's price index $\log P^s = \sum_i s_{jt-1} \log(p_i)$ (Blanciforti et al., 1986). An alternative solution proposed by the literature is to apply the "Three-Stage Least Square estimation" method using as an instrument the logged prices and logged total expenditure (Alston et al., 1994; Buse, 1994).

A third issue with the LA-AIDS is that the Stone's price index is not invariant to the unit of measurement of prices (the commensurability property). This was revealed by Moschini (1995) that suggested the following alternative price indexes

a) Paasche-like Price Index

$$\log P_t^P = \sum_i s_{it} \log \frac{p_{it}}{p_{i0}} = \log P_t^S - \sum_i s_{it} \log p_{i0} \tag{2.36}$$

b) Laspeyres-like Price Index

$$\log P_t^L = \sum_i s_{i0} \log \frac{p_{it}}{p_{i0}} \tag{2.37}$$

c) Törnqvist Price Index

$$\log P^T = \frac{1}{2} \sum_i (s_{it} + s_{i0}) \log \frac{p_{it}}{p_{j0}} \tag{2.38}$$

where s_{i0} and p_{i0} indicate expenditure shares and prices in the base period or at the sample mean values. The Paasche-like Price Index is a Stone's index modified to be invariant to the unit of measurement. However, it is revealed to perform unsatisfactorily by Buse and Chan (2000). The authors also emphasize that the alternatives above remain approximations to the true price index and, therefore, will still create biased and inconsistent estimators. If the linear approximation is to be estimated, the authors suggest the Laspeyres-like price index for the case of strong positive collinearity of prices and the Törnqvist Index for the case of zero or mixed collinearity.

Finally, from the theoretical point of view, the LA-AIDS model will satisfy restrictions of demand theory only locally. For most combination of prices and expenditures, linear approximated models is not an integrable demand system (Alston et al., 1994) as it may not have satisfactory theoretical properties such as symmetry restrictions (Hahn, 1994; Pashardes, 1993). Asche and Wessells (1997) shows that the LA-AIDS model is identical to its original model only at the point of normalization, that is when all prices are unity.

Studies have focused on studying how well the LA-AIDS model approximates the original model and discuss the correct specification of the elasticities for the linear model (Buse, 1994; Green and Alston, 1990). In the following section, the elasticities for the LA-AIDS are presented. The specification of elasticities for linear approximations with alternative price index can be found in Barnett and Seck (2008).

2.2.2 Elasticities

The parameters of most demand systems do not have a straight-forward interpretation since slopes of the demand curves depend on arbitrary units of measurements. The interpretation of results are most commonly considered in terms of elasticities.

The income elasticities measure the reaction of demanded quantity to a change in total expenditure (income and expenditure are equivalent when it is assumed that the entire income is spent for consumption). If total income w increases by 1%, the income elasticity $\xi_{i,w}$ indicates by how many percent the demanded quantity of good i changes.

The uncompensated and compensated price elasticities measure different types of demand response to prices. A price change in one good generates a substitution effect and an income effect that together will result in a change in demand. The substitution effect captures how when the relative price of one good increases, the consumer substitutes away from this good towards other goods. The income effect considers the effect of an increase (decrease) in the purchasing power of a consumer as a result of a price decrease (increase), the consumer can (cannot) now afford better products or more of the same products and will reoptimize its entire bundle.

The Marshallian (uncompensated) price elasticities measure the reaction of demanded quantity to a change in the consumer price holding total expenditure constant. If a consumer price p_j increases by 1%, the price elasticity ξ_{ij} indicates by how many percent the demanded quantity of good i changes when income and the price of other goods are constant. The uncompensated elasticity thus incorporate both income and substitution effects.

The income (expenditure) elasticities and uncompensated (Marshallian) price elasticities of the AIDS model are derived from 2.32, respectively[8],

[8] The elasticities can be derived from equation 2.32 considering that from the definition of s_i, $\log q_i = \log s_i + \log w - \log p_i$.

$$\xi_{i,w} = \frac{\partial \log q_i}{\partial \log w} \;=\; 1 + \frac{\beta_i}{s_i} \tag{2.39}$$

$$\xi_{ij} = \frac{\partial \log q_i}{\partial \log p_j} \;=\; \frac{\gamma_{ij} - \beta_i \left(\alpha_j + \frac{1}{2}\sum_i (\gamma_{ij} + \gamma_{ji}) \log p_i\right)}{s_i} - \delta_{ij} \tag{2.40}$$

where $\delta_{ij} = 1$ if $i = j$; $\delta_{ij} = 0$ otherwise. It's common (Deaton and Muellbauer, 1980a; Anderson and Blundell, 1983; Green and Alston, 1990) to consider the elasticity formula under the symmetry hypothesis ($\gamma_{ij} = \gamma_{ji}$)

$$\xi_{ij} = \frac{\gamma_{ij} + \beta_i \left(\alpha_j + \sum_i \gamma_{ij} \log p_i\right)}{s_i} - \delta_{ij} \tag{2.41}$$

Hicksian (compensated) price elasticities measure the reaction of demanded quantity to a change in the consumer price holding the utility level constant, that is, after a price change, the consumer will be given an amount of wealth (the "compensation") sufficient to maintain the same utility level as experienced before the price change. If a consumer price p_j increases by 1%, the price elasticity ξ_{ij}^C indicates by how many percent the demanded quantity of good i changes considering only substitution effects. The compensated (Hicksian) elasticity demand can be obtained from the Slutsky equation

$$\xi_{ij}^c = \xi_{ij} + \xi_{i,w} s_j \tag{2.42}$$

The uncompensated price elasticities are most commonly reported by the literature given that the case of a price rise while consumers' money income are held constant is more frequently observed (Femenia et al., 2019). However, when the purpose is to know the response when consumers' **real** income remains unchanged, the compensated elasticities is useful. This is the case when a tax is imposed on consumption of a specific good and the revenue from the tax is redistributed back to consumers as a lump-sum. This keeps real income unchanged and the impact of a 1% rise in the price of the good in the demand of other goods will be given by compensated elasticity.

With linear approximation, the price elasticities can be formulated using different approaches as discussed in Green and Alston (1990). A common approach assumes that expenditures share are constant (Chalfant, 1987) which leads to the following uncompensated and compensated price elasticities, respectively,

$$\xi_{ij} \;=\; \frac{\gamma_{ij} - \beta_i s_j}{s_i} - \delta_{ij} \tag{2.43}$$

$$\xi_{ij}^c \;=\; \frac{\gamma_{ij}}{s_i} + s_j - \delta_{ij} \tag{2.44}$$

where δ_{ij} is the Kronecker delta.

2.2.3 Incorporating Demographics

The importance of demographic variables such as family size and age composition in explaining household consumption patterns is well evidenced by the literature. As specifying the demographic effects correctly is necessary for precise estimation of elasticities and for the purpose of welfare analysis, an entire literature has developed to address the incorporation of demographic in empirical demand models. The specification of demographically extended demand systems that are theoretically plausible dates from Barten (1964) and other methods were since presented (Pollak and Wales, 1981; Ray, 1983; Blundell et al., 1993). The focus here will be two popular approaches for incorporating demographic variables to demand functions termed by Pollak and Wales (1981) as demographic translating and demographic scaling.

The demographic translating procedure was first employed by Pollak and Wales (1978) and redefines the demand system as a function of the demographic profile of the household by adding terms that do not interact with the price and income terms. Therefore, the parameters of the original system are invariant to the demographic characteristics, but the elasticities can vary. Several works has applied this method to the AIDS model (Rossi, 1988; Heien and Wesseils, 1990; Piggott et al., 1996; Fisher et al., 2001; Liu et al., 2016) by adding demand shifters to the constant term as

$$\alpha_i(\mathbf{z}) = \alpha_i + \sum_k^D \alpha_{ik} z_k \quad i = 1, ..., G \tag{2.45}$$

where α_i and α_{ik} are the new parameters to be estimated and $\mathbf{z}$ is the vector with z_k demographic variables ($k = 1, ..., D$). The demand system will now be

$$s_i = \alpha_i + \sum_k^D \alpha_{ik} z_k + \sum_j \gamma_{ij} \log(p_j) + \beta_i \log\left(\frac{w}{g(\mathbf{p})}\right) \quad \forall i = 1, ..., G \tag{2.46}$$

where $g(\mathbf{p})$ is the price index defined by

$$\log g(\mathbf{p}) = \alpha_0 + \sum_i \left(\alpha_i + \sum_k \alpha_{ik} z_k\right) \log(p_i) + \frac{1}{2} \sum_i \sum_j \gamma_{ij} \log(p_i) \log(p_j) \tag{2.47}$$

or linearized by other price indexes for the linear version of the model. The adding-up conditions require that $\sum_i \alpha_i = 1$ and $\sum_i \alpha_{ik} = 0, \quad \forall k = 1, ..., D$. The translating method preserves the linearity for the case of linear systems, but one caveat of this method is that only the "subsistence" or "necessary" parameters of the demand system are considered to depend on demographic variables (Pollak and Wales, 1981)[9].

It is possible to introduce demand variables as modifiers not only of the intercept terms, but also of the price and income coefficients or any combination of them. As general rule, unlike price coefficients, the intercept terms in share equations can easily be kept consistent with underlying restrictions (Piggott et al., 1996). Blundell et al. (1993) and Moro and Sckokai (2000)'s approach introduce demographic effects by letting the constant and income parameters to depend on demographics according to a linear formula. In this case, the AIDS share equations are

$$s_i = \alpha_i + \sum_k^D \alpha_{ik} z_k + \sum_j \gamma_{ij} \log(p_j) + \sum_k^D \left(\beta_i + \sum_k^D \beta_{ik} z_k \right) \log \left(\frac{w}{g(\mathbf{p}, \mathbf{z})} \right) \tag{2.48}$$

where $g(\mathbf{p})$ is also defined by equation 2.47. The new adding-up restrictions are: $\sum_i \alpha_i = 1$ and $\sum_i \beta_i = \sum_i \alpha_{ik} = \sum_i \beta_{ik} = 0, \quad \forall k = 1, ..., D$. In this case, both $\log a(\mathbf{p})$ and $\log b(\mathbf{p})$ depends on demographics with specifications given by

$$\log a(\mathbf{p}) = \alpha_0 + \sum_i \left(\alpha_i + \sum_k \alpha_{ik} z_k \right) \log(p_i) + \frac{1}{2} \sum_i \sum_j \gamma_{ij} \log(p_i) \log(p_j) \tag{2.49}$$

and

$$\log b(\mathbf{p}) = \log a(\mathbf{p}) + \beta_0 \prod_i p_i^{\beta_i + \sum_k^D \beta_{ik} z_k} \tag{2.50}$$

Ray (1983) introduced the method known as demographic scaling. This method redefines the parameters of the demand system as functions of household demographic variables by "scaling" the demand system with functions which depend on the demographic profile of the household. Several authors has applied this method to the AIDS model or to its quadratic extension (Gould et al., 1990; Duffy, 1995; Poi, 2012; Blacklow et al., 2010). The expenditure function of each household is scaled by a function that takes account household characteristics as

$$c(u, \mathbf{p}, \mathbf{z}) = m_0(u, \mathbf{p}, \mathbf{z}) c^R(u, \mathbf{p}, \mathbf{z}) \tag{2.51}$$

where $\mathbf{z}$ is a vector of D demographic characteristics, $c^R(u, \mathbf{p}, \mathbf{z})$ is the cost function of a reference household and $m_0(u, \mathbf{p}, \mathbf{z})$ is the scaling function given by

$$m_0(u, \mathbf{p}, \mathbf{z}) = \overline{m_0}(\mathbf{z}) \phi(u, \mathbf{p}, \mathbf{z}) \tag{2.52}$$

[9] The subsistence cost function is now $\log a(\mathbf{p}) = \alpha_0 + \sum_i \left(\alpha_i + \sum_k \alpha_{ik} z_k \right) \log(p_i) + \frac{1}{2} \sum_i \sum_j \gamma_{ij} \log(p_i) \log(p_j)$

where following Ray (1983), Poi (2012) parameterizes as

$$\overline{m_0}(\mathbf{z}) = 1 + \sum_{k}^{D} \rho_{ik} z_k \tag{2.53}$$

and

$$\phi(u, \mathbf{p}, \mathbf{z}) = u \left(\prod_i p_i^{\beta_i} \left(\prod_i p_i^{\sum_k^D \eta_{ik} z_k} - 1 \right) \right) \tag{2.54}$$

The first term $\overline{m_0}(\mathbf{z})$ of the scaling function measures the increase in a household's expenditures as a function of $\mathbf{z}$, not controlling for any changes in consumption patterns; considering household size, a household with four members will naturally have higher expenditures than one with a single member, even ignoring that the composition of goods consumed may change. The second term $\phi(u, \mathbf{p}, \mathbf{z})$ controls for changes in relative prices and the actual goods consumed; a household composed by two adults and two children will have different consumption patterns than one composed by four adults. The demographically modified AIDS system takes the form

$$s_i = \alpha_i + \sum_j \gamma_{ij} \log(p_j) + (\beta_i + \sum_i \eta_{ik} z_k) \log \left(\frac{w}{\overline{m_0}(\mathbf{z}) g(\mathbf{p})} \right) \tag{2.55}$$

The adding-up conditions requires that $\sum_i \eta_{ik} = 0$ for $k = 1, ..., D$. The price functions of the expenditure function are now specified as

$$\log a(\mathbf{p}) = \alpha_0 + \sum_i \left(\alpha_i + \sum_k \alpha_{ik} z_k \right) \log(p_i) + \frac{1}{2} \sum_i \sum_j \gamma_{ij} \log(p_i) \log(p_j) + \overline{m_0}(\mathbf{z}) \tag{2.56}$$

and

$$\log b(\mathbf{p}) = \log a(\mathbf{p}) + \beta_0 \prod_i p_i^{\beta_i + \sum_k^D \beta_{ik} z_k} \tag{2.57}$$

For further review of alternative methods that incorporates demographics variables by directly modifying the expenditure share equations Pollak and Wales (1981) can be consulted. Another important reference is Lewbel (1985) that presents a general method of including demographic effects into demand systems using modifying functions which allows for interactions of demographic variables with prices and expenditures. The properties that modifying functions must attend for valid cost functions are also derived. Finally, Perali (2003) applies the Lewbel (1985) technique to derive demand systems based on the AIDS and Translog models.

2.2.4 Incorporating Dynamics

The static AIDS model has been viewed as a long run model as it implicitly assumes that consumer behavior is always in equilibrium by immediately and fully adjusting to changes in prices and income (Duffy, 2003). However, this adjustment may not occur due to habit formation behavior, imperfect information, adjustment costs, incorrect expectations and interpretations of real price changes (Anderson and Blundell, 1983). Therefore, one important extension of the AIDS model is to introduce dynamic structure to it.

The challenge is to obtain a dynamic demand system theoretically consistent with the cost minimization problem. This means that for the dynamics AIDS to be a valid demand system it must satisfy the adding-up condition and the cost or expenditure function must satisfy the theoretical properties of a cost function[10]. Blanciforti et al. (1986) summarized and analysis theoretically three basic methods for the direct incorporation of dynamics into the AIDS model in the form of habit formation. All these methods are seen as ad hoc, but has frequently been applied in empirical demand analysis.

The first method, adopted by Pollak and Wales (1969) and Blanciforti et al. (1986), connects with the demographic translating method by specifying the constant parameters α_i to be linear functions of the previous consumption levels, that is,

$$\alpha_i = \alpha_i^* + \sum_i \alpha_i^{**} q_{it-1} \quad \forall i = 1, ..., G \tag{2.58}$$

By replacing expression 2.58 into 2.32, the dynamic demand system will be

$$s_i = \alpha_i^* + \sum_i \alpha_i^{**} q_{it-1} + \sum_j \gamma_{ij} \log(p_j) + \beta_i \log\left(\frac{w}{g(\mathbf{p})}\right) \quad \forall i = 1, ..., G \tag{2.59}$$

where $g(\mathbf{p})$ is a price index defined by

$$\log g(\mathbf{p}) = \alpha_0 + \sum_i (\alpha_i^* + \sum_i \alpha_i^{**} q_{it-1}) \log(p_i) + \frac{1}{2} \sum_i \sum_j \gamma_{ij}^* \log(p_i) \log(p_j) \tag{2.60}$$

The cost (expenditure) function from which the above system is derived is given by

$$\log c(u, \mathbf{p}) = \alpha_0^* + \sum_i (\alpha_i^* + \sum_i \alpha_i^{**} q_{it-1}) \log(p_i) + \frac{1}{2} \sum_i \sum_j \gamma_{ij}^* \log(p_i) \log(p_j) + u\beta_0 \prod_i p_i^{\beta_i} \tag{2.61}$$

As proved by Blanciforti et al. (1986), the conditions for the dynamic cost function to be linearly homogeneous of degree one in current prices are $\sum_i \beta_k = \sum_i \gamma_{ij} = 0$ and $\sum_k (\alpha_i^* + \sum_i \alpha_i^{**} q_{it-1}) = 1$. The cost function only holds at points where the restrictions hold, that is, it is only locally valid.

[10]That is, be homogeneous of degree one in current prices, nonnegative, increasing in u, nondecreasing in p, increasing in at least one price, and be concave in current prices.

Another method for the dynamic extension of the AIDS model was suggested by Ray (1984) and consists of adding the term $\sum_i \alpha_i^{**} q_{it-1}$ to the expenditure function as

$$\log c(u, \mathbf{p}) = \alpha_0^* + \sum_i \alpha_i^{**} q_{it-1} + \sum_i \alpha_i^* \log(p_i) + \frac{1}{2} \sum_i \sum_j \gamma_{ij}^* \log(p_i) \log(p_j) + u\beta_0 \prod_i p_i^{\beta_i} \tag{2.62}$$

The dynamic cost function is proven to be globally homogeneous of degree one in current prices and gives rise to the demand system

$$s_i = \alpha_i^* + \sum_j \gamma_{ij} \log(p_j) + \beta_i \log\left(\frac{w}{g(\mathbf{p}, q_{it-1})}\right) \quad \forall i = 1, ..., G \tag{2.63}$$

where $g(\mathbf{p}, q_{it-1})$ is a price index defined by

$$\log g(\mathbf{p}, q_{it-1}) = \alpha_0^* + \sum_i \alpha_i^{**} q_{it-1} + \sum_k \alpha_i^* \log(p_i) + \frac{1}{2} \sum_i \sum_j \gamma_{ij}^* \log(p_i) \log(p_j) \tag{2.64}$$

A limitation of this method is that the habits influence the demand function only through an income effect by shifting the price index. To be linearly homogeneous, the restrictions $\sum_i \alpha_i^{**} = 1$ and $\sum_i \gamma_{ij}^* = \sum_i \beta_i = 0$ must be attended.

The last method applied by Alessie and Kapteyn (1991), Edgerton et al. (1996), Verhelst and Van den Poel (2014) and others specifies the constant parameters α_i of the share equation as the linear functions of the previous expenditure share levels, that is,

$$\alpha_i = \alpha_i^* + \sum_j \theta_{ij} s_{it-1} \quad \forall i = 1, ..., G \tag{2.65}$$

since α_i represents the budget share for the i^{th} good when expenditures are at subsistence level, this translating method can be interpreted as the way subsistence expenditures vary according to previous consumption patterns. The share equations are

$$s_{it} = \alpha_i + \sum_j \theta_{ij} s_{jt-1} + \sum_j \gamma_{ij} \log(p_{jt}) + \beta_i \log\left(\frac{w_t}{g(\mathbf{p}, s_{t-1})}\right) \quad \forall i = 1, ..., G \tag{2.66}$$

where $g(\mathbf{p})$ is a price index defined by

$$\log g(\mathbf{p}) = \alpha_0 + \sum_i (\alpha_i^* + \sum_j \theta_{ij} s_{it-1}) \log(p_{it}) + \frac{1}{2} \sum_i \sum_j \gamma_{ij}^* \log(p_{it}) \log(p_{jt}) \tag{2.67}$$

Identification requires that $\sum_j \theta_{ij} = 0$ and for adding up $\sum_i \theta_{ij} = 0$ must occur. The problem with this approach is that it's validity is only local as in the first method (Blanciforti et al., 1986).

2.3 Demand estimation for food

Understanding how households spend their income among the various categories of consumer goods is relevant given its policy implications related to urban transportation, health, education, sanitation, culture or agriculture (Deaton, 1997). Traditionally greater importance is given to expenditures with food due to its relevance to lower-income families. In this case, policies related to nutrition and food safety are the focus. Recently, a growing concern with the negative consequences of unhealthy diet[11] has provoked policymakers to design policies to promote healthy food choices and consumption patterns.

Studies of demand estimation are heterogeneous not only in product aggregation and the regional context but also in the type (aggregate, cross-sectional household survey or longitudinal survey data) and frequency (annual or monthly frequency) of the data used, in the functional form of the demand model (AIDS, variants of the AIDS or others) considered, in the estimation method (least squares, seemingly unrelated regression, maximum likelihood or others) applied, in the use of control for censoring in data (two-step method following Heien and Wesseils (1990) or Shonkwiler and Yen (1999)), and in the type of price data used (e.g., quality-adjusted unit prices, retail or consumer price index data, self-reported prices, constructed by expenditure divided by quantity).

Given the extensive and heterogeneous literature, several researchers have conducted meta-analysis of elasticity estimations for food demand. Andreyeva et al. (2010) presents a meta-analysis of studies on the price elasticity of demand for major food categories in the United States context. Green et al. (2013) and Cornelsen et al. (2015) conduct meta-analysis to provide estimates own price and cross-price elasticities by country income group. Femenia et al. (2019) is the most recent one and contributes by identifying the main sources of heterogeneity between the elasticity estimates across the literature, focusing on income elasticity and the specification of the demand system.

In the United States context, Andreyeva et al. (2010) finds that in terms of data used, of all the identified studies, 62% uses time-series data, 21% uses household survey data and 17% scanner data. In terms of the food category studied, consumer demand for meat has received the most attention than other goods like fresh fruits and vegetables. The mean price elasticity estimates were found to range from 0.27 to 0.81 in absolute numbers. The most elastic categories are food away from home, soft drinks, juice, meats, and fruit, and the most inelastic demand is for eggs.

The author concludes that although demand for food is relatively inelastic, even a small price change, mainly focused on foods most responsive to such changes, can lead to

[11] For instance, recent meta-analysis reveal increasing evidence suggesting that high consumption of ultra-processed foods is associated with an increase in non-communicable diseases such as for overweight and obesity (Askari et al., 2020; Pagliai et al., 2020).

accumulative effects across a population. The food policy implications are that price changes combined with effective use of revenues, such as public education campaigns, may positively affect diet improvement, particularly among high-risk population groups. This concern is more severe in times of economic shocks as we were living in 2020. A recession with a decrease in income and increases in food prices can lead to the purchase of more processed and calorie-dense food, especially in households with lower income.

Cornelsen et al. (2015) provides a meta-analysis with global evidence on how food consumption patterns change with price variation. The authors shed light on the importance of cross-price elasticities analysis to policy recommendations and individual results by groups of countries per income. In middle-income and high-income countries, the population spends on average less on food, ranging from 6% to 30% of their income. In these countries, the main challenge is to address unhealthy diets with policies such as the "fat tax" on products with higher saturated fat levels. In low-income countries, their own-price effects were significant, with higher response to changes in food prices. The authors found fewer studies with cross-price elasticity analysis for low and middle-income countries, although there is evidence that these substitution effects are important as they can affect a price increase's direct impact.

Femenia et al. (2019) presents a meta-analysis of price and income elasticities of food demand, focusing on understanding how the heterogeneity of elasticity estimates found can be explained by differences in the methodological approaches adopted across studies. The study emphasizes the importance of income elasticities in long-run projections and policy simulations; for both income and price elasticities, the higher the income at both country and household levels, the lower elasticity. Beyond the difference of location and category of food, the author finds that functional forms used to represent food demand significantly affect price elasticity estimates. Therefore, sensitivity tests are recommended.

Studies on consumption and budgets of Brazilian families find that spending pattern is related to income, price of goods, level of education, lifestyle changes, demographic composition, and family structure (Carvalho and Alves, 2010). Evidence reveals that the proportion of spending on food-related products falls as household income increases, while the proportion of spending on leisure and education rises. There is also evidence of spending on health and education being influenced by the age composition of families (Bertasso et al., 2006).

The influence of gender on household spending is also the subject of several studies. Results suggest that the reallocation of resources between men and women interferes with the family consumption patterns, especially concerning the health care expenditures with children (Thomas and Chen, 1995). For the Brazilian case, Pinheiro and Fontoura (2007) find that family structures directly impact household expenditures.

In their thesis, Coelho (2006) and Pereda (2008) presents a review of the early literature of demand estimation in Brazil. By analyzing food demand, Coelho et al. (2010) finds that the higher a family's income, the smaller is the probability of purchasing staple foods, and the more significant is the probability of purchasing meat, milk, and other products. Regional variables were also important in the demand system. They were important not only for the so-called region-specific foods, such as manioc flour in the north but also for almost all the commodities.

3 SOCIAL EFFECTS IN CONSUMPTION BEHAVIOR

As social beings, our environment and interactions with our social contacts shape our behavior and outcomes — we share information, learn from others and influence each other on many dimensions and in many contexts of life. Sociologists and economists have long recognized the importance of such interactions. However, until the 1970s, nonmarket interactions were considered peripheral to or outside the domain of economics. The economic field was primarily viewed as the study of markets, a class of institutions in which agents interact through an anonymous process of price formation. This scenario changed with major theoretical developments in microeconomics, labor economics, and macroeconomics in the last decades of the twentieth-century (Manski, 2000).

In microeconomics, developments in game theory encouraged economists to view all interactions as games, with markets as special cases (Akerlof, 1980). In labor economics, studies recognized the importance of a wide range of family and household behaviors concerning marriage, fertility, education, health to models of the discipline (Becker, 1974). Lastly, the emergence of endogenous growth theory in macroeconomics focused on the relevance of spillovers in the human capital formation (Lucas Jr, 1988; Romer, 1990). All these developments broadened the view of economics that now has concerns in understanding how incentives shape all social interactions that affect resource allocation.

Since, a voluminous and growing literature have found evidence of social influences in education achievements (e.g., Sacerdote, 2001; Bobonis and Finan, 2009), financial decisions (e.g., Hong et al., 2004; Bursztyn et al., 2014), adoption and diffusion of new technologies (e.g., Conley and Udry, 2010), labor-market referrals and workers productivity (e.g., Mas and Moretti, 2009), criminal behaviors (e.g., Glaeser et al., 1996), smoking and other unhealthy behaviors (e.g., Powell et al., 2005; Lundborg, 2006), bullying (e.g., Salmivalli, 2010), participation in welfare programs (e.g., Bertrand et al., 2000; Dahl et al., 2014), product adoption (e.g., Bollinger and Gillingham, 2012; Wu, 2020) and consumption (e.g., Moretti, 2011; De Giorgi et al., 2020); to mention a few.

Defining what is meant by social influence is challenging. This social interactions has been called by the literature as “social norms”, “imitation”, “contagion”, “herd behavior”, “bandwagon effects” (Leibenstein, 1950), “peer influences” (Duncan et al., 1968), “neighborhood effects” (Case, 1991), and “conformity” (Bernheim, 1994). The social interactions can be thought as taking place within a “social space” defined by a reference group of potential influential members (Topa and Zenou, 2015). This social space has been modeled in many ways by the literature.

Due to data limitation, one large strand of literature models the social space by simply characterizing the reference group of each agent. The literature of neighborhood effects, for example, usually considers how the composition of one's residential neighborhood affects one's outcomes. Another growing strand of literature has focused on the structure of connections within the abstract social space and its implications for outcomes, which is often modeled using tools of social network theory. Here, I will focus on social interaction defined as peer effects[1]. The broad definition of peer effects commonly applied considers nearly any externality in which peers' backgrounds, current behavior, or outcomes affect an outcome. By limiting peer effects to externalities, market-based or price-based effects are excluded (Sacerdote, 2011).

This chapter reviews the literature of peer effects and neighborhood effects when the outcome is consumption. The influence of friends, neighbors, relatives, colleagues, and other society members in one's consumption is observed as well as felt by the majority of us. In economics, the idea of social influence in consumption behavior dates back to Smith (1759) and Veblen (1899). However, neoclassical consumer theory has rejected the idea of preference interactions that occur when an agent's preference ordering over the alternatives in a choice set depends on the actions chosen by other agents. The first micro-theoretic foundations of interdependence in preferences were provided by Duesenberry et al. (1949), Leibenstein (1950), Gaertner (1974) and Pollak (1976). Duesenberry finds that the percentage of income spent on consumption is highly correlated with the person's rank order in the local income distribution, and Leibenstein formally incorporates the phenomenon of "conspicuous consumption" into a theory of consumer demand (Yang and Allenby, 2003).

Many authors after that postulated that individuals derive utility not only from the level of their current consumption but also from how their consumption compares to their past consumption (internal habit) and to the consumption of some outside reference group — typically the average consumption of the people around them, the community, or the overall economy (external habits). This has been referred to as 'envy' as in Varian (1974), 'catching up with the Joneses' as in Abel (1990), 'keeping up with the Joneses' as in Gali (1994), 'status' as in Corneo and Jeanne (2001), 'jealousy' as in Dupor and Liu (2003) or 'rivalry' as in Bruni and Porta (2005) or 'consumption externalities' as in Liu and Turnovsky (2005) (Hayakawa and Venieris, 1977).

At the empirical level, seminal works on econometric models and estimation methods that incorporate interpersonal dependence were those of Pollak (1976) and Kapteyn et al. (1977). Early empirical applications to understand interdependent preference in consumer expenditure allocations are typically at aggregate level with consumption reflecting average behavior within a geographic region (e.g., Case, 1991; Alessie and Kapteyn, 1991; Kapteyn et al., 1997). In addition, they also mainly rely on observational data and suffer from endogeneity problems (Boneva, 2014). Over the last few years, with more data and strategies to overcome identification issues, a sizable body of studies on peer influences in consumption

[1]Some studies such that of De Giorgi et al. (2020) uses the terms "peer effect" and "network effect" interchangeably, although the last is most commonly used in the context of congestion or economies of scale.

has emerged (Kuhn et al., 2011; Moretti, 2011; De Giorgi et al., 2020). However, there are still few applications to underdeveloped countries (Roychowdhury, 2019) and disaggregated consumption (Boneva, 2014; Verhelst and Van den Poel, 2014).

Studying the social effect on consumption is considered crucial in the context of underdeveloped countries (Roychowdhury, 2019) and is relevant for at least two reasons (De Giorgi et al., 2016). The first considers the distortions in social welfare observed in the isolated decision context. If the peer effect is relevant, in a behavior known in the literature as *keeping up with the Joneses*, a household may be saving and consuming sub-optimally or even borrowing excessively to keep pace with increased consumption of the neighbor. An intratemporal distortion can also occur due to conspicuous consumption. In this case, in pursuit of social status, the consumption of more conspicuous goods, usually luxury goods, has an excessive weight on the household budget.

The second reason is related to planning and evaluating policies that concern consumption, such as income transfer programs and tax policies. If the existence and magnitude of the peer effect are not considered, the social effect of the policy would be imprecise since, in addition to the direct effects, the spillover effects may not be negligible. Thus, depending on the character and degree of connection between social groups, policies directed at specific groups may cause impacts not foreseen to the others, and traditional analyses of consumption intervention programs may lead to inaccurate evaluation of the cost-effectiveness of such policies.

Regardless of the outcome explained, the literature on social effects is notoriously challenging. From the theoretical point of view, different mechanisms can be consistent with the presence of social effects. Few studies have taken further steps to identify the underlying channel through which a given estimated social effect operates, given that it can be a near-impossible task when accessible data are limited, as most common (Sacerdote, 2011). From the empirical point of view, two main problems have to be addressed for identifying causal social effects: the definition of the relevant social interactions and the endogeneity of the social effects. In the following sections, these challenges will be discussed in the context of peer effects in consumption literature.

Unlike the literature on peer effects in education, there is a lack of surveys dedicated to the literature on peer effects in consumption. One of the objectives of this chapter is to contribute with a (non-exhaustive) review of the last. The remainder of the chapter is organized as follows. Section 3.1 discusses the theoretical challenges of identifying the social effects focusing on the mechanisms underlying them. Section 3.2 discusses the identification issues in estimating peer effects and strategies used by the literature to overcome them. Section 3.3 compiles the most relevant results found by studies so far on peer effects in consumption. Lastly, the final section (3.4) of the chapter will develop and present the spatial demand model to be estimated by this study.

3.1 Mechanisms underlying social effects

The economic issues regarding the presence and importance of peer effects are both theoretically and empirically challenging. From the theoretical point of view, several mechanisms through which social interactions may affect behavior and outcomes have been discussed by the literature. Social interactions may influence agents' choices by facilitating the flow of information about, for instance, the profitability of new technology, job opportunities, and quality of products or services. Social contacts may also affect one's preference for certain goods by provoking conformism behavior in order to "fit in" or the opposite, in the sense of the desire to stand out. These underlying reasons for social interactions can further interact in a complex way and lead to different welfare implications.

In the literature of peer effects on consumption, studies have developed theories for possible economic reasons that explain the correlation between one's consumption to that of its peer group. One of them is known as "keeping up with the Joneses" behavior in which one's utility may depend not only on its own consumption but also on keeping a similar level of consumption to that of its social contacts. In macroeconomics, variants of this behavior have been used to explain portfolio choice, growth, and tax policy (e.g., Gali, 1994). Maurer and Meier (2008), Ravina (2019), and De Giorgi et al. (2020) presents evidence of this behavior in the context of a life-cycle model where rational, forward-looking individuals attempt to maintain their relative position within their peer group as a means of smoothing their marginal utility with consumption. This implies that excessive current consumption to increase social status is not necessarily observed.

The conspicuous consumption explanation, coined by Veblen (1899), suggests that the expenditure with specific goods such as jewelry, cars, and restaurants, provides greater utility because of their social visibility and status signaling. Studies have found that consumers cares not only about the direct utility received from consumption, but also about how her consumption patterns affects her social contacts belief about her well-being (Charles et al., 2009; Jinkins, 2016). Heffetz (2011) contributes with an index of visibility of consumption goods and identifies that relatively visible goods are used as means to signal income. Based on the randomized conditional cash transfer program, Roth et al. (2014) finds that an increase in reference group visible consumption results in an increase (decrease) in an individual's visible (nonvisible) expenditure shares.

Another explanation for correlated consumption between peers is based on the risk-sharing behavior adopted by peer groups. Through income transfers, negative or positive shocks faced by one member of the group are shared between them, and ultimately similar consumption decisions can be observed. For example, households that receive the income shock from transfer programs might share their increases in income with neighboring households, which allows the latter to consume more. This risk-sharing and consumption smoothing phenomenon has been found especially important in developing countries (Townsend, 1994; Angelucci and De Giorgi, 2009).

This income effect is in nature different from the peer effects. Using data from Mexico, Boneva (2014) separately identify them by considering the composition of household expenditure as the outcome. De Giorgi et al. (2020) propose and implement tests to understand whether peer effects emerge because of intertemporal substitution in consumption or across periods substitution across goods within a given period, or because of risk-sharing among members of a network. The results found indicate that there is little evidence that peer effects emerge in the Denmark context as a way of rationalizing risk-sharing agreements.

For consumption choices, a branch of studies is interested in separating the social learning explanation from other conforming behaviors. In the first explanation, peer effects are argued to be caused by one's belief that others have information not available to the decision-maker. The conforming behavior, in turn, arises when individuals could simply follow their peers because they are gaining some kind of network externality or psychological benefit from doing what other people are doing. Network externality occurs when a consumer's utility of purchasing one good depends directly on the number of peers who have also purchased the good.

The literature that points to the exact mechanism that underlies conformity is still small. Moretti (2011) finds evidence of social learning in the context of movie sales. Based on field experiment, Bursztyn et al. (2014) finds that information transmission between friends and social network externalities play a role in peer effects in the demand for financial products. Cai et al. (2009) applies an experimental design in the restaurant context to reveal that information content of other's choices affect the demand for dishes. Grohmann and Sakha (2019) applies a lab-in-field experiment to find evidence o both information and psychological channel underlying peer effects.

In the literature of games on networks, social interaction is modeled as a game where individual pay-offs depend on the actions of their peers. Two distinct models commonly describe the social interaction model: the local-aggregate model and the local-average model. In the first, what matters to explain an agent's outcome is the sum of peers outcomes, whereas the latter considers that agents derive a utility from conforming to the average behavior of their peers' (Akerlof, 1980; Bernheim, 1994). In the game theory, both models are considered strategic complementary as an increase in a player's outcome increases the marginal utility (or pay-off) of the other player's outcome.

For the microeconomic foundation of the models, let's consider a static game with the notation as follows. There is a finite set of agents $N_r = 1, ..., n_r$ in network or group $\mathbf{g_r}$, where

$r = 1, ..., \bar{r}$ is the total number of groups; $\mathbf{G_r}$ is the $n_r \times n_r$ adjacency matrix with elements $g_{ij,r}$ where $g_{ii,r} = 0$ and

$$\begin{cases} g_{ij,r} = 1 & \text{if agent } i \text{ is connected to agent } j \\ g_{ij,r} = 0 & \text{otherwise} \end{cases} \tag{3.1}$$

The row normalized adjacency matrix $\mathbf{G_r}$ is the social interaction matrix $\mathbf{G_r^*}$, such that rows of $\mathbf{G_r}$ sum 1, whose elements are defined as

$$\begin{cases} g^*_{ij,r} = \frac{g_{ij,r}}{\sum_j g_{ij,r}} & \text{if agent } i \text{ is influenced by } j \\ g^*_{ij,r} = 0 & \text{otherwise} \end{cases} \tag{3.2}$$

The utility function for agent i member of group $\mathbf{g_r}$ is a function of its outcome $y_{i,r}$, of a vector of M exogenous variables $\mathbf{x_{i,r}}$, the outcome of the peer group represented by $\mathbf{y_{-i,r}}$, and the characteristics of the peer group represented by $\mathbf{x_{-i,r}}$. Consider the following quadratic utility functions

$$u_i(y_{i,r}; \mathbf{x_{i,r}}, \mathbf{y_{-i,r}}, \mathbf{x_{-i,r}}, \mathbf{G_r}) = \pi_{i,r}(\mathbf{x_{i,r}}, \mathbf{G_r}) y_{i,r} - \frac{1}{2} y_{i,r}^2 + \phi_1 \sum_j^{n_r} g_{ij,r} y_{i,r} y_{j,r} \tag{3.3}$$

$$v_i(y_{i,r}; \mathbf{x_{i,r}}, \mathbf{y_{-i,r}}, \mathbf{x_{-i,r}}, \mathbf{G_r^*}) = \pi_{i,r}(\mathbf{x_{i,r}}, \mathbf{G_r}) y_{i,r} - \frac{1}{2} y_{i,r}^2 - \frac{\lambda}{2} (y_{i,r} - \bar{y}_{i,r})^2 \tag{3.4}$$

where $\phi_1 \in [0, 1)$ and $\lambda \geq 0$ and

$$\bar{y}_{i,r} = \sum_{j=1}^{n_r} g^*_{ij,r} y_{j,r}$$

Each expression on the right-hand side of the utility equations has economic intuitions. The first two expressions are shared by both equations and represent the private sub-utility. In the first expression, $\pi_{i,r}(\mathbf{x_{i,r}}, \mathbf{G_r})$ is the marginal benefit of increasing $y_{i,r}$ given by

$$\pi_{i,r}(\mathbf{x_{i,r}}, \mathbf{G_r}) = \sum_{m=1}^{M} \beta_m x^m_{i,r} + \sum_{m=1}^{M} \sum_{j=1}^{n_r} g^*_{ij,r} x^m_{j,r} \gamma_m + \eta_r + \epsilon_{i,r} \tag{3.5}$$

where the first two right-hand side denotes the exogenous heterogeneity of agent i which in turn captures the observable characteristics of individual i and the observable average of characteristics of i's peer group, known as contextual effects; η_r denotes the unobservable group characteristics, and ϵ is the error term with unobservable heterogeneity. The second expression of the private sub-utility $y_{i,r}/2$ is the cost of spending (producing or providing effort) $y_{i,r}$.

Now to the difference between the two utility functions 3.3 and 3.4: the third element that represents the social sub-utility in which the social interactions operate. The first utility equation represents the local-aggregate model in which $\phi_1 \sum_j^{n_r} g_{ij,r} y_{i,r} y_{j,r}$ corresponds to the aggregate effect. Each agent i is affected by the sum of the outcome levels of the agents of their peer group. The higher the number of interactions or connections, the higher the marginal utility of increasing $y_{i,r}$. In this model, agents adopt a complementary behavior as an increase in $y_{-i,r}$ positively influences one's marginal utility in increasing $y_{i,r}$

$$\frac{\partial^2 u_{i,r}}{\partial y_{i,r} \partial y_{j,r}} = \phi_1 g_{ij,r} \geq 0 \tag{3.6}$$

In the second utility function, the last term $-\frac{\lambda_2}{2}(y_{i,r} - \bar{y}_{i,r})^2$ reflects the influence of the agents peer's behavior on the agent's own action. It also represents the utility loss for not conforming with peers; thus, agents will minimize the social distance between him and his reference group. This utility represents the local-average model, and in this case, there is no complementary, just pure conformity due, for example, to social norms or emulation behavior (Boucher and Fortin, 2016). This is also the standard way economists have been modeling conformity.

In this model, each individual i chooses his outcome to maximize its utility function that depends on his outcome, characteristics, and reference group's outcome and characteristics. When $\phi_1 \in [0, 1)$ and $\lambda \geq 0$, the social interaction game reaches a non-cooperative unique Nash equilibrium at which expected outcomes are realized[2]. Respectively for Equations 3.3 and 3.4, the best response functions for each $i = 1, ..., n$ derived from the first-order condition are given by

$$y_{i,g}^u = \phi_1 \sum_{j=1}^{n_r} g_{ij,r} y_{j,r} + \sum_{m=1}^{M} \beta_m x_{i,r}^m + \sum_{m=1}^{M} \sum_{j=1}^{n_r} g_{ij,r}^* x_{j,r}^m \gamma_m + \eta_r + \epsilon_{i,r} \tag{3.7}$$

$$y_{i,g}^v = \phi_2 \sum_{j=1}^{n_r} g_{ij,r}^* y_{j,r} + \sum_{m=1}^{M} \beta_m^* x_{i,r}^m + \sum_{m=1}^{M} \sum_{j=1}^{n_r} g_{ij,r}^* x_{j,r}^m \gamma_m^* + \eta_r^* + \epsilon_{i,r}^* \tag{3.8}$$

where $\phi_2 = \lambda/(1+\lambda)$, $\beta_m^* = \beta_m/(1+\lambda)$, $\gamma_m^* = \gamma_m/(1+\lambda)$, $\eta_m^* = \eta_m/(1+\lambda)$, and $\epsilon_m^* = \epsilon_m/(1+\lambda)$. Although from the technical point of view, the local-average and the local-aggregate models lead to almost observationally equivalent outcome functions in equilibrium, they have different economic interpretations. In the local-aggregate model, the agents' position in the

[2] See Ballester et al. (2006) for the Nash equilibrium solution of the local-aggregate model. For the local-average model, Patacchini and Zenou (2012) derive the condition under which a Nash equilibrium exists and characterize properties of this equilibrium.

network or group is important since its outcome depends on the sum of the outcomes of its direct contacts. Whereas the position is not relevant for the local-average model since it is the deviation from the average outcome of peers that matters (Topa and Zenou, 2015).

One local-average model is known as the linear-in-means model, the most popular social interaction model used as a benchmark by many studies as in Manski (1993), and Bramoullé et al. (2009). In the following section, the identification issues concerning this model will be discussed as well as the strategies that the literature has proposed to overcome them.

3.2 Identification of social effects

The issues involved in the identification and estimation of peer effect models have been extensively discussed by the literature (Manski, 1993; Moffitt et al., 2001; Brock and Durlauf, 2001; Bramoullé et al., 2009, among others). Identifying causal peer effects is not trivial as it is now well acknowledged that observed correlation between individual and peers' outcomes may be due to several effects other than the caused by peer's outcomes. Manski (1993) formalized these possible confounding effects in three categories: (a) endogenous effects; (b) contextual or exogenous effects; and (c) correlated effects.

The endogenous effects (a) capture the influence of peer's outcomes on an agent's outcome, that is, when the outcome is consumption, how an agent's consumption changes as a response to a change in peers' consumption. Exogenous or contextual effects (b) captures the effects of peers' exogenous characteristics. Agents with similar characteristics such as income or education level might share similar consumption patterns. Lastly, the correlated effects (c) are the effects of unobservables or common variables the agents and their peers face. For instance, a common shock could be a local marketing campaign or the closure of a supermarket in the neighborhood that may affect the consumption's of all group members.

Disentangling the contextual effects from the endogenous peer effect can be impossible due to the simultaneity in social interaction ("Who interacts with whom?"). This challenge is known as the "reflection problem" as named by Manski (1993) and stressed by several studies thereafter as Moffitt et al. (2001) and Bramoullé et al. (2009), among others. Because only endogenous peer effects generate social multiplier, identifying the two effects has great importance for policy implementation and evaluation. In the presence of endogenous effects, consumption programs to stimulate or discourage consumption targeting one specific population group might affect other groups indirectly.

A further complication is when correlated effects are present. This problem is known as the "correlated problem" that has to be solved as it provokes omitted variables estimation bias. A potential source of correlated unobservables is non-random peer group formation that would imply that unobservable characteristics of an agent are correlated with the characteristics of the group.

We can understand better how these effects and econometric problems operate considering a standard social interaction model: the linear-in-means model. Most of the empirical literature on social interactions has involved variations of this model in which the outcome of each individual depends linearly on his own characteristics, on the mean outcome of his reference group, and its mean characteristics. This model can be derived from the choice-theoretic approach presented in the previous section

$$y_{i,r} = \phi_2 \mathbb{E}(y_r|r) + \gamma \mathbb{E}(x_r|r) + \beta x_{i,r} + \epsilon_{i,r}$$

where in the consumption context, y_{ir} denotes consumption of individual or household i from group r; x_{ir} are the observable characteristics related to i; $\mathbb{E}(y_r|r)$ and $\mathbb{E}(x_r|r)$ are, respectively, the average consumption and average characteristics in the peer group r of individual i; and $\epsilon_{i,r}$ the error term. The coefficient ϕ_2 measures the endogenous peer-group effects and γ captures the contextual effects, that is, the effect of characteristics of the reference group, such as household size, proportion of children, proportion of elders and household head's education.

The reduced form of the model is given by

$$y_{i,r} = \frac{\phi_2 \beta + \gamma}{1 - \phi_2} \mathbb{E}(x_r|r) + \beta x_{i,r} + \epsilon_{ir}$$

where only β and $\frac{\phi_2 \beta + \gamma}{1 - \phi_2}$ can be identified. This explicit the "reflection problem" where the endogenous effect ϕ_2 can not be separated from the contextual effects γ. In this case, with M total characteristics, there are $2M+1$ coefficients corresponding to $2M+2$ structural parameters to estimate. Intuitively, the linear-in-means model is a system of simultaneous equations, and as all exogenous explanatory variables of all individuals appear directly in the structural form of the outcome $y_{i,r}$, the model is not identified.

The correlated problem is also potentially present in this model. For instance, a household's choice for neighborhoods can be endogenous, and there can be omitted common characteristics that might explain every household's consumption. This means that the error term is probably given by

$$\epsilon_{ir} = \alpha_r + u_{ir}$$

where α_r represents the unobserved characteristics that are common to all group members. If the correlations between α_r and the group unobservables and the outcome are positive, then the parameters representing social interaction effects will tend to be overestimated.

Many studies have demonstrated how network interactions can be used to overcome the correlated effects and reflection problems. The identification of peer effects has been greatly benefited from the literature on network interactions that is fast-growing with a number of recent surveys on the topic (Bramoullé et al., 2020; Advani and Malde, 2018; Boucher and Fortin, 2016; De Paula, 2017; Blume et al., 2015).

Bramoullé et al. (2020) points out that the following four studies independently understood that the reflection problem is naturally solved by network interactions: Bramoullé et al. (2009); De Giorgi et al. (2010); Lin (2010); Laschever (2005). Bramoullé et al. (2009) demonstrates that endogenous and contextual effects are identified through intransitive triads, that is, when peers of peers are not peers. De Giorgi et al. (2010) also demonstrates that in a context where peer groups do not overlap fully, it is possible to identify all the relevant parameters of the standard linear-in-means model of social interactions. Lin (2010) shows that the model is identified when there is variation in group size.

To see this where the identification comes from, following Bramoullé et al. (2009) consider the model in the matrix notation

$$\mathbf{y} = \alpha\boldsymbol{\iota} + \lambda\mathbf{G}\mathbf{y} + \beta\mathbf{x} + \gamma\mathbf{G}\mathbf{x} + \boldsymbol{\epsilon} \tag{3.9}$$

where $\mathbf{y}$ is an $n \times 1$ vector of outcomes, ι is an $n \times 1$ vector of ones, $\mathbf{x}$ is an $n \times 1$ vector of exogenous characteristics, and $\mathbf{G}$ is an $n \times n$ interaction matrix defined in the previous section. When $|\beta| < 1$, $(\mathbf{I} - \beta\mathbf{G})$ is invertible the reduced form of the model is

$$\mathbf{y} = \alpha(\mathbf{I} - \lambda\mathbf{G})^{-1}\boldsymbol{\iota} + (\mathbf{I} - \lambda\mathbf{G})^{-1}(\beta\mathbf{I} + \gamma\mathbf{G})\mathbf{x} + (\mathbf{I} - \lambda\mathbf{G})^{-1}\boldsymbol{\epsilon} \tag{3.10}$$

When no individual is isolated, that is, $g_{ij} \neq 0 \ \forall j$, and considering $(\mathbf{I} - \lambda\mathbf{G})^{-1} = \sum_{k=0}^{\infty} \lambda^k \mathbf{G}^k$, the reduced form can be written as

$$\mathbf{y} = \frac{\alpha}{(1-\lambda)}\boldsymbol{\iota} + (\beta\lambda + \gamma)\sum_{k=0}^{\infty} \lambda^k \mathbf{G}^{k+1}\mathbf{x} + \sum_{k=0}^{\infty} \lambda^k \mathbf{G}^k \boldsymbol{\epsilon} \tag{3.11}$$

Bramoullé et al. (2009) demonstrates that when no individual is isolated and $(\beta\lambda+\gamma) \neq 0$ (peer's characteristics has effect on one individual's expected outcome), this model is identified if and only if the conditional expected mean $\mathbb{E}(\mathbf{Gy}|\mathbf{x})$ is not perfectly collinear with the regressors $(\boldsymbol{\iota}, \mathbf{x}, \mathbf{Gx})$. In this case, the variables $\mathbf{G}^2\mathbf{x}$, $\mathbf{G}^3\mathbf{x}$, ... can be used as identifying instruments for $\mathbf{Gy}$, as the peer's exogenous variable x_k will affect the outcome variable of the individual y_i only indirectly through its effect on peer's outcome y_j, and therefore can be used to estimate the parameters consistently. This condition is the same as considering that the matrices $\mathbf{I}$, $\mathbf{G}$ and $\mathbf{G}^2$ are linearly independent. This occurs as long as networks are partially overlapping, which means that some individual may not be peers with her peer's peer [3].

[3] The author shows that the results of lack of identification of the specifications of Manski (1993) and Moffitt et al. (2001) and identification of Lee (2007) with groups of different sizes directly follow from these general

To address the correlated problem and identify peer effects, the strategies developed by the literature can be classified in the broad categories (Bramoullé et al., 2020): random peers, random shocks, and panel data. Using econometric terminology, the strategies may use experimental data, instrumental variable estimation methods, and fixed effects control.

The random peer's strategy relies on randomized peer formation through natural or artificial experiments. With random peers, individual's observed, and unobserved characteristics are uncorrelated with his peers' observed and unobserved characteristics. However, a random assignment does not alone allow consistent estimation of endogenous and correlated effects as the problem of omitted variables can still be present. Without other sources of exogenous variations, this method has to be combined with, for instance, control for relevant variables.

Some examples are the studies of Sacerdote (2001), and De Giorgi et al. (2010) that uses random students assignment of college students to, respectively, dorms and classes to analyze peer effects in education. Mas and Moretti (2009) randomizes workers in different shift hours to evaluate peer effects in work productivity. Grohmann and Sakha (2019) randomizes peers in an experimental design to find evidence of peer effects and conformity in consumption choice. Another group of studies considers a quasi-random context where the network is considered random conditional on observables (Calvó-Armengol et al., 2009).

The random shocks strategy uses other sources of exogenous variations, such as randomized interventions. Studies have explored exogenous wealth shocks of neighbors in consumption literature to find peer effects on consumption expenditure. Roychowdhury (2019) uses negative income shocks of peer's as an instrument for peer consumption to identify peer effect. Kuhn et al. (2011) uses lottery data to exploits unexpected income gains from peers. Angelucci and De Giorgi (2009), Boneva (2014) and Roth et al. (2014) uses a conditional cash transfer program with randomized treatment.

The panel data strategy can address the problems of correlated effects with the introduction of individual fixed effects. This will control for individual's time-invariant unobserved characteristics. Using the time extension of the social interaction model is not only limited by data availability but also has the challenge that the network may be endogenously evolving; therefore, individual's outcomes may be affected by peers' time-invariant unobserved characteristics and lagged peer effects may matter. In consumption literature, De Giorgi et al. (2020) Verhelst and Van den Poel (2014) are examples of studies that make use of such strategy.

Lastly, another challenge of identifying peer effects is the definition of the reference groups. The theory does not provide guidance for the correct measurement of groups, and data availability imposes important constraints. The reference groups has been defined mostly based on geographical proximity such as agents from the same city, census strata (Ravina, 2019; Alvarez-Cuadrado et al., 2016; Verhelst and Van den Poel, 2014) or narrower spatial units

conditions.

(Grinblatt et al., 2008; Kuhn et al., 2011; Boneva, 2014) and on similarity in socio-demographic characteristics (Maurer and Meier, 2008) as racial groups (Charles et al., 2009) or age group (Jinkins, 2016) living in the same region. Different approaches can be taken when rich data on individual's networks are available as in De Giorgi et al. (2020) that exploits the social network of the households at the family and firm level.

3.3 Review of empirical results

A substantial body of literature on peer effects in consumption has emerged in the past years. The literature can be separated into two strands. The first is concerned with the intertemporal allocation decision, in other words, the first stage of the budgeting procedure. The second strand is concerned with intra-period consumption patterns referred to as the second stage of a two-stage budgeting procedure. The majority of the studies investigating peer effects in consumption have looked at commodity demand, either interested in the expenditure with it alone or considering allocating total expenditure to other categories of consumption. Here we will present the empirical results of selected studies from each strand.

From the first strand, Maurer and Meier (2008), Alvarez-Cuadrado et al. (2016), and Ravina (2019) are three papers that consider habit formation and interdependent preference on the evolution of the optimal consumption path using a similar approach. Roychowdhury (2019) and De Giorgi et al. (2020) stands out as one of the few papers to identify the neighborhood effect for aggregate household consumption. The last also considers intratemporal consumption and will be reviewed last. All studies find evidence that households care about "keeping up with the Joneses".

Maurer and Meier (2008) incorporates peer-group effects in the Euler Equation from the life-cycle modeling framework. Due to data limitation, aggregated consumption is represented by expenditure with food that is a category ranked in the upper middle distribution of conspicuousness index created by Heffetz (2011). To disentangle consumption externalities from correlated effects, an instrumental variable approach for contemporaneous consumption externalities is applied. The externalities are estimated from a social multiplier; that is, the indirect effects on a peer's optimal consumption growth operate through peer-group averages of explanatory variables such as the averages of family size changes, the average log after-tax interest rate, and demographics dummies. Based on US data from 1974-1987 and reference groups defined by similarities in socio-demographic characteristics (age, gender, race, family status, education, occupation, and urbanity), the authors find that much of the co-movement of individual consumption within groups reflect correlated effects. Once these effects are controlled, substantial evidence of consumption externalities remains present.

Alvarez-Cuadrado et al. (2016) investigates the importance of habit formation and envy on individual consumption choices using Spanish family expenditure data. The author considers consumption of nondurable goods and services, which accounts for approximately 80% of total consumption expenditures. The reference group of the household is composed of others that live in the same geographical census tract, although alternative reference groups such as based on socio-demographic variables were tested. The identification strategy adopted uses lagged value of the endogenous regressors as instrumental variables following Arellano and Bond (1991). To address specifically the confounding issues of peer-group effect estimation, the authors use demographic variables of reference group as controls and explores the degree of heterogeneity in the observable characteristics of households within and across reference groups. The results from this last exercise suggest that although household heads in the same reference groups were more likely to share some common characteristics than those in different reference groups, the difference is small and not statistically significant.

Ravina (2019) uses expenditure data between 1999 and 2002 from the Californian credit-card database to study the role of internal and external habits for intertemporal consumption choice. Even though credit cards seem to be heavily used by households, one caveat of this data set is that consumption may be incomplete since it only includes purchases made using a single credit card. The reference group of the household is defined by the city in which it is located, and the external consumption is given by the city-level quarterly per capita taxable sales. The estimation strategy of the paper is again based on instrumental variables for past household consumption and city-level consumption. The instruments used were marginal tax rate, the local unemployment rate, the inflation rate, aggregate disposable income growth rate, mortgage rate, and some individual variables such as lags of the growth rate of debt, automatic credit line changes, and a credit-constrained indicator. After scaling city-level consumption by the ratio of the standard deviations of individual and city-level, the author finds an external habit of strength 0.29 (where 1 would mean that the household cares only about its consumption compared to the neighbors' and not about the absolute level).

Roychowdhury (2019) investigates peer effects in consumption in the context of India. The authors used the 2012 Indian Human Development Survey (IHDS) that contains detailed information on income, consumption expenditure, and expenditure shocks, and demographic characteristics of households. The empirical strategy used to disentangle the endogenous peer effects from the exogenous ones uses negative exogenous income shocks faced by neighbors as instrumental variables. The author finds that one standard deviation increase in average consumption expenditure of a household's peers causes the household's own consumption expenditure to increase by 0.42 standard deviations. This is an effect greater than the effect of an equivalent direct increase in family income.

Moving to the second strand of the literature focused on disaggregated consumption, we can further classify the studies into two categories: the ones focused on the expenditure on specific products or categories of goods; and the ones interested in how peer effects affect the budget allocation with different goods. In the first, the literature is quite diverse, pointing to peer effects in a car purchase, movie tickets, water consumption, technology and product adoption, and a category of goods or services known as conspicuous, to mention a few. In the second category, earlier theoretical work of Gaertner (1974), Pollak (1976), Alessie and Kapteyn (1991) and Kapteyn et al. (1977), for instance, have shown that peer effects are important for estimating budget share equations. However, most of them lack the awareness of the empirical identification issues related to peer effects estimation. Since few empirical studies that make efforts to address these issues have been made. In fact, the works of Boneva (2014) and Verhelst and Van den Poel (2014) were the only ones we found.

Grinblatt et al. (2008) was one of the first empirical studies in this literature strand. Using Finnish data, they provide evidence of endogenous peer effects in automobile purchases; specifically, the probability of buying a car any given day increases by 12% for each one of your 10 nearest neighbors that purchased a car in the last 10 days. Kuhn et al. (2011) also finds significant evidence of peer effects in car consumption in the context of the Netherlands. Using lottery data, they adopt an instrumental variable strategy using unexpected income gains from peers. Another paper that applies a peer effect model to the car market is that by Yang and Allenby (2003). This greatly cited paper, in special by the marketing literature, employs a Bayesian spatial autoregressive discrete-choice model to study the interdependent preferences in a consumer choice context. The authors find evidence for preference interdependence that reflects conformity, being the geographically defined network more important than the demographic network.

Moretti (2011) estimate peer effects in consumption of movies using detailed box-office sales data from the United States. Specifically, the paper aims to identify social learning: how much the consumption of individuals depends on the information they receive from their peers when product quality is difficult to observe in advance. Based on the unique characteristic of the movie industry, the author develops a model to estimate information diffusion on movie quality followed by surprises in quality. The surprise is measured by the difference between realized sales and predicted sales given by the number of screens dedicated to a movie in its opening weeks. To separate social learning from network externalities–when consumers draw utility from how many friends have seen a movie, irrespective of their reasons from choosing to see it–a test using an instrumental variable strategy based on bad weather shocks was implemented. The author finds strong evidence for the presence of social learning that may account for 32% of sales for the typical movie with a positive surprise. The evidence of a significant social multiplier indicates that aggregate demand elasticity is larger than the elasticity of individual demand to quality.

A body of the literature has focused on investigating the consumption of conspicuous goods or services. Conspicuous consumption can be defined as using resources for consumption to signal social status to others Veblen (1899). With a survey applied in the US, Heffetz (2011) develops an index of visibility of consumption goods used as a reference by several studies that followed. The author finds evidence that the relatively visible goods are being used as means to signal income.

To compare conspicuous consumption in the US and China, Jinkins (2016) develops a model of conspicuous consumption in which a consumer cares not only about the direct utility caused by the consumption but also about how her consumption pattern affects her peer's belief about her well-being. Charles et al. (2009) showed that racial and ethnic minorities in the United States are more susceptible to conspicuous consumption compared to whites with similar characteristics. Using data from a randomized conditional cash transfer program in Indonesia, Roth et al. (2014) finds that the untreated households in treated districts increase expenditure share with visible goods when there is an exogenous increase in the visible consumption of the reference group.

Wu (2020) investigates how social influence affects demand, market competition, and firm pricing strategies using data from the Chinese smartphone market. The author finds that a 10 percent increase in the share of friends using a given product doubles the probability of choosing that product. In addition, there is evidence that suggests that status-seeking motivations may be important drivers of social influence.

Few research looks into the mechanisms behind peer effects and what leads to conformity. Grohmann and Sakha (2019) provides the first insight into mechanisms by conducting a lab-in-field experiment linked to a very detailed household survey. The identification problems found in studies on peer effects are addressed based on the experimental design and the use of a large number of control variables. Individuals were randomly selected to perform the experiment given the sampling procedure, and also peer and control treatments were randomized according to villages. The authors find evidence of peer effects and conclude that peer observation leads to conformity. The results also point to information and psychological channel underlying peer effects. Furthermore, individuals with high cognitive ability are less likely to be influenced by peers, whereas those who live in closer-knit communities are more likely to conform.

As pointed out by Roychowdhury (2019), a small part of this literature has exploited peer effects in the context of low-income countries. The few other papers devoted to the study of effect in the context of underdeveloped countries include those of Angelucci and De Giorgi (2009), Boneva (2014) and Angelucci et al. (2017). All three mentioned used data from Progresa's Mexican income transfer program. As the only study estimating the effects of a change in neighbors' income on the composition of household consumption, Boneva (2014) finds evidence for a substantial presence of the neighborhood effect not explained by income transfer behavior among households.

The research done by Verhelst and Van den Poel (2014) is the closest to mine. Using scanner data from a large European retailer, they investigate both internal and external deep habit formation in consumption by estimating a dynamic time–space simultaneous model for consumption expenditure at different levels of product aggregation. The spatial unit is by zip code area, and the reference group is given by geographical proximity. The internal habit formation is captured by persistence in consumption, and the external is given by preference interdependence across households, captured by a spatial lag. The authors find mixed evidence concerning internal habit formation, whereas the external habit effect is positive and significant in estimations at all levels of product aggregation.

Lastly, De Giorgi et al. (2020) fits both strands of the literature review by investigating social effects in consumption choices within and between periods. Using administrative data on tax records from Denmark for the period of 1980-1996 matched with a consumption survey, the authors construct a rich data set with individual income information, working information, and expenditure. This data set allowed the definition of reference groups formed by co-workers with similar traits, particularly occupation and education. To identify peer effect, the paper combines the strategy of random shocks with the use of fixed effects and rich controls to address endogeneity issues. The paper innovates with its identification strategy that exploits the social network of the households at the family level and firm level to create intransitive triads. The shocks and demographic variables of distance-3 peers (a worker's spouse is distance-3 peers from the spouse of the workers' co-worker) become the instrumental variable for peer consumption. In addition, the paper contributes by proposing and implementing tests to understand the economic mechanisms behind peer effects on consumption. The results indicate that the peer effect affects intertemporal consumption but does not distort the demand for goods in the intratemporal problem. Lastly, there was little evidence that indicated that risk-sharing was the mechanism behind the estimated peer effects.

Table 3.1: Summary of selected evidence from literature

Study	Outcome	Data	Reference group	Empirical Approach	Main findings
Maurer and Meier (2008)	Food consumption	US Panel Study of Income Dynamics (1974-1987)	Peer group as that set of households which shares common socio-demographic characteristics.	Instrumental variable strategy	Substantial evidence of consumption externalities remains present after control for correlated effects.
Alvarez-Cuadrado et al. (2016)	Household's expenditures with non-durable goods and services	12 years (1985–96) of the Spanish Household Budget Continuous Survey (ECPF)	Composed by other households that live in the same census tract	Instrumental variable strategy; Panel estimation with fixed effects	Almost one-third of household's consumption of services derive from comparisons between their consumption and that of their neighbor's consumption.
Ravina (2019)	Total purchase made with credit card	Credit card data from California (1999 – 2002)	The city in which the household is located.	Instrumental variable strategy	The significant strength of external habit found is 0.29.
Roychowdhury (2019)	Household consumption expenditure	Indian Human Development Survey (IHDS) 2012	Households living in the same village or neighborhood	Instrumental/fixed effect approach; adverse exogenous expenditure shocks faced by peers are used as instruments	One standard deviation increase in average consumption expenditure of a household's peers causes the household's own consumption expenditure to increase by 0.42 standard deviations.
De Giorgi et al. (2020)	Aggregated consumption; product demand	Administrative tax records from Denmark for the period 1980–96 and Consumption Survey	Social network formed by co-workers similar in occupation and education	Random shocks; fixed effects and rich controls to deal with the endogeneity concerns	Peers effect affect intertemporal consumption, but do not distort the demand for goods in the intratemporal problem; little evidence for the presence of risk-sharing behavior.
Grinblatt et al. (2008)	Automobile purchase	Finnish data on vehicle ownership and purchases and data from income tax returns (1999-2001)	Neighbors who are geographically most proximate	Logit model with the nearest neighbors methodology	Closest neighbors' purchases significantly increase a consumer's decision to purchase. The influence is strongest among the lowest income classes.
Moretti (2011)	Movie sales	Box-office sales by movie and week from US (1982-2000)	Market-level data, demand of similar peers	Exogenous shocks and instrumental variable	Social learning that may account for 32% of sales for the typical movie with a positive surprise.

Table 3.2: Summary of selected evidence from literature

Study	Outcome	Data	Reference group	Empirical Approach	Main findings
Leonard et al. (2014)	Food demand and nutritional intake behaviors	Cross-sectional data of low-income, minority neighborhood in Dallas, Texas (2009–2010)	Defined by geographic proximity	Estimate a cross-sectional spatial (SAR) model for food consumption	Coefficient on the average of geographic peers' dietary intake (0.175) is statistically significant only in the fruits and vegetables model.
Boneva (2014)	Disaggregated consumption; food products	Data from the Mexican conditional cash transfer program Progresa - 1999	Defined by households from the same neighborhood.	Instrumental variable using income shocks from the randomized Progresa program	Neighbourhood effects are of substantial size and cannot be explained by income sharing between households.
Verhelst and Van den Poel (2014)	Expenditure with products categorized at different levels.	Scanner data from a large European retailer running from January 2002 until November 2004.	Zip codes are the spatial unit; geographic neighbors	Estimates a dynamic spatial panel data model with time and spatial fixed effects	Both internal and external habit formation are significant for the consumption for virtually all product groups and more than half of the product categories considered.
Grohmann and Sakha (2019)	Temptation goods (sweet and savory snacks)	Experiment with 552 individuals that live in 66 Thai villages	Those sit in close proximity to each other	Lab-in-field experiment	Individuals with high cognitive ability are less likely to be influenced by peers whereas those who live in closer-knit communities are more likely to conform
Bollinger et al. (2020)	Residencial water consumption	Water bills, remote sensing images, and housing transaction data. +300,000 households in Phoenix, Arizona from 2004 to 2012	Based on geography	Instrumental variable strategy that leverages consumer migration into the peer group. Housing turnover in nearby homes is used as an instrument for the lagged peer water consumption.	A one-gallon decrease in the mean summer water consumption of households within a 500-foot radius of a home reduces the summer water consumption of that home in the next year by 0.25 ccf. Dry landscape adoption is the primary factor that generates our water peer effects results.
Wu (2020)	Product choice and Market competition	Geocoded social interaction data from mobile phone trackers	Social network of friends	Exploits the partially overlapping network of friends and residential neighbors and the intertemporal variation in friend circles.	A 10 percent increase in the share of friends using a given product doubles the probability of choosing that product. Consumers are more likely to conform to wealthier friends and choose visually distinct features, suggesting that status-seeking motivations may be important drivers of social influence.

3.4 The Spatial Almost Ideal Demand System

This section is dedicated to presenting the spatial extension of the AIDS model applied for the empirical analysis. The spatial system will be derived in the context of models developed by past studies that incorporated interdependence in consumption preference. As for the other extensions presented previously, the conditions for the theoretical consistency of the spatial extension will also be discussed. Lastly, the specifications for elasticities considering the direct, indirect, and total effects from the spatial econometric analysis are derived.

3.4.1 Incorporating Interdependence

As reviewed in the previous chapter, there is a large body of literature that examines the theory and empirical evidence of interdependent preferences in the context of consumption. Duesenberry et al. (1949) and Leibenstein (1950) were pioneers to consider the importance of interdependence in consumer demand theory formally. Gaertner (1974) and Pollak (1976) are two seminal papers that have studied theoretical implications of the incorporation of preference interdependence in the Linear Expenditure System (LES). Kapteyn et al. (1997) also considers interdependence in the LES model and exploits cross-sectional data on consumer expenditure, while Alessie and Kapteyn (1991) estimates an AIDS system with habit formation and interdependence. Interdependent preferences in consumer choice have also attracted marketing researchers' attention as Yang and Allenby (2003) that develops and estimates a Bayesian spatial autoregressive discrete-choice model.

To consider the influence of the neighbor's consumption on one household's consumption, the demand system specification adopted here incorporates a Spatial Autoregressive Model (SAR) model into the Almost Ideal Demand System model (AIDS) in the nature of the models adopted by Boneva (2014) and Verhelst and Van den Poel (2014). Similar to the derivation of the original AIDS model, the spatial demand system is obtained following the steps:

1. Consider an indirect utility representing a specific class of preferences known as *Price independent generalized logarithmic* (PIGLOG).

2. Define the functional forms for the components of the indirect utility function.

3. Find the Marshallian (uncompensated) demand functions by applying the Roy's Identity.

Because of the social interaction component, the model is now specified by household. The following notation will be considered: the index h is used to denote households and the indices $\_h$ or l to denote households with which household h interacts (referred to as "neighbors"); the indices i and j are used to denote particular categories or goods; the index

k is used to denote the explanatory variables. The total number of households is N, the index G sum over all goods, and the total number of explanatory variables is D.

Following Blundell et al. (1994) and De Giorgi et al. (2020), the preferences is represented by the conditional indirect utility function in the general form

$$U(\mathbf{p}, \mathbf{q}_h, \mathbf{z}_h) = V(\mathbf{p}, y_h, \mathbf{z}_h) \tag{3.12}$$

This function gives the maximum utility in the period for a household h that has total expenditure y_h spent with goods $\mathbf{q}_h$ with prices $\mathbf{p}$ (where $y_h = \sum_{i=1}^{G} p_i q_{hi}$) conditional on the vector $\mathbf{z}_h$ of characteristics that may include observed and unobserved taste shifters, demographics, peer's consumption or peer's exogenous characteristics

$$\mathbf{z}_h = (\mathbf{X}_h, \epsilon_h, \mathbf{y}\_h, \mathbf{X}\_h) \tag{3.13}$$

where $\mathbf{X}_h$ and ϵ_i are observed and unobserved taste shifters, respectively, $\mathbf{y}\_h$ is the vector of peer's consumption and $\mathbf{X}\_h$ is the vector of peer's characteristics.

The within-period allocation of total expenditure y to individual goods with prices $\mathbf{p}$ is completely characterized by the indirect utility and is invariant to monotonic transformations. The PIGLOG specification for the indirect utility is

$$V(\mathbf{p}, \mathbf{y}_h, \mathbf{z}_h) = \frac{\log y_h - \log a(\mathbf{p}, \mathbf{z}_h)}{b^*(\mathbf{p})} \tag{3.14}$$

where $a(\mathbf{p}, \mathbf{z}_h)$, $b^*(\mathbf{p})$ are price functions and the first can be considered the subsistence cost (when $u = 0$)[4]. The functional forms chosen for $\log a(\mathbf{p}, \mathbf{z}_h)$ and $\log b^*(\mathbf{p})$ are

$$\begin{aligned} \log a(\mathbf{p}, \mathbf{z}_h) = \alpha_0 + \sum_i \left[\alpha_{i0} + \sum_k \alpha_{ik} x_k + \sum_k \delta_{ik} \mathbf{X}\_{hk} + \lambda_i S\_{hi} \right] \log(p_i) + \\ + \frac{1}{2} \sum_i \sum_j \gamma_{ij}^* \log(p_i) \log(p_j) \end{aligned} \tag{3.15}$$

with $X\_{hk} = \sum_{l=1}^{N} w_{hl} x_{lk}$; $S\_{hi} = \sum_{l=1}^{N} w_{hl} s_{li}$ and

$$\log b^*(\mathbf{p}) = \sum_i \beta_i \log(p_i) \tag{3.16}$$

where $i, j = 1, ..., G$ are the goods available for consumption; $h, l = 1, ..., N$ are the households; s_{hi} denotes the household h's expenditure share with good i; p_i is the price of good i; w_{hl} is the spatial weight of household l to household h.

[4] Note that the $b^*(\mathbf{p})$ function here is not the same as the $b(\mathbf{p})$ functions specified in the original AIDS model derivation. In fact $b^*(\mathbf{p}) = \log b(\mathbf{p}) - \log a(\mathbf{p})$.

By replacing equations 3.15 and 3.16 in equation 3.14 the AIDS indirect utility function is written

$$V(\mathbf{p}, \mathbf{y}_h, \mathbf{z}_h) = \frac{\log y_h - \alpha_0 - \sum_i \left(\alpha_{i0} - \sum_k \alpha_{ik} x_k - \sum_k \delta_{ik} \mathbf{X}\_{hk} - \lambda_i S\_{hi}\right) \log(p_i)}{\sum_i \beta_i \log(p_i)} - \\ - \frac{\frac{1}{2} \sum_i \sum_j \gamma^*_{ij} \log(p_i) \log(p_j)}{\sum_i \beta_i \log(p_i)} \tag{3.17}$$

The last step is to apply Roy's Identity from which follows the relation

$$-\frac{\partial \log V(.)/\partial \log(p_i)}{\partial \log V(.)/\partial \log(y_h)} = -\frac{\partial \log V(.)/(\partial \log(p_i)/p_i)}{\partial \log V(.)/(\partial \log(y_h)/y_h)} = -\frac{\partial \log V(.)/\partial p_i}{\partial \log V(.)/\partial y_h} \frac{p_i}{y_h} = \frac{q_{hi} p_i}{y_h} = s_{hi} \tag{3.18}$$

where q_{hi} is the household h's Marshallian demand for good i and s_{hi} denotes the budget share with good i in total expenditure of household h. Now, partially deviating 3.17 in terms of $\log(p_i)$ and $\log(w_h)$ and using equation 3.18 followed by some manipulations results in the demand equations

$$s_{hi} = \alpha_{i0} + \sum_k \alpha_{ik} x_k + \sum_k \delta_{ik} \mathbf{X}\_{hk} + \lambda_i S\_{hi} + \sum_j \gamma_{ij} \log p_j + \beta_i \log \left(\frac{y_h}{g(\mathbf{p}, \mathbf{z}_h)}\right) \tag{3.19}$$

$$\forall h = 1, ..., N \quad \forall i = 1, ..., G$$

where $\gamma_{ij} = \frac{\gamma^*_{ij} + \gamma^*_{ji}}{2}$ and

$$\begin{aligned} \log g(\mathbf{p}, \mathbf{z}_h) =& \alpha_0 + \sum_i \left[\alpha_{i0} + \sum_k \alpha_{ik} x_k + \sum_k \delta_{ik} \mathbf{X}\_{hk} + \lambda_i S\_{hi}\right] \log(p_i) + \\ & + \frac{1}{2} \sum_i \sum_j \gamma^*_{ij} \log(p_i) \log(p_j) \end{aligned} \tag{3.20}$$

and

$$X\_{hk} = \sum_{l=1}^{N} w_{hl} x_{lk} \quad S\_{hi} = \sum_{l=1}^{N} w_{hl} s_{li} \tag{3.21}$$

where $i, j = 1, ..., G$ are the goods available for consumption; $h, l = 1, ..., N$ are the households; s_{hi} denote the household h's expenditure share of good i; p_i is the price of good i; w_{hl} is the spatial weight of household l to household h; and α, β, γ^* and λ are the parameters.

With the spatial demand model, a household's decision of expenditure across the different goods is allowed to depend on the composition of its neighbor's expenditure. The specification of the model implies that subsistence levels are subject to social influences. This is a common approach adopted by many authors (Kapteyn et al., 1997; Boneva, 2014; Verhelst and Van den Poel, 2014; De Giorgi et al., 2020) and collaborated by evidence of the influence of real disposable income per capita on levels of subsistence expenditure.

3.4.2 Theoretical consistency

For the spatial demand system to be consistent with the consumer theory, its cost function must have the theoretical properties of a cost function, and the adding-up, homogeneity, and symmetry restrictions must be satisfied. It will be shown here that the properties can be attended by imposing restrictions on the model's parameters.

The cost function is homogeneous of degree one in prices if

$$c(u, \theta \mathbf{p}) = \theta c(u, \mathbf{p})$$

or in logarithmic terms

$$\log c(u, \theta \mathbf{p}) = \log \theta + \log c(u, \mathbf{p}) \tag{3.22}$$

where θ is any positive parameter. With the functional forms, the expenditure function for the spatial demand system derived previously is

$$\begin{aligned} \log c(u, \mathbf{p}) = \alpha_0 + \sum_i \left[\alpha_{i0} + \sum_k \alpha_{ik} x_k + \sum_k \delta_{ik} \mathbf{X}\_{hk} + \lambda_i S\_{hi} \right] \log(p_i) + \\ + \frac{1}{2} \sum_i \sum_j \gamma^*_{ij} \log(p_i) \log(p_j) + u \sum_i \beta_i \log(p_i) \end{aligned} \tag{3.23}$$

Now

$$\begin{aligned} \log c(u, \theta \mathbf{p}) = & \quad \alpha_0 + \textstyle\sum_i \left[\alpha_{i0} + \sum_k \alpha_{ik} x_k + \sum_k \delta_{ik} \mathbf{X}\_{hk} + \lambda_i S\_{hi} \right] \log(\theta p_i) + \\ + & \quad \tfrac{1}{2} \textstyle\sum_i \sum_j \gamma^*_{ij} \log(\theta p_i) \log(\theta p_j) + u \sum_i \beta_i \log(\theta p_i) \\ = & \quad \log c(u, \mathbf{p}) + \log(\theta) \textstyle\sum_i \left[\alpha_{i0} + \sum_k \alpha_{ik} x_k + \sum_k \delta_{ik} \mathbf{X}\_{hk} + \lambda_i S\_{hi} \right] + \\ + & \quad \tfrac{1}{2} \log^2 \theta \textstyle\sum_i \sum_j \gamma^*_{ij} + \tfrac{1}{2} \log \theta \sum_i \sum_j \gamma^*_{ij} \log(p_i) + \tfrac{1}{2} \log \theta \sum_i \sum_j \gamma^*_{ij} \log(p_j) + \\ + & \quad u \log(\theta) \textstyle\sum_i \beta_i \end{aligned} \tag{3.24}$$

The adding-up restriction holds when $\sum_{i=1}^{G} \alpha_i = 1$, $\sum_{i=1}^{G} \gamma_{ij} = 0 \ \forall j$, $\sum_{i=1}^{G} \beta_i = 0$, and $\sum_{i=1}^{G} \lambda_i = 0$. This restriction is considered when one equation of the demand system is left out of the estimation. The homogeneity imposes that $\sum_j \gamma_{ij} = 0 \ \forall i$. Finally, the symmetry restriction imposes that $\gamma_{ij} = \gamma_{ji}\ \forall i, j$. The adding-up restriction holds when $\sum_{i=1}^{G} \alpha_i = 1$, $\sum_{i=1}^{G} \gamma_{ij} = 0\ \forall j$, $\sum_{i=1}^{G} \beta_i = 0$, and $\sum_{i=1}^{G} \lambda_i = 0$. This restriction is considered when one equation of the demand system is left out of the estimation. The homogeneity imposes that $\sum_j \gamma_{ij} = 0\ \forall i$. Finally, the symmetry restriction imposes that $\gamma_{ij} = \gamma_{ji}\ \forall i, j$.

3.4.3 Elasticities by Direct, Indirect and Total Effects

With the spatial model, the coefficient λ_i cannot be directly interpreted as the partial neighborhood's effect. The effect of a change in the value of a regressor on the explained variable is, in general, nonlinear and may spill over non uniformly over the space. In every point of space, the impact on the explained variable depends on its location in relation to the point of intervention. LeSage and Pace (2009) distinguishes two types of effect, the direct and the indirect effects. Because of the feedback effects, the partial derivate of s concerning the explanatory variable x_k will depend on the point in space that is impacted. For each equation and every regressor, we can evaluate three effects

1. Direct Effects: measure the impact of a unitary change in the value of an explanatory variable x_{ik} of household ℓ on the value of its own s_i. Include the feedback effects.

$$\frac{\partial s_i^{\ell}}{\partial x_{ik}^{\ell}} \tag{3.25}$$

2. Indirect Effects: measure the impact of a unitary change in the value of an explanatory variable x_{ik} of household ℓ on the value of s_i of household h, where $h \neq \ell$.

$$\frac{\partial s_i^{\ell}}{\partial x_{ik}^{h}} \tag{3.26}$$

3. Total Effects: the sum of Direct and Indirect Effects.

To report the results compactly, Lesage and Pace (2010) propose averaging each effect over all spatial units. The Average Direct Effects measure the average impact, over the spatial units, of a unitary change in the value of an explanatory variable on the value of the explained variable located in the same spatial unit of the regressor. The Average Indirect Effects measure the average impact, over all spatial units, of a unitary change in the value of an explanatory variable on the value of the corresponding explained variable, located in a different spatial unit of the regressor. Both are calculated for all the regressors that appear in all equations of the model. The Average Total Effects is the sum of Direct and Indirect Effects.

The income (η_i) and price elasticities (ϵ_{ij} and ϵ_{ij}^{H}) of the spatial demand model are now specific to each partial effect $e = \{\text{Direct Effect}, \text{Indirect Effect}, \text{Total Effect}\}$. Following Chalfant (1987), the elasticities are formulated as

$$
\begin{aligned}
\eta_i^e &= 1 + \frac{\beta_i^e}{s_i} \\
\epsilon_{ij}^e &= \frac{\gamma_{ij}^e - \beta_i^e s_j}{s_i} - \delta_{ij} \\
\epsilon_{ij}^{He} &= \epsilon_{ij}^e + s_j \eta_i^e
\end{aligned}
$$

where $\delta_{ij} = 1$ if $i = j$; $\delta_{ij} = 0$ otherwise; and ϵ_{ij}^H is the uncompensated or Hicksian elasticity. The above elasticities are conditional elasticities estimated within-category and computed for a given amount spent on category i. Details of the unconditional elasticity estimation are further described in the following chapter.

The price and income elasticities considering direct effects reveal the average effect of respectively, a price variation or income variation observed by household h on its demand for a category of products i considering the feedback effects of the social interaction. For example, if the social interaction in the demand for i is relevant, the households will react to price and income variations and demand variations of their neighbors. The price and income elasticities considering indirect effects reveal the average effect of respectively, a price variation or income variation observed by household h's neighbors on household h's demand for a category of products i.

4 EMPIRICAL STRATEGY

4.1 Data

The empirical investigation of this research is based on data from the *Pesquisa de Orçamentos Familiares* (POF – "Household Budget Survey") conducted by the *Fundação Instituto de Pesquisa Econômica* (Fipe - "Institute of Economic Research Foundation")[1]. The POF-Fipe collects information on the expenditure on goods and services of households from the municipality of São Paulo, the most populous city in Brazil. Till now, six waves of the survey were carried out at the maximum interval of ten years (1971-1972; 1981-1982; 1990-1991; 1998-1999; 2008-2010; and 2011-2013) from which the information collected about expenditure patterns are used to construct the weighting structure behind the Consumer Price Index (IPC-Fipe) — the most traditional indicator of the cost-of-living trends of the city of São Paulo.

The basic unit considered by the surveys is the unit of consumption (hereafter referred to as household) that can be composed of one person or a group of people who share a budget or perform expenses collectively. In order to obtain a representative sample of households of the city of São Paulo, these units were selected by a two steps systemic sampling process using the population of addresses obtained from the cities electricity distributor's registry (Carmo, 1999). The size of the sample surveyed was defined considering the city's household's income distribution and the refusal to respond rate.

With questions organized in six forms, the survey collects information of household composition (reference person and relationships to him/her), characteristics of the dwelling (address, type of housing, form of possession, housing facilities, vehicles), socioeconomic characteristics of its members (gender, age, employment status, income, education level), personal and collective expenses (with habitation, services, transportation, health, education, communication, the food inside and outside the home) and information of the most frequented purchasing locations (name and address). Data collection involves a combination of one or weekly interviews during a 30-day period where households and/or individuals maintain daily expenditure logs. One simplified or compact form is applied when households were not available to answer the complete survey.

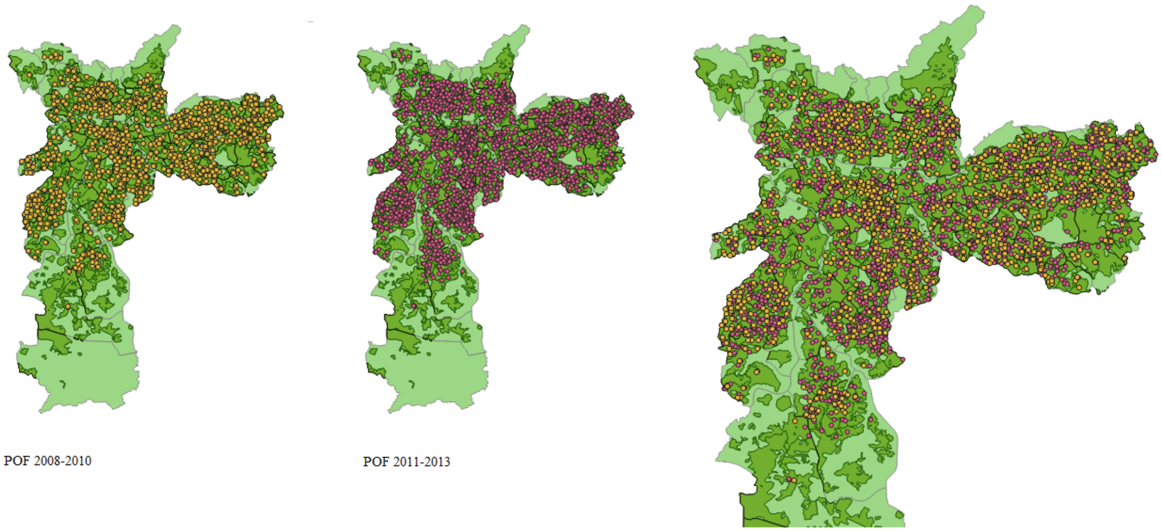
The POF-Fipe microdata is not publicly available; however, for this study, Fipe provided access to the survey's complete data between 2008 and 2013. Therefore, the data from the last two waves of the POF-Fipe will be used for this research. The 2008-2010 survey was conducted between November of 2008 and October of 2010 and interviewed 1,136 households.

[1]Fipe is a private nonprofit organization created in 1973 that offer research support for the Department of Economics of the Faculty of Economics, Administration and Accounting of the University of São Paulo (FEA-USP). Fipe also has a traditional role in elaborating price indexes and economic indicators with national relevance (see www.fipe.org.br/en-us/indexes-and-indicators).

The 2011-2013 edition was applied between May of 2011 and April of 2013 to 1,984 households. The address of the households interviewed was converted to geographic coordinates[2] and figure 4.1 show the spatial distribution of the sample.

The Figure shows how the sample is composed of households in most of the living areas of the city.

Figure 4.1: Household's distribution



Source: Authors' elaboration

The POF-Fipe data source was chosen for this research because it contains information that serves my purpose of investigating peer effects in consumption, as expenditure information and most importantly, the geographical location of households was provided. Other works have used the same data source to study price trends (Yuba et al., 2013), demand for food (Claro et al., 2007; Claro and Monteiro, 2010) and demand for energy (Uhr et al., 2019). To the best of my knowledge, the household's precise location was not yet explored by any other studies that used the same data source. The following subsection will detail the data manipulation process, after which other descriptive statistics will be presented.

4.1.1 Data preparation

Before the estimation of the spatial demand system, several variables must be carefully specified. First, the groups or categories of goods are defined. Due to computational limitations, goods are classified into aggregated categories according to the study's interest to reduce the number of parameters to be estimated. Second, expenditure share, total expenditure, and price for each category must be calculated with corrections when necessary. Third, the relevant socioeconomic variables and lastly the reference group of each household are defined.

[2]The complete address composed of the street, number, and zip code were converted into latitude and longitude coordinates through the Google Maps API. Six observations were dropped after this process due to missing or inconsistent data.

Product Classification

The POF-Fipe survey has a record of approximately 1,369 types of goods and services purchased by households. With the complete questionnaire, item purchase records collect information on the name of the item, brand, and type of product (further description), amount or total quantity purchased, purchase unit of measurement (kilograms, liters, small package, can, unit, etc.), cost per unit (in Brazilian reais), total amount spent, and place of purchase (bakery, supermarket, local market, drugstore, gas station, etc.). The compact questionnaire only collects information on the name of the item purchased and the total amount spent with it.

Fipe classifies the items registered by the households into seven broad categories: (1) Housing, (2) Food, (3) Transportation, (4) Personal Care, (5) Health, (6) Clothing, and (7) Education. We further aggregate food items into nine sub categories[3], namely: (1) Cereals, legumes, and oil-seeds; (2) Flour and starch products; (3) Vegetables; (4) Sugar, sweets, and sweetened beverages; (5) Fruits and natural juices; (6) Meat and Fish; (7) Poultry and eggs; (8) Dairy products; and (9) Oils and Fats. Table 4.1 presents examples of items from each category.

Table 4.1: Examples of Category Components

	Example of Items
Broad Categories	
(1) Habitation	Rent, electricity, gas, water, TV, internet, cleaning supplies, home appliances
(2) Food	Meat, fruits, bread, vegetables, ready-to-eat foods, drinks
(3) Transportation	Fuel, transport fares, vehicle purchase and maintenance
(4) Personal Expenses	Hygiene and beauty products, salon, liquor, cigarette, travel
(5) Health	Medical appointments, health plan, medicines, medical corrective devices
(6) Clothing	Jackets, blouse, footwear, accessories
(7) Education	Tuition, school supplies, language courses
Food Categories	
(1) Cereals, legumes and oil-seeds	Rice, beans, oats, peas
(2) Flour and starch products	Wheat flour, cassava flour, pasta, bread
(3) Vegetables	Greens (lettuce, celery, other leafs), roots (radish, potatoes, carrots, cassava)
(4) Sugar, sweets and sweetened beverages	White refined sugar, crystal sugar, jams, chocolates, ice cream, candy, cookies, cakes, soft drinks and artificial juices and teas
(5) Fruits and natural juices	Fresh and dried fruits (bananas, oranges, apples) and natural fruit juices
(6) Meat and Fish	Beef, pork, processed meats (ham, sausages, hamburgers), fish, seafood
(7) Poultry and eggs	Chicken, duck, eggs
(8) Dairy products	Milk (liquid, powdered), cream, yogurt, cheese, butter
(9) Oils and Fats	Soybean oil, vegetable fat, olive oil

With the categories defined, the next step was to calculate the total expenditure,

[3] Canned and preserved food, salt and spices, and alcoholic beverages were not included. The purchase patterns for the first two categories usually involve intertemporal aspects not compatible with our econometric specification.

expenditure share, and price by category. All values were deflated into Brazilian reais (R$)[4] as of December of 2013 (the last month surveyed) using the Consumer Price Index also calculated by Fipe (IPC/FIPE) for São Paulo.

Total expenditure and expenditure share

Although POF-Fipe collects information on the income of household members, household-reported income is regarded as particularly unreliable, and the household's total expenditure in the month (sum of all collective and individual expenditures registered) is considered a more accurate representation of permanent income and purchase power (Claro et al., 2007). For this reason, monthly household expenditures were considered as a proxy for monthly household income.

As the dependent variables of the demand system, each category's expenditure or budget share is defined as the percentage of total household expenditure spent on the category.

$$s_{hi} = \frac{\text{Household } h\text{'s total expenditure with category } i}{\text{Household } h\text{'s total expenditure}} \tag{4.1}$$

Due to the design of household surveys, the registry of zero expenditures of some categories from households is expected, as seen from Table 4.4. The treatment for these zero values will be addressed in the empirical specification section (2.2).

Price correction, imputation, and aggregation

With the complete questionnaire, POF-Fipe collects information about price per unit, quantity purchased, and total expenditure. However, about 30% of the households interviewed filled out a compact version of the questionnaire with no information on price. Another difficulty is that the units of measurement of purchases are not standardized[5]. When prices are not available, two common approaches proposed by the literature are considered. The first is to incorporate external sources of price, such as Consumer Price Indices. The second approach is to consider the unit value calculated by dividing the total expenditure by the quantity acquired as a proxy of the good's price.

In a multi-stage budget allocation, consumers first choose how to spend their income among broad categories, then in the second stage, expenditure allocated to food items is further distributed among food subcategories. For the first-stage estimation, I will use expenditure weights and nominal price information by sub-items collected by Fipe for the Consumer Price

[4] The R$ real/U$ dollar exchange rate in the period in question ranged between 1.54 and 2.51. The current rate is 5.2 (December 2020).

[5] The POF-Fipe registered approximately 817 types of units of measurements (grams, milliliters, cups, bottles, boxes, meter, piece, package,...). Unfortunately, no standardized conversion was provided as the case of the national Household Budget Survey conducted by the Brazilian Institute of Geography and Statistics (*Instituto Brasileiro de Geografia e Estatística* - IBGE), which provides quantities purchased in the original unit and also converted in kilogram.

Index to construct price indices for each broad category. The price index of each category for each month is given by a Stone price index with weighted geometric mean

$$\ln P_{sm} = \sum_{i \in I_s} w_i \ln p_{im} \tag{4.2}$$

where w_i is the participation of good i from broad category s; p_{sm} is the price of product i, from broad category s, in the month m. The disadvantage of this approach is that it does not account for spatial and household variability.

For the demand estimation for food subcategories, I followed the unit value approach. In order to reach comparable prices for aggregation, it was necessary to standardize all quantities registered into the same unit of measurement. I initially converted to kilograms any purchase records expressed in other units, then all records referring to the same category of goods were grouped. Still, the unit value procedure has limitations. First, for those households that answered the compact questionnaire and for those without expenditures registered for a given good, the unit value will be missing. Second, as items purchased varies in, for example, quality and packaging across households, differences in unit value might reflect differences in quality choice rather than differences in the price level; moreover, measurement errors might be significant (Boysen et al., 2012).

I follow the typical approach for price correction and imputation proposed by Cox and Wohlgenant (1986). The idea behind this approach is that households within a cluster (households from the same district and surveyed in the same period) should face essentially the same price. Therefore, differences in unit values paid by the household from the corresponding district mean unit value are assumed to result from quality and measurement error, which can be attributed to household characteristics. To obtain quality-adjusted prices, the quality effects are the mean-deviated unit values regressed on household characteristics

$$UV_{hi} - \overline{UV}_n = \sum_{j}^{m} b_{hj} D_{hj} + \epsilon_i \tag{4.3}$$

where UV_{hi} is the unit value paid by household h for item i, $\overline{UV}_n$ is the corresponding district mean, and D_{hj} are the household h's characteristics being them the household size, the shares of members of the male gender, the age below 5, between 5 and 15, and above 60 (Boysen et al., 2012). The quality-adjusted price for each item p_i is generated by adding the mean unit value to the residual derived from Equation 4.3:

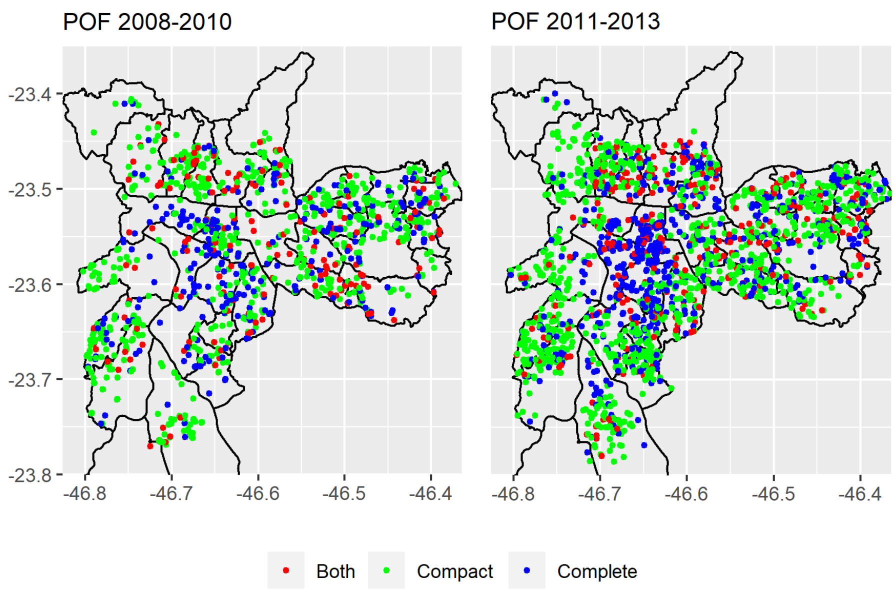
$$p_i = \overline{UV}_n + \hat{\epsilon}_i \tag{4.4}$$

The missing prices are imputed by a regression procedure, where the estimated coefficients from the regression of observed prices against dummies for districts and total household expenditure were used to predict the prices. Figure 4.2 shows that there are at least some households who answered the complete questionnaire in each district. Finally, the aggregated price for each category or group is obtained with the following Stone price index (weighted geometric mean)

$$\ln p_s = \sum_{i \in I_s} w_i \ln p_i \tag{4.5}$$

where I_s is the set of items included in aggregate item group s; p_s is the price from Equation 4.4; and w_i is the expenditure shares for item i in each household.

Figure 4.2: Type of questionnaire answered



Socioeconomic Variables

The POF-Fipe also collects a set of socioeconomic information, including household composition, age, gender, race, education, and employment status of each member of the household. As control variables for demand, the following variables are defined for each household

- Household size: Number of household members.
- Gender composition of the household: dummy for male head of household.
- Age composition of the household: dummies for age intervals; household head age.
- Dummy for the presence of a child: Number of Children
- Education of the household head: years of education and dummy for higher education.

4.1.2 Descriptive statistics

This section presents descriptive statistics for the relevant variables of our study. The summary statistics of a selection of demographic and socioeconomic variables extracted from the 2008-2010 and 2011-2013 household surveys are presented, respectively, in the Tables 4.2 and 4.3. To observe heterogeneity in the sample, the statistics are considered according to quintiles of monthly household income. Mean per capita monthly income was R$1,553 in the first survey and R$1,790.2 in the second. The average number of household members is 3.2 in the first survey and 2.9 in the second.

For both samples, households with lower income present a higher number of residents with higher chances of one of them being a child. Income increased with the mean age and schooling of the head of household. The household composition tends to have older members in higher-income households. Head of households of the black race and with only elementary education are more frequently observed in lower-income households. The great majority of households with lower income live in a house, usually in a renting condition.

Table 4.2: Summary Statistics according to per capita monthly income quintiles - POF-Fipe 2008-2010

Sociodemographic/economic characteristic	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**	**Total**
	N = 225	N = 225	N = 225	N = 225	N = 225	N = 1125
Members per household	4.16	3.42	3.01	2.84	2.56	3.20
	(1.77)	(1.56)	(1.27)	(1.40)	(1.22)	(1.56)
Per capita monthly income (R$)	343.33	653.75	987.26	1516.95	4263.81	1553.02
	(109.25)	(79.86)	(116.18)	(233.88)	(2965.90)	(1939.18)
% of households living in House	95.56	93.78	89.33	86.67	55.56	84.18
% of households with Self-owned dwelling	42.67	56.00	62.22	66.22	66.67	58.76
% of females in household	55.02	54.25	54.78	57.62	56.94	55.72
% of household with child	58.22	34.67	20.44	15.11	9.78	27.64
Members in age group (%)						
0|- 4	10.50	4.48	2.41	1.93	1.15	4.10
4|- 11	10.25	6.33	4.30	2.74	2.06	5.14
11|- 19	22.10	17.39	11.00	9.12	5.05	12.93
19|- 40	28.66	26.11	28.77	28.99	26.61	27.83
40|- 60	20.79	23.97	29.10	32.07	33.30	27.85
>= 60	7.70	21.72	24.41	25.14	31.84	22.16
Head of Households						
Age (years)	44.20	52.00	53.14	54.04	56.61	52.00
	(13.58)	(15.77)	(15.07)	(14.73)	(14.14)	(15.24)
% that are female	40.00	36.00	32.89	38.22	37.78	36.98
% that are married	62.22	63.11	65.78	61.33	56.00	61.69
% that are white	48.00	60.44	71.11	77.33	79.56	67.29
% that are black	13.33	9.33	8.00	4.44	2.67	7.56
% with elementary education	59.56	61.78	52.89	46.22	16.44	47.38
% with high school education	32.89	24.44	28.44	31.56	28.44	29.16
% with higher education	3.11	5.33	15.56	18.22	55.11	19.47

Standard Deviation in Parentheses

In comparison with the previous survey, the most recent one shows that the proportion of heads of households with only elementary education is lower (47% compared to 40%), and the proportion of heads of households that are married is also lower (62% compared to 55%).

Table 4.3: Summary Statistics according to per capita monthly income quintiles - POF-Fipe 2011-2013

Demographic and socioeconomic variables	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**	**Total**
	N = 398	N = 398	N = 398	N = 398	N = 398	N = 1988
Members per household	3.91	3.23	2.68	2.58	2.31	2.94
	(1.82)	(1.52)	(1.35)	(1.26)	(1.17)	(1.55)
Per capita monthly income (R$)	437.65	791.24	1172.98	1794.39	4760.42	1790.16
	(142.08)	(87.34)	(131.67)	(254.44)	(3750.11)	(2286.88)
% of households living in House	93.72	93.47	84.89	79.15	47.36	79.73
% of households with Self-owned dwelling	43.47	59.30	58.69	61.56	70.53	58.70
% of females in household	57.56	58.38	59.97	55.77	55.47	57.43
% of household with child	56.53	35.18	18.14	14.32	7.30	26.31
Members in age group (%)						
0|- 4	9.71	5.49	2.99	1.86	1.30	4.27
4|- 11	10.36	5.19	2.54	2.80	1.28	4.44
11|- 19	19.77	13.03	9.01	5.95	3.67	10.29
19|- 40	25.40	25.62	28.66	30.27	27.24	27.44
40|- 60	21.66	26.07	28.31	29.66	31.36	27.41
>= 60	13.10	24.61	28.50	29.46	35.16	26.16
Head of Households						
Age (years)	47.54	52.91	53.73	54.61	56.78	53.11
	(15.90)	(16.94)	(16.41)	(16.15)	(14.45)	(16.27)
% that are female	37.69	37.19	40.05	36.68	35.26	37.37
% that are married	59.80	58.04	53.15	53.02	49.12	54.63
% that are white	60.80	65.33	69.02	71.11	84.13	70.07
% that are black	11.06	8.04	6.55	8.04	4.53	7.65
% with elementary education	56.53	50.25	45.09	33.92	13.85	39.94
% with high school education	29.15	34.42	38.79	38.44	22.42	32.65
% with higher education	4.52	7.04	10.58	23.12	62.47	21.53

Standard Deviation in Parentheses

Figures 4.3 and 4.4 shows, respectively, the spatial pattern distribution of household income per capita in minimum wages and education of the head of household. Households with higher income and that with head with more years of education are concentrated in the central and western part of the city. The maps further indicate that in comparison with the previous survey, in the 2011-2013 survey, households are richer (especially in households with the lowest income) and are more educated (especially for the households with the lowest education).

Figure 4.3: Income distribution by minimum wage range

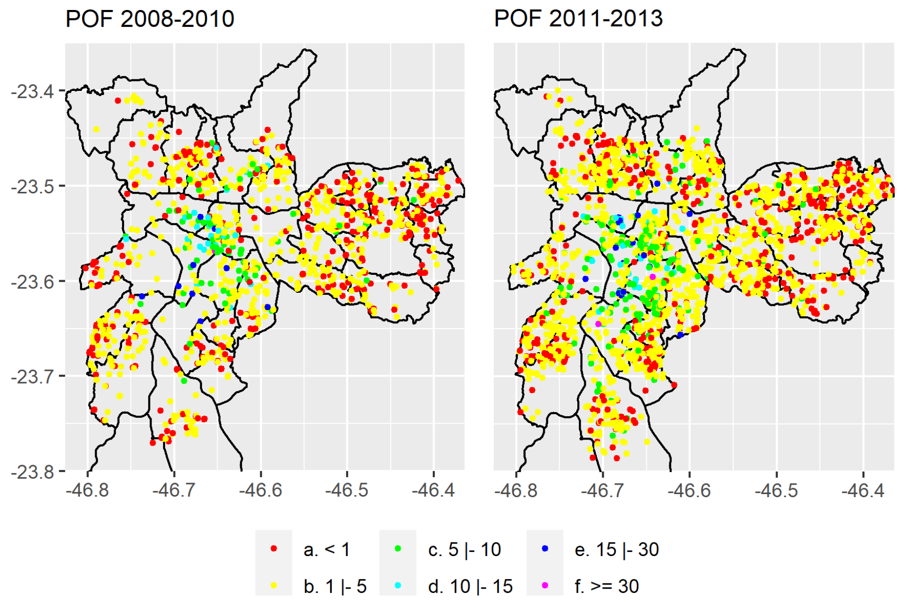
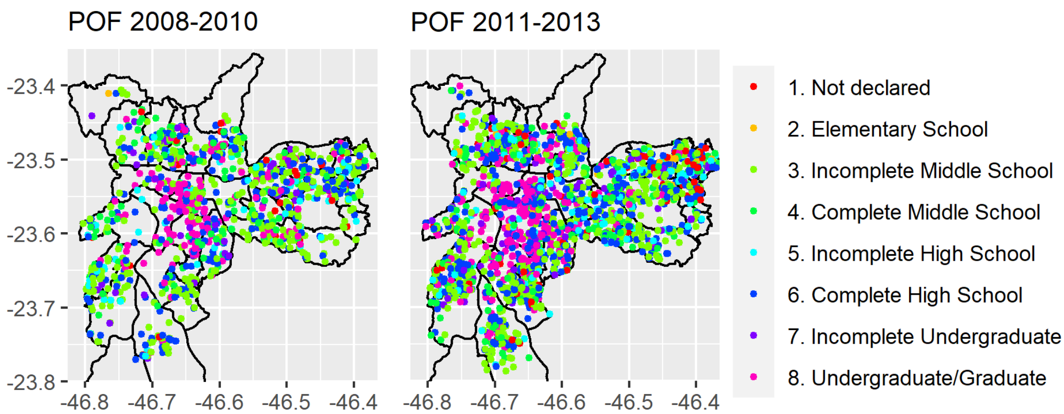


Figure 4.4: Education distribution



The following tables and figures present statistics for the expenditure behavior of households. Tables 4.4 and 4.5 shows the mean budget shares, the zero expenditure frequency, and the price index of each broad and food category, as well as the mean total expenditure. Figures 4.5 and 4.11 plots the budget shares of, respectively, broad categories and food groups for each survey sample. Figures 4.6, 4.7 and 4.12 presents the average expenditure share by household income. Finally, 4.8 presents the average expenditure share with broad categories by the age of the head of household.

Table 4.4: Summary Statistics on Expenditure - Broad Categories

Broad Categories	**POF 2008-2010**			**POF 2011-2013**		
	Share	Zero (%)	Price Index	Share	Zero (%)	Price Index
Habitation	33.34	0.36	286.50	31.54	0.10	274.69
	(17.04)		(6.41)	(14.32)		(12.79)
Food	24.25	3.11	28.80	26.45	0.00	47.72
	(12.07)		(34.87)	(11.85)		(11.86)
Transportation	12.23	14.84	197.03	11.31	12.68	114.15
	(11.99)		(13.72)	(9.73)		(6.32)
Personal Expenses	11.87	2.49	143.89	13.06	0.20	136.76
	(9.19)		(10.23)	(8.22)		(4.97)
Health	9.55	20.00	436.53	7.98	23.84	517.15
	(11.72)		(12.13)	(10.42)		(11.39)
Clothing	4.85	38.93	81.34	6.72	32.34	78.70
	(6.78)		(1.39)	(8.32)		(2.01)
Education	3.91	66.40	1087.05	2.94	70.12	1460.62
	(8.67)		(96.82)	(6.89)		(15.97)
Real Expenditure		638.21			673.29	
		(703.28)			(678.73)	
Total Expenditure		3191.98			3394.26	
		(3725.37)			(3549.61)	
Observations		1125			1988	

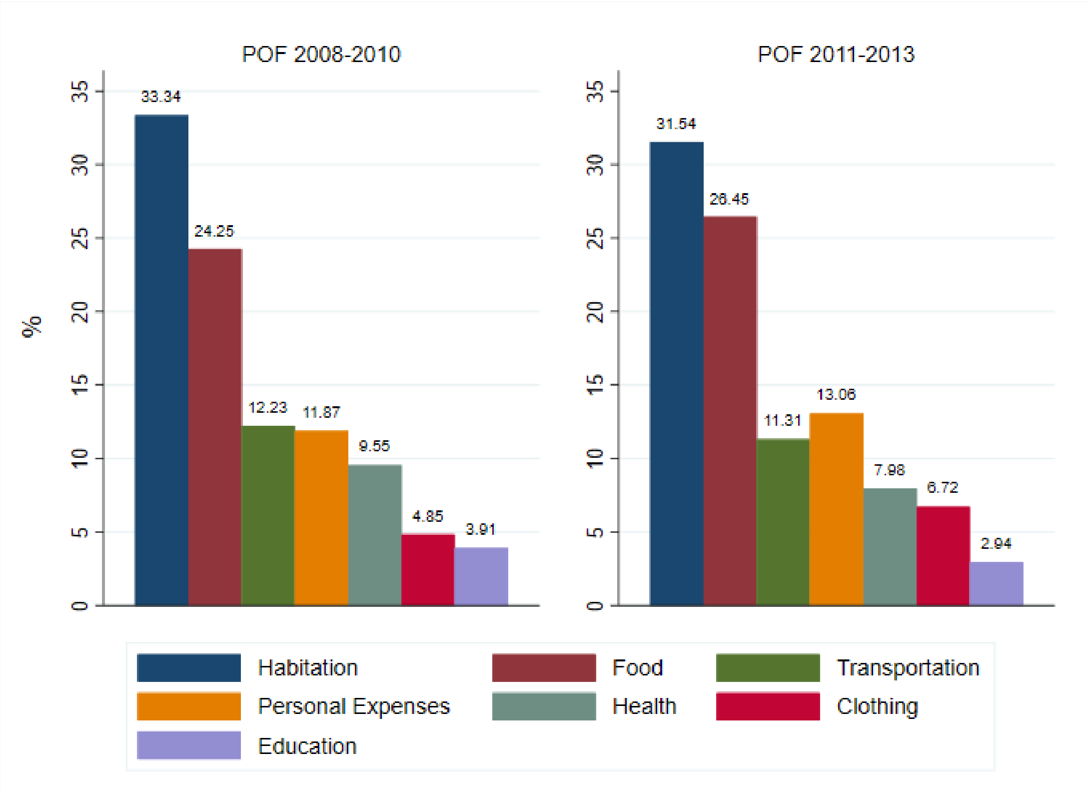
Standard Deviation in Parentheses

In the broad categories samples, Table 4.4 and Figure 4.5 shows that for both surveys, on average, the categories with the highest shares are Habitation (33.2% and 31.52%) and Food (24.25% and 28.45%), and the lowest are Clothing (4.85% and 6.72%) and Education (3.9% and 6.72%). Compared to the first survey, in POF 2011-2013, the mean expenditure share with Food, Personal Expenses, and Clothing are higher, whereas expenditure share with Habitation, Transportation, and Health are lower. The categories with the highest price index are Education and Health, while Food and Clothing had the lowest index. Budget share variations depend on the dynamics of demand and price, and the expenditure share variation between the two surveys is mainly related to changes in income and relative prices between the periods of the two POFs (Chagas et al., 2015).

Figures 4.6 and 4.7 show that expenditure with Habitation and Food has the highest shares for all income quintiles, being especially important for households of lower income. In all income quantiles except the fourth, expenditure share with Habitation was higher in the first survey. In all income quantiles expenditure share with Health and Education was higher in the first survey and expenditure share with Food and Clothing was higher in the second survey. In the 2011-2013 survey, the average expenditure share with Food was higher than the average expenditure share with Habitation for the first income quintile. As expected, the average expenditure share with Food decreases significantly as income increases, whereas shares with Health and Education increase with income.

Grouping households by minimum wage ranges reveals further heterogeneity in

Figure 4.5: Average expenditure share - Broad categories



expenditure patterns. In the 2008-2010 survey, households with incomes between 5 and 10 minimum wages and incomes between 15 and 30 minimum wages dedicated an average of more than 35% of their total expenditure with Habitation. In the same survey, Health was one of the categories with the highest budget share for households with incomes of more than 15 times the minimum wage. In the 2011-2013 survey, the last category represented an average of 25% of the budget of households with the highest wage range.

Expenditure with the Health category is also correlated with the age of the head of the household. Figure 4.8 shows that households headed by older individuals dedicated a greater proportion of their budget to Health for both samples. Expenditure share with Clothing and Transportation, in turn, were lower in households headed by older individuals. Compared with the 2008-2010 survey, the 2011-2013 survey indicates that households with the youngest heads expended on average less with Habitation, Transportation, Health, and Education and more with personal expenditure and clothing.

Figure 4.11 presents the spatial distribution of households budget shares with Food. The Food category's expenditure share seems lower for households located in the center and higher in households located farther from the center, where the poorest are concentrated. This is consistent with the negative correlation we have previously observed between income and expenditure share with Food. Again, in the POF 2011-2013, there was an increase in the expenditure share.

Figure 4.6: Average expenditure share by income - Broad categories POF 2008-2010

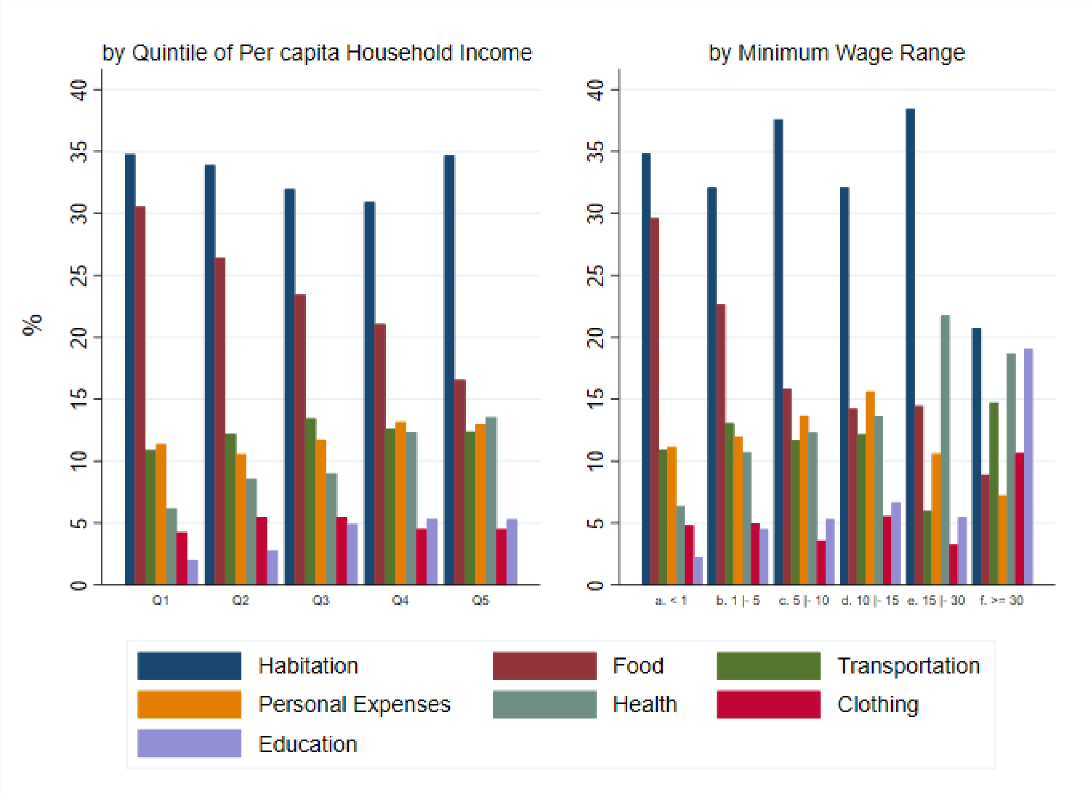


Figure 4.7: Average expenditure share by income - Broad categories POF 2011-2013

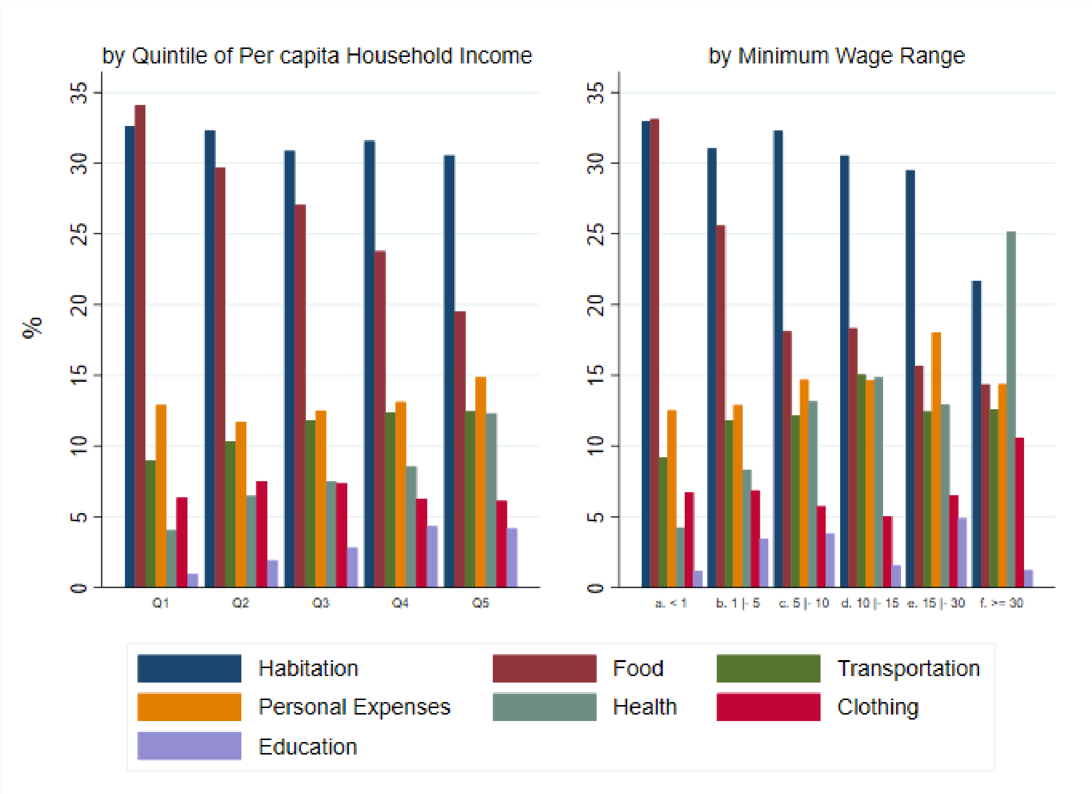


Figure 4.8: Average expenditure share by head of household's age - Broad categories

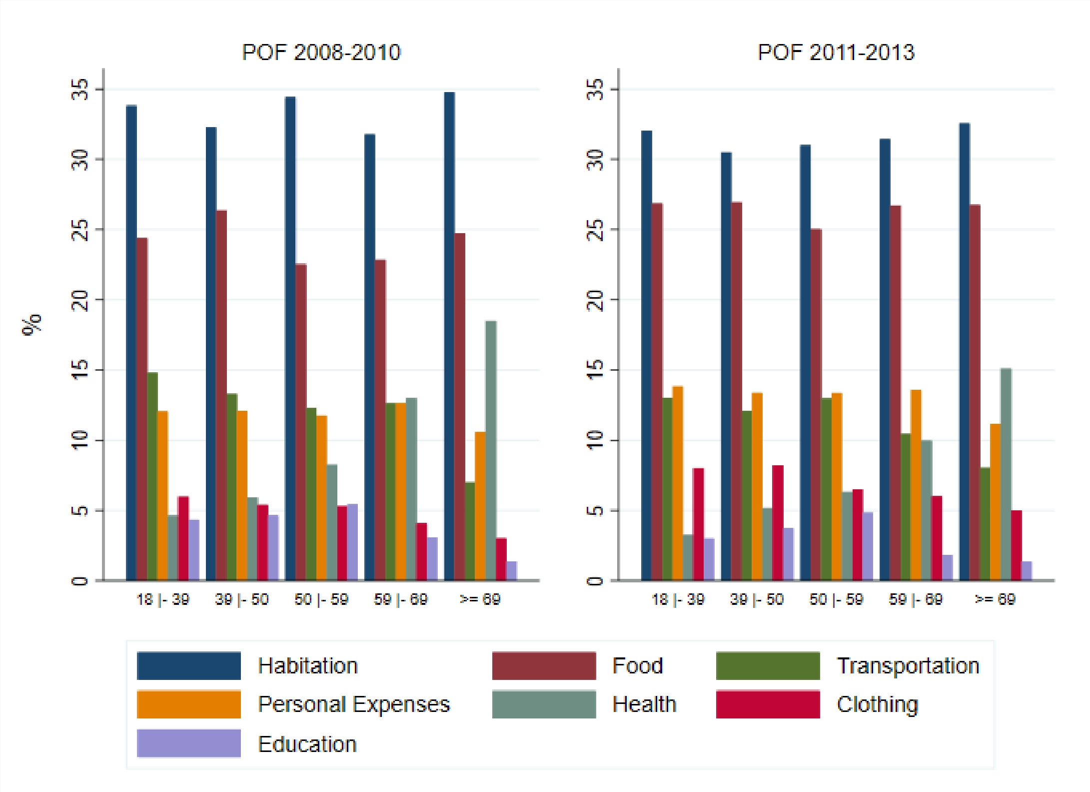
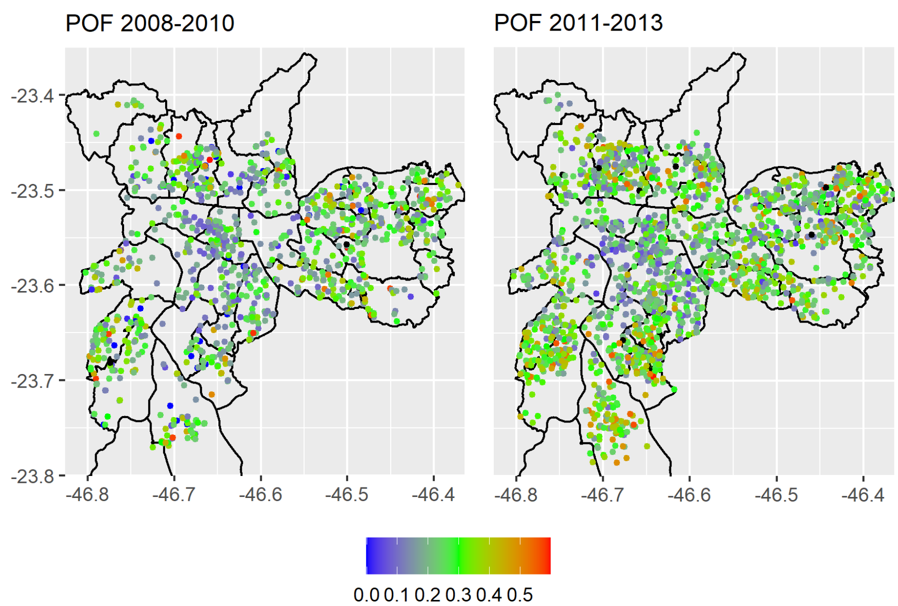
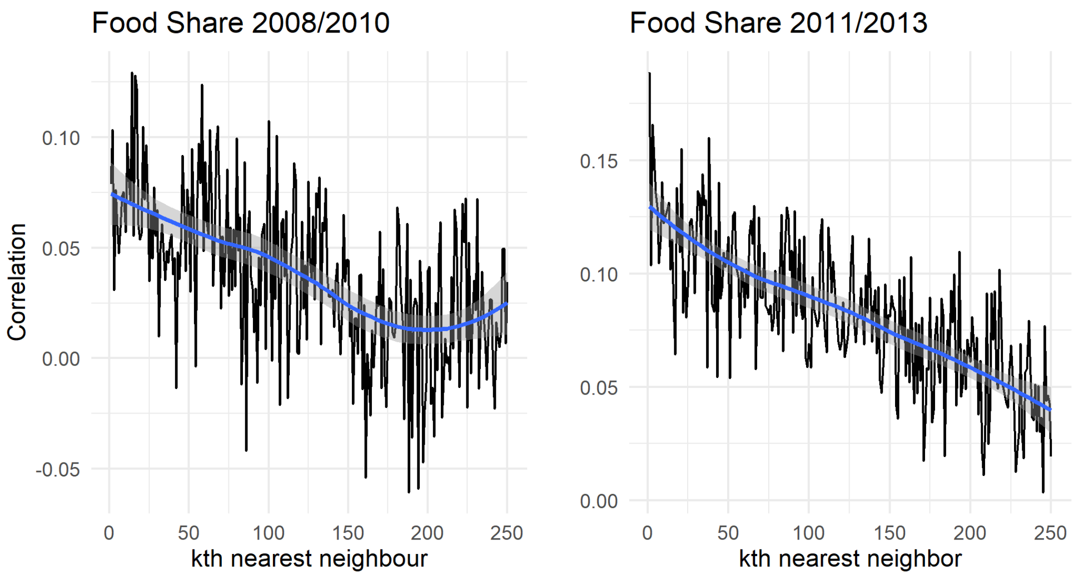


Figure 4.9: Food share distribution



To find evidence of potential spatial relation in expenditure composition, we estimated the spatial correlation between the expenditure share by category of each household and the expenditure share of the respective category of its neighbors. Figure 4.10 presents the correlations between budget shares with Food from the first to 250th neighbor. Among all

Figure 4.10: Correlation by kth nearest neighbor



categories, only the food category presented the highest correlations. Additionally, the similarity is highest for the nearest neighbor and decreases the further the neighbor is away.

Table 4.5 and Figure 4.11 present the average expenditure share with the food subcategories considered by our study. In both surveys, Meat and Fish and Flour products are the most relevant categories in budget share. These categories are followed by Sugar and Sweets and Vegetables for the 2008-2010 survey and by Vegetables and Fruits for the most recent survey. The lowest average shares are Poultry and eggs, Cereals, and Oils and fats. Foods groups Meat and fish, and Dairy Products are the most expensive on average, and the least expensive are the Vegetables, Fruits, and Cereals groups. Figure 4.12 presents the expenditure shares by household income quintiles. Meat is the most relevant category for all ranges of income. As income increase, Vegetables and Fruits categories gain importance, whereas Cereal loses importance.

Table 4.5: Summary Statistics on Expenditure - Food categories

Food Categories	**POF 2008-2010**			**POF 2011-2013**		
	Share	Zero (%)	Unit Value	Share	Zero (%)	Unit Value
Cereals	7.58	16.42	3.38	6.71	17.96	3.28
	(7.70)		(1.54)	(6.73)		(1.34)
Flour Products	15.58	2.78	8.13	14.39	2.29	8.99
	(11.49)		(4.43)	(9.80)		(5.68)
Vegetables	10.51	6.86	2.98	12.89	5.04	2.51
	(7.76)		(1.17)	(8.31)		(1.15)
Sugar and Sweets	11.23	6.68	8.84	10.25	7.07	9.69
	(8.83)		(5.11)	(8.34)		(5.10)
Fruits	9.91	10.30	3.16	11.50	6.56	3.64
	(9.93)		(1.21)	(9.52)		(1.06)
Meat and Fish	23.89	6.12	12.45	23.89	5.29	12.75
	(13.50)		(4.10)	(12.57)		(3.39)
Poultry and Eggs	7.38	12.62	4.71	7.45	12.01	5.08
	(6.19)		(1.56)	(6.03)		(2.02)
Dairy Products	11.14	10.48	12.91	9.88	12.16	14.30
	(10.19)		(7.33)	(9.11)		(13.41)
Oil and Fats	2.77	23.01	5.47	3.04	20.00	6.06
	(2.59)		(2.64)	(2.71)		(2.52)
Real Expenditure	216.63			234.63		
	(142.05)			(150.21)		
Total Expenditure	410.70			440.14		
	(299.11)			(304.54)		
Observations	1078			1965		

Standard Deviation in Parentheses

Figure 4.11: Average expenditure share - Food categories

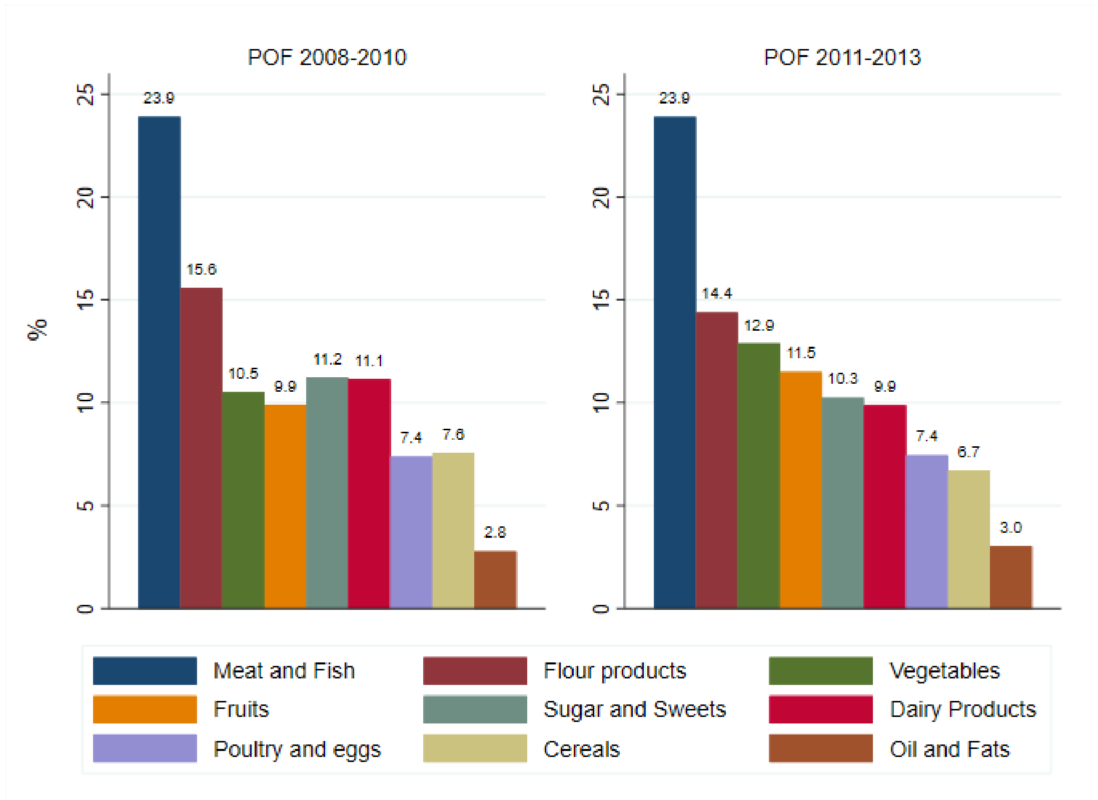
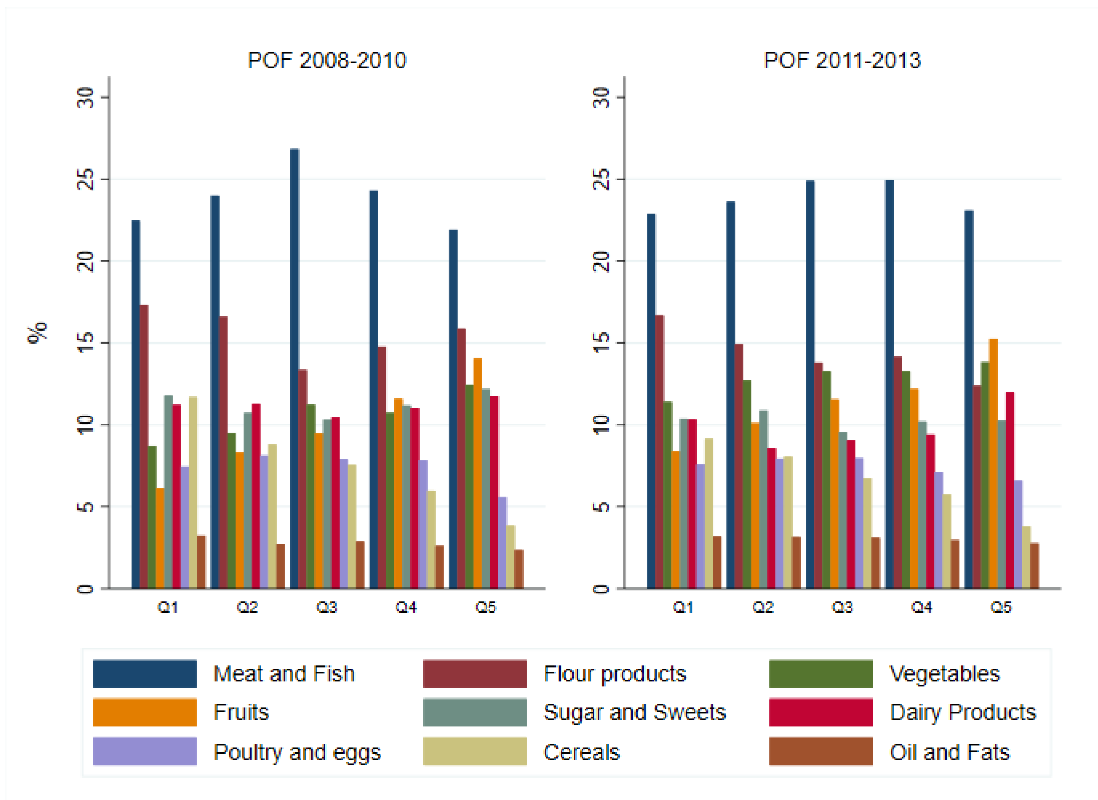


Figure 4.12: Average expenditure share by quintile of per capita household income - Food categories



4.2 Empirical Specification

A multi-stage budgeting framework is considered, which requires the assumption of weak separability between consumption decisions. In the first stage, each household decides how much of its total income will be allocated to each broad category: Habitation, Food, Transportation, Personal Expenses, Health, Clothing, and Education. In the second stage, households allocate the total food expenditure among different subcategories, namely, Cereals, Flour Products, Vegetables, Sugar and Sweets, Fruits, Meat and Fish, Poultry and Eggs, Dairy products, and Oil and Fats. A procedure to account for censoring is considered in both stages, and allocation decisions are jointly modeled in a system of demand equations that considers peer effects.

As shown in Tables 4.4 and 4.5 there is a significant number of missing observations for some group purchases. Zero expenditures incidence is common in fixed-duration[6] expenditure surveys and might occur due to several reasons. During the period when households are interviewed, the respondent might not have consumed the items because the household refrained from consuming the good (due to non-preference, non-affordability, infrequent purchases or sufficient inventory, or non-availability of the good), or even because of imperfect recalling.

Discarding zero expenditure observations or keeping them as zero in the demand system estimation regressions (in this case, the corner solution interpretation is implicitly assumed) without any adjustment for censoring would typically lead to biased parameter estimates. One popular approach to take into account the fact that the dependent variable is truncated and the sample is censored is the one proposed by Heien and Wesseils (1990)[7]. In this procedure, households first decide on consumption versus non-consumption and then decide on the budget share to spend on each category. This is a generalization of the Heckman two-step procedure with the difference that the Heckman's estimator is estimated on the subsample of positive consumption households only.

In the first stage, the probability that a given household would purchase the goods from the category i is determined using a Probit regression[8]

$$Z_{hi} = f(\mathbf{d_{hi}}, \mathbf{a_i})$$

where the variable Z_{ih} is a dichotomous variable that takes the value of 1 if the

[6] Compared to the Brazilian national expenditure survey, Fipe's survey has a more extended period of survey — 30 days (compared to 7 days of IBGE's POF) which in general is adequate to characterize households consumption pattern (Claro et al., 2007).

[7] Although the posterior work of Shonkwiler and Yen (1999) showed that the Heien and Wesseils method might present inconsistent estimators, the last remains popular in current applications due to the simplicity of its estimation. As a robustness test, the Shonkwiler and Yen method is considered.

[8] A model where the explained variable takes only two values and where the probabilities of an observation with particular characteristics belonging to each one of the two categories are estimated.

household h reports non-zero expenditures on category i, zero otherwise; $\mathbf{d_{hi}}$ represents the variables that affect market participation, including price and socioeconomic variables of household h; and $\mathbf{a_i}$ are the corresponding coefficients. The specific form of $f(\mathbf{d_{hi}}, \mathbf{a_i})$ for broad categories and food categories are respectively given by[9]

$$\begin{aligned} f_B(\mathbf{d_{hi}}, \mathbf{a_i}) = a_0 + a_1 HAge_h + a_2 HEduc_h + a_3 HWoman_h + a_4 Size_h + a_5 Child_h + \\ + a_6 Young_h + a_7 Adult_h + a_8 Income_h + a_9 Price_{hi} \end{aligned} \tag{4.6}$$

$$\begin{aligned} f_F(\mathbf{d_{hi}}, \mathbf{a_i}) = a_0 + a_1 HAge_h + a_2 HEduc_h + a_3 HWoman_h + a_4 Size_h + a_5 Child_h + \\ + a_6 Young_h + a_7 Adult_h + a_8 Eldery_h + a_9 Income_h + a_{10} Price_{hi} + \\ + \sum_{j=1}^{4} a_{10+j} Region_{jh} \end{aligned} \tag{4.7}$$

where $HAge_h$ is the age of the head of the household, $HEduc_h$ is the years of education of the head of the household, $HWoman_h$ is a dummy for a female head of the household, $Size_h$ is the number of members of the household, $Child_h$ is the number of children in the household (below 11 years old), $Young_h$ is the number of youngsters in the household (between 11 and 19 years old), $Adult_h$ is the number of adults in the household (above 20 years old for f_B and between 20 and 59 years old for f_F), $Eldery_h$ is the number of elder in the household (above 60 years old), $Income_h$ is the total income of the household; $Price_{hi}$ is the price of category i faced by household h; and $Region_{jh}$ are dummies for the location of the household (South, North, West, East, where Center was left out of the estimation).

From the first stage, using all available observations, I obtain estimates of the Inverse Mill's Ratio (R_{hi}) with the estimates of the standard normal cumulative distribution (Φ) and the standard normal probability density functions (ϕ) in the following way

$$\begin{cases} \hat{R}_{hi} = \dfrac{\phi\big(\hat{f}(d'_{hi}\hat{a}_i)\big)}{\Phi\big(\hat{f}(d'_{hi}\hat{a}_i)\big)} & \text{if} \quad Z_i = 1 \\ \hat{R}_{hi} = \dfrac{\phi\big(\hat{f}(d'_{hi}\hat{a}_i)\big)}{1 - \Phi\big(\hat{f}(d'_{hi}\hat{a}_i)\big)} & \text{if} \quad Z_i = 0 \end{cases} \tag{4.8}$$

In the second stage, the Inverse Mill's Ratio is used as an instrument to incorporate the censoring latent variable in the estimation of the share equations. Therefore, the final system of demand equations to be estimated take the form

[9] The specifications were defined considering traditional demand analysis (Lazaridis, 2003; Leifert and Lucinda, 2015) and restricted to variables with sufficient variability in the sample.

$$s_{hi} = \alpha_{i0} + \sum_{k}^{D} \alpha_{ik} x_{hk} + \lambda_i \sum_{l=1}^{N} w_{hl} s_{li} + \sum_{j}^{G} \gamma_{ij} \log p_j + \beta_i \log\left(\frac{y_h}{P^*}\right) + \Psi_i \hat{R}_{hi} \tag{4.9}$$

where $i, j = 1, ..., G$ are the categories available for consumption with $G = 7$ for the first-stage estimation (broad categories) and $G = 9$ for the second-stage estimation (food subcategories); $h, l = 1, ..., N$ are the households; $k = 1, ..., D$ are the demographic shifters; s_{hi} denote the household h's expenditure share of category i; p_i is the price of category i; w_l^h is the spatial weight of household l to household h; and α, β, γ^*, λ and Ψ_i are the parameters.

In practice, the non-linearity of the demand system that comes from the translog price index $\log P^*$ can be troublesome for the estimation. The parameter α_{i0} might not be identified when individual prices are closely collinear. Deaton and Muellbauer (1980a) proposed approximating the translog price index P^* by the Stone index; however, as discussed earlier, the Stone price index is not invariant to changes in the units of measurement. We use the log-linear analog of the Laspeyres price index as proposed by Moschini (1995):

$$\log P^* = \sum_{j}^{G} s_j^0 \log(p_j) \tag{4.10}$$

where s_{j0} indicates expenditure shares in a "base" period (at the sample mean values). The demographic shifters used in the demand system are described in the Table 4.6 below.

Table 4.6: Demographic shifters for the demand system estimation

Variables	Description	
Age	Age in years of the head of the household.	Continuous
Education	Education level of the head of the household.	Categorical
Gender	Dummy variable for gender of the head of the household.	Equal to 1 if head of household is female.
Size	Total number of members of the household.	Continuous
Nº of children	Number of household members below 10 years old.	Continuous
Nº of youngsters	Number of household members between 10 and 19 years old.	Continuous
Nº of adults	Number of household members between 20 and 59 years old.	Continuous
Nº of elders	Number of household members above 59 years old.	Continuous

Since the expenditure shares sum 1 in the equation systems for each household, one of the share equations must be dropped from the system to avoid the singularity problem of the variance and covariance matrices. We chose to drop the categories with the lowest expenditure share, namely, Education for the broad categories and Oil and Fats for the food sub-categories.

The restrictions of homogeneity and symmetry are imposed onto each system of equations, respectively:

$$\sum_{j}^{G} \gamma_{ij} = 0 \quad \forall i \quad \text{and} \quad \gamma_{ij} = \gamma_{ji} \quad \forall i, j$$

The addictivity property can recover the parameters associated with the excluded equation. The adding-up condition requires that

$$\sum_{i}^{G} \alpha_{i0} = 1, \quad \sum_{i}^{G} \gamma_{ij} = 0 \quad \forall j, \quad \sum_{i}^{G} \beta_i = 0,$$

$$\sum_{i}^{G} \alpha_{ik} = 0 \quad \forall k, \quad \sum_{i}^{G} \lambda_i = 0 \quad \text{and} \quad \sum_{i}^{G} \Psi_i = 0$$

Note that the additional restrictions $\sum_i^G \lambda_i = 0$ and $\sum_i^G \Psi_i = 0$ are imposed to enable identification of the system.

Elasticities

For the first-stage estimation, expenditure (η_b^e), uncompensated (ξ_{bc}^e) and compensated ($\xi_{bc}^{h,e}$) price elasticities specific to the direct, indirect, and total effects explained in the previous chapter are calculated respectively as

$$\eta_b^e = 1 + \frac{\beta_b^e}{s_b} \tag{4.11}$$

$$\xi_{bc}^e = \frac{\gamma_{bc}^e - \beta_b^e s_c}{s_b} - \delta_{bc} \tag{4.12}$$

$$\xi_{bc}^{h,e} = \xi_{bc}^e + s_c \eta_b^e \tag{4.13}$$

where $e = \{D, I, T\}$ represents the direct, indirect and total effects; $b, c = 1, ..., 7$ are the broad categories; β_b^e is the mean e effect of the real income in the category b equation; γ_{bc}^e is the mean e effect of the log price of category c in category b equation; and $\delta_{bc} = 1$ is the Kronecker delta that is equal to 1 for the own-price elasticity ($i = j$) and to 0 for the cross-price elasticity.

In the second stage, where food subcategories are considered, the conditional income and price-elasticities are estimated within-group and computed for a given amount spent on category F

$$\eta^e_{i|F} = 1 + \frac{\beta^e_i}{s_{i|F}} \tag{4.14}$$

$$\xi^e_{ij|F} = \frac{\gamma^e_{ij} - \beta^e_i s_{j|F}}{s_{i|F}} - \delta_{ij} \tag{4.15}$$

$$\xi^{h,e}_{ij} = \xi^e_{ij} + s_j \eta^e_i \tag{4.16}$$

where F denotes statistics from the first stage estimation for total food demand, and the share of the category i in the total expenditure within the Food group is given by

$$s_{i|F} = \frac{p_i q_i}{x_F}$$

Following Edgerton (1997), Menezes et al. (2008) and Pereda et al. (2019), the unconditional income and price elasticities for the subcategories of the Food group are given by

$$\eta^{un,e}_i = \left(\eta^e_{i|F}\right)\left(\eta^e_F\right) \tag{4.17}$$

$$\xi^{un,e}_{ij} = \xi^e_{ij} + s_{j|F}\left(\frac{1}{\eta^e_{i|F}} + \xi^e_F\right) \times \left(\eta^e_{i|F}\right)\left(\eta^e_{j|F}\right) + \left(s_F\right)\left(s_{j|F}\right)\left(\eta^e_F\right)\left(\eta^e_{i|F}\right) \times \left(\eta^e_{j|F} - 1\right)$$

$$\xi^{un,h,e}_{ij} = \xi^{h,e}_{ij} + \left(s_{j|F}\right)\left(\xi^{h,e}_F\right)\left(\eta^e_{i|F}\right)\left(\eta^e_{j|F}\right)$$

From a multistage budgeting perspective, a change in the price of one subcategory of food will not only directly affect the demand for other subcategories within the food category. However, it will also modify the price index for food and consequently the expenditure allocation to food and the other broad categories from the previous budgeting stage, which will cause additional indirect effects within the food category (Klonaris and Hallam, 2003).

4.3 Estimation and Identification

In the model considered, each spatial unit (household) decides, simultaneously, about its budget shares for each G category of commodities. Because equations can be correlated due to unobservable household-specific attributes that influence the consumption of all categories, rather than equation-by-equation, the demand equations are estimated as a system using the Seemingly Unrelated Regression (SUR from now on) method first introduced by Zellner (1962). In this model, contemporaneously correlated errors are accounted for, and the cross-equation parameter restriction can be imposed. The following SUR-SARAR model (Kelejian and Prucha (2004)) specification is considered.

$$
\begin{aligned}
\mathbf{s}_i &= \lambda_i \mathbf{W} \mathbf{s}_i + \mathbf{X}_i \beta_i + \mathbf{u}_i \\
\mathbf{u}_i &= \rho_i \mathbf{W} \mathbf{u}_i + \epsilon_i \qquad\qquad i = 1, ..., K
\end{aligned}
\tag{4.18}
$$

where $E[\epsilon_i] = 0$ and $E[\epsilon_i \epsilon_j'] = \sigma_{ij} \mathbf{I}_n$ for $i \neq j$. With $\mathbf{A}_i = \mathbf{I}_n - \lambda_i \mathbf{W}$ and $\mathbf{B}_i = \mathbf{I}_n - \rho_i \mathbf{W}$, equation X will be:

$$
\begin{aligned}
\mathbf{A}_i \mathbf{s}_i &= \mathbf{X}_i \beta_i + \mathbf{u}_i \\
\mathbf{B}_i \mathbf{u}_i &= \epsilon_i \qquad\qquad i = 1, ..., K
\end{aligned}
\tag{4.19}
$$

where $\mathbf{s}_i$, $\mathbf{u}_i$ and ϵ_i are $(N \times 1)$ vectors; $\mathbf{X}_i$ is a matrix of exogenous variables of order $(N \times D)$; β_i is a vector of parameters of order $(D \times 1)$; λ_i and ρ_i are two scalars; $\mathbf{I}_n$ is the identity matrix of order $(N \times N)$ and $\mathbf{W}$ is the weight matrix of the same order that captures the spatial interaction. The weighting matrix for the spatial lag of the endogenous variable is the same as the one for the spatial lag of the errors.

Using the matrix notation:

$$
\begin{aligned}
\mathbf{As} &= \mathbf{X}\beta + \mathbf{u} \\
\mathbf{Bu} &= \epsilon \qquad\qquad \epsilon \sim N(\mathbf{0}, \mathbf{\Omega}_\epsilon)
\end{aligned}
\tag{4.20}
$$

$$
\mathbf{s} = \begin{bmatrix} \mathbf{s_1} \\ \mathbf{s_2} \\ \vdots \\ \mathbf{s_K} \end{bmatrix}_{(KN \times 1)} = \begin{bmatrix} s_{11} & s_{12} & \cdots & s_{1N} & \cdots & s_{K1} & s_{K2} & \cdots & s_{KN} \end{bmatrix}^T
$$

$$
\mathbf{X} = \begin{bmatrix} \mathbf{X_1} \\ \mathbf{X_2} \\ \vdots \\ \mathbf{X_K} \end{bmatrix}_{(KN \times D)} \qquad \mathbf{X_K} = \begin{bmatrix} x_{K1} & 0 & \cdots & 0 \\ 0 & x_{K2} & & \\ \vdots & & \ddots & \vdots \\ 0 & \cdots & & x_{KN} \end{bmatrix}_{(N \times D)} \qquad \beta = \begin{bmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_K \end{bmatrix}_{(D \times 1)}
$$

$$
\mathbf{u} = \begin{bmatrix} \mathbf{u_1} \\ \mathbf{u_2} \\ \vdots \\ \mathbf{u_K} \end{bmatrix}_{(KN \times 1)} \qquad \epsilon = \begin{bmatrix} \epsilon_\mathbf{1} \\ \epsilon_\mathbf{2} \\ \vdots \\ \epsilon_\mathbf{K} \end{bmatrix}_{(KN \times 1)}
$$

where D is the total of exogenous variables (the same for each of the k equations); $\mathbf{A} = \mathbf{I_{KN}} - \mathbf{\Lambda} \otimes \mathbf{W}$ and $\mathbf{B} = \mathbf{I_{KN}} - \mathbf{\Upsilon} \otimes \mathbf{W}$ are $(KN \times KN)$ order matrices; $\mathbf{\Lambda}$ and $\mathbf{\Psi}$ are $(K \times K)$ diagonal matrices with parameters λ and ρ, respectively, in the main diagonal; $\otimes$ is the Kronecker product. The variance–covariance matrix of the error component are given by $\mathbf{\Omega}_\epsilon = \mathbf{\Sigma} \otimes \mathbf{I_N}$, where $\mathbf{\Sigma}$ is a $(K \times K)$ matrix which elements are σ_{ij}, where $i, j = 1, ..., K$.

Consequently, the variance-covariance matrix of **u** is given by: $\mathbf{\Omega}_u = \mathbf{B}^{-1}\mathbf{\Omega}_\epsilon(\mathbf{B}')^{-1} = \mathbf{B}^{-1}(\mathbf{\Sigma}\otimes \mathbf{I_N})(\mathbf{B}')^{-1}$.

The vector of parameters (β_i, $i = 1, ..., K$) and of spatial dependence (λ_i, ρ_i, $i = 1, ..., K$) are constant across individuals. As in López et al. (2014) following Kelejian and Prucha (2004), I consider the hypotheses: the elements on the main diagonal of the weighting matrix **W** are zero, the matrices $\mathbf{A_i}$ and $\mathbf{B_i}$ are non singular, and the row and column sums of the matrices **W**, $\mathbf{A_i^{-1}}$ and $\mathbf{B_i^{-1}}$ are uniformly bounded in absolute value; the matrix of exogenous variables, **X**, is of full column rank, and its elements are uniformly bounded in absolute value; the error terms $\epsilon_\mathbf{n} = [\epsilon_{n1}, ..., \epsilon_{nK}]$' for each n are i.i.d. with normal distribution with zero mean and a non singular variance–covariance matrix $\mathbf{\Sigma}$.

The Ordinary Least Square (OLS) estimator in models with spatial dependence is inconsistent due to the presence of the spatial lag. The estimation of Equation 4.18 will be carried out using the Maximum Likelihood (ML) approach. Based on a joint standard normal distribution for the error term $\mathbf{v} = \mathbf{\Omega}_u^{-\frac{1}{2}}\mathbf{u} = \mathbf{\Omega}_u^{-\frac{1}{2}}\mathbf{B}(\mathbf{Ay} - \mathbf{X}\beta)$, the log-likelihood function for the joint vector of observations **s** is given by[10]:

$$\log L = -\frac{KN}{2}\log(2\pi) - \frac{1}{2}\log(|\mathbf{\Omega}_u|) + \log|\mathbf{B}| + \log|\mathbf{A}| - \frac{1}{2}\mathbf{v}'\mathbf{v} \tag{4.21}$$

with

$$\mathbf{v}'\mathbf{v} = (\mathbf{As} - \mathbf{X}\beta)'\mathbf{B}'\mathbf{\Omega}_\epsilon^{-1}\mathbf{B}(\mathbf{As} - \mathbf{X}\beta) = (\mathbf{As} - \mathbf{X}\beta)'\mathbf{\Omega}_u^{-1}(\mathbf{As} - \mathbf{X}\beta) \tag{4.22}$$

The log-likelihood function can also be written as:

$$\begin{aligned}\log L = &- \frac{KN}{2}\log(2\pi) - \frac{N}{2}\log(|\Sigma|) + \sum_{i=1}^{K}\log|\mathbf{B}_i| + \sum_{i=1}^{K}\log|\mathbf{A}_i| \\ &- \frac{1}{2}(\mathbf{As} - \mathbf{X}\beta)'\mathbf{B}'(\mathbf{\Sigma}^{-1}\otimes\mathbf{I_N})(\mathbf{B})(\mathbf{As} - \mathbf{X}\beta)\end{aligned} \tag{4.23}$$

$$\log L = -\frac{KN}{2}\log(2\pi\sigma^2) + K\log|I_N - \lambda W| - \frac{1}{2\sigma^2}\sum_{i=1}^{K}\sum_{h=1}^{N}(s_{ih} - \lambda\sum_{l=1}^{N}w_{hl}s_{ih} - x_{ih}\beta - \mu_h)^2 \tag{4.24}$$

The third and fourth elements of the right side of the Equation 4.23 represents the Jacobian term that can be decomposed in terms of the eigenvalues of the spatial weights matrix to reduce its dimension and facilitate estimation: $\log|I_N - \lambda_i W| = \sum_i \log(1 - \omega_i)$.

Wang and Kockelman (2007) and Baltagi and Bresson (2011) use the following three-step numerical optimization method to solve the maximum likelihood estimators:

[10] From $\mathbf{v} = \mathbf{\Omega}_u^{-\frac{1}{2}}\mathbf{u} = \mathbf{\Omega}_u^{-\frac{1}{2}}\mathbf{B}(\mathbf{As} - \mathbf{X}\beta)$ we have $\mathbf{s} = \mathbf{A}^{-1}\mathbf{B}^{-1}\mathbf{\Omega}_u^{\frac{1}{2}}\mathbf{v} + \mathbf{A}^{-1}\mathbf{X}\beta$. Because $\mathbf{v} \sim N(\mathbf{0}, \mathbf{1})$, **s** will have the distribution $\mathbf{s} \sim N(\mathbf{0}, \mathbf{A}^{-1}\mathbf{B}^{-1}\mathbf{\Omega}_u[(\mathbf{A}^{-1}\mathbf{B}^{-1})']^{-1})$

1. β is estimated using a Generalized Least Squares Model (GLS), conditional on $\mathbf{\Omega}_u$, λ and ρ. I.e., the conditional likelihood $L(\beta|\lambda, \rho, \mathbf{\Omega}_u)$ is maximized.

2. Then $\mathbf{\Omega}_u$ can be estimated conditional on β, λ and ρ. That is, the conditional likelihood $L(\mathbf{\Omega}_u|\lambda, \rho, \beta)$ is maximized. This step together with the first are iterated until convergence (when the optimal $\mathbf{\Omega}_u$ and β are found conditional on λ and ρ).

3. The values of estimated $\mathbf{\Omega}_u$ and β values are substituted and the concentrated log-likelihood function is maximized over λ and ρ. I.e., the conditional likelihood $L(\lambda, \rho|\beta, \mathbf{\Omega}_u)$ is maximized. The estimated λ and ρ then re-enters the estimation of $\mathbf{\Omega}_u$ and β. I.e., the conditional likelihood $L(\beta, \mathbf{\Omega}_u|\lambda, \rho)$ is maximized. Both functions are iteratively maximized to find the complete MLE parameter.

The categories chosen to be the excluded equation from the demand system estimations were the ones with the smallest share of consumer's expenditure — Education for first-stage and Oils and Fats for the second-stage estimations. Their coefficients are recovered considering the Adding-up property.

Software

In terms of the practical computation of the model proposed, till now, there are no command packages available in the most commonly used statistical software (namely STATA, R, Python and MATLAB) that proposes to estimate specifically a spatial demand system. In the first two software mentioned, there are specific commands programmed for the AIDS estimation, although they do not incorporate methods to handle for censoring[11]. In the R software, Angulo et al. (2019) developed the `spsur` package for the estimation of Spatial Seemingly Unrelated Regression Models[12]. Previously, the same authors developed commands in MATLAB for the same purpose, although these codes are not fully integrated (López et al., 2014). Similarly, in the Python software, the `spsur` from the PySAL library allows for the Spatial SUR model estimation (Rey et al., 2021). In order to estimate the spatial demand system and calculate elasticities considering direct and indirect impacts, we programmed and implemented a procedure in MATLAB building on and adapting the codes of the Spatial SUR proposed by López et al. (2014), and Angulo et al. (2019).

Reference group definition

The reference group of each household is defined via the spatial weight matrix $\mathbf{W}$ structure. The weights of $\mathbf{W}$ measure the intensity of the relationship among pairs of spatial units. This matrix cannot be estimated in the context of spatial econometric applications, and

[11]For STATA, see the estimation procedure suggested by Poi (2008) and the `quaids` package by Poi (2012). For R, see the `micEconAids` package by Henningsen (2011).

[12]The `spsur` package is the first with utilities aimed to solve inference of spatial SUR models. Other R packages has focused separately either in the analysis of cross-sectional spatial data (`spdep`), panel spatial data (`spml`) or SUR models without considering spatial effects (`systemfit`).

we do not have further information on the social network of the households; therefore, **W** needs to be specified in advance. The k-nearest neighbors (KNN) method was chosen to construct it and select the k geographically nearest points for each unit as neighbors. That is, the elements w_{ij} of the matrix **W** are given by

$$w_{ij} = \begin{cases} 1 & \text{if household } j \text{ is one of the } k \text{ nearest households for } i \\ 0 & \text{otherwise} \end{cases} \tag{4.25}$$

In practice, a row-standardized version of the weight matrix $\mathbf{W^s}$ is used, whose element w^s_{ij} is given by

$$w^s_{ij} = \frac{w_{ij}}{\sum_j w_{ij}} \tag{4.26}$$

After normalization, all weights ranges between 0 and 1, the sum of each row of $\mathbf{W^s}$ is 1 and the sum of all weights is equal to the total number of spatial units $\left(\sum_i \sum_j w_{ij} = N\right)$. This weight standardization is a common procedure as it has several advantages. First, it simplifies the interpretation of the weight matrix, now $\sum_j w_{ij}x_j$ represents the average of variable x on all neighbors of unit i and w_{ij} can be interpreted as the fraction of spatial influence neighbor j has on neighbor i. Second, the row-standardized weights matrix ensures comparability between the spatial parameter in many spatial stochastic processes of different models, and $\mathbf{W^s}$ is also important for asymptotic properties of estimators and test statistics (Anselin and Bera, 1998).

There is no consensus in the literature of spatial econometrics on the influence of the definition of the weight matrix on results (Loonis and de Bellefon, 2018). Although numerical investigations have found that modeling results are usually robust to the choice of k (LeSage and Pace, 2014), we adopt Akaike's information criterion (AIC) for a less arbitrary choice. By comparing the AIC values of spatially lagged models using different orders of KNN, the order that presented the lowest value for each sample was chosen and used in the final estimations (Figure 4.13). Figure 4.14 shows the network layouts with $k = 5$ nearest neighbors. The average distance between neighbors is approximately 713 meters for the 2008-2010 sample and 543 meters for the 2011-2013 sample.

Figure 4.13: Akaike's information criterion (AIC) values of Spatial Lag Models by KNN order

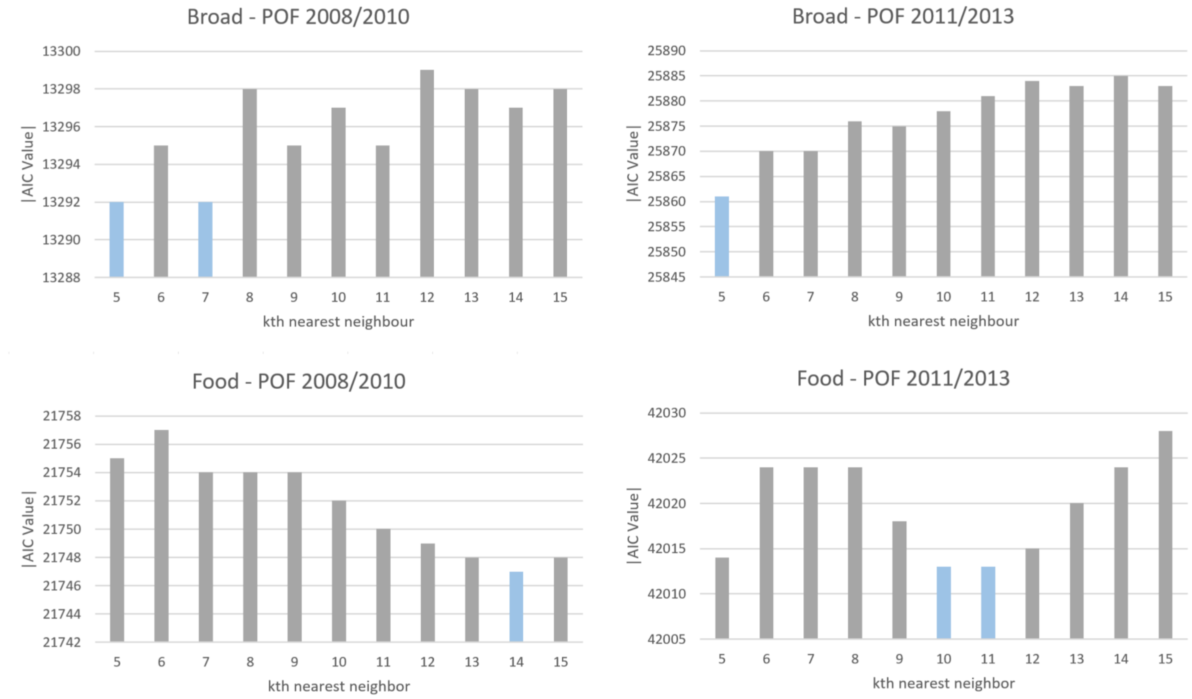
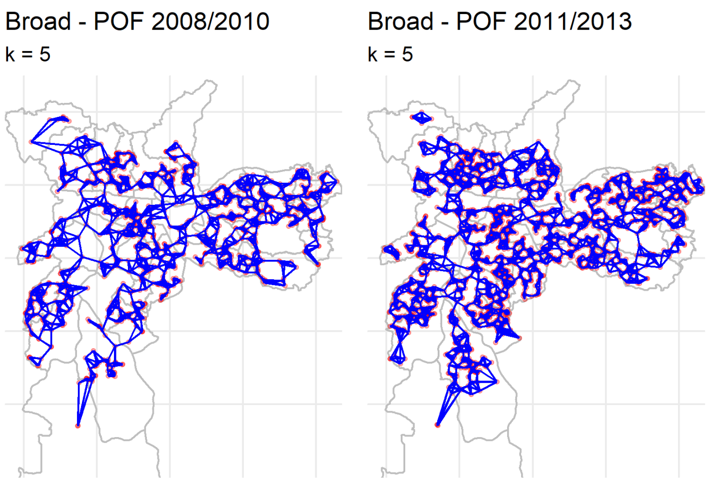


Figure 4.14: Network layout - Broad categories



5 RESULTS AND DISCUSSION

This chapter presents the results of the empirical investigation. We consider a two-stage budgeting system estimating a spatial demand system for broad categories in the first stage and a spatial demand system for food subcategories in the second stage. For each stage, the censoring problem is attended based on the Heien and Wesseils (1990) method as described in the previous chapter. We present and discuss first the estimation results by stage. Next, the expenditure and price elasticities for each estimation are analyzed. Lastly, results from robustness exercises for the importance of spatial effects are discussed.

5.1 First-stage results - Broad Categories

The first step of the estimation procedure consists of estimating equations using the probit model for each category to obtain Mill Ratios used in the demand system estimation. The statistical results of the probit analyses for the broad categories are presented in the Table A.1 found in the Appendix.

The probit results for broad categories show that all expenditure probabilities except for Food responses positively and with significance to an increase in income. An increase in the age of the head of household causes a decrease in the expenditure probability with Transportation and Clothing and an increase in the expenditure probability with Health. Households with female head have higher probabilities of spending with Health and Clothing.

The size of the household presents a significant and positive coefficient for Transportation and Education. In terms of household composition, households with a higher number of adults have a higher probability of expending on Transportation. In comparison, households with a higher number of elders present lower expenditure probability with Transportation, Clothing and Education and higher probability of expending with Health. The educational level of the head of households causes positive impacts in expenditure with Health and Education.

Now to the demand system estimation results. I estimated two demand systems for each sample period. The first is the traditional AIDS model without the spatial component, and the second is the spatial AIDS model described in the previous chapter. The parameter estimates of the coefficients obtained in the demand estimation are found, respectively, in Tables 5.1 and 5.3 for POF 2008-2010 and in Tables 5.2 and 5.4 for POF 2011-2013. The coefficient estimates of the variable $Mills$ were statistically significant in all equations except Habitation in both demand estimations and samples. This indicates that deleting the observations corresponding to zero expenditure levels would have introduced sample selection bias.

Concerning the socio-demographic shifters, some are found to have statistically significant impacts on the intercepts of the demand equations. In the 2008-2010 sample, the size of the household increases the expenditure share with Food and Transportation and reduces expenditure share with Health for both traditional and spatial demand systems. In the same sample, households with older heads spend smaller shares on Transportation and larger shares on Health. Furthermore, households with a higher number of children and youngsters increase the expenditure share with Food, while the higher the household head's level of education, the smaller the share spend on Food.

In the 2011-2013 sample, the size of the household increases the expenditure share with Food, Transportation, and Education and reduces the expenditure share with Habitation and Health. Households with a higher number of children and youngsters increase the expenditure share with Habitation and decrease the expenditure share with Transportation and personal expenses. The higher the household head's level of education, the smaller the share spend on Food and the larger the share expenditure on Health. Furthermore, for both samples, households with female heads spend smaller shares on Transportation.

The spatial lag in the spatial demand systems is significant only for the Personal Expenses and Education demand for the POF 2008-2010 sample and significant for all categories except for Transportation for the POF 2011-2013 sample. With exception to the Education variable, all coefficients indicate positive effects of neighbor's demand. The negative spatial effect for the Education demand occurs naturally as the adding-up restriction recovers it. This indicates that the results are not invariant to the choice for the excluded equation.

The average impact effects for food categories presented in Tables A.4, A.5 and A.6 for sample POF 2008-2010 and in Tables A.7, A.8 and A.9 for sample POF 2011-2013 are found in the Appendix. Besides the average direct, indirect and total multipliers for each coefficient an indirect a measure of statistical significance according to the randomization approach described in LeSage and Pace (2009) is presented. Over all, the impacts are small in magnitude. In the 2008-2013 sample, indirect effects are not significant at all for all categories except for Personal expenses and Education. To understand the importance of the impacts relative to the coefficients estimates, Table 5.10 presents summary statistics for the feedback and spillover impacts.

In the 2008-2010 sample, the highest relative feedback effect[1] is observed for the Education category with the feedback effects corresponding in average to 1.64% of the coefficients estimates. In the 2011-2013 sample, the highest relative feedback effect is observed for the Habitation demand (3.39%). The spillover is expressive for Education given the high and negative lag effect found for its demand. Disregarding the excluded equation, in the 2008-2010 sample, the spillover effect corresponds from 3.34% (Health) to 10.82% (Personal expenses) of the total effect, while in the 2011-2013 sample, the spillover effect corresponds from 4.04% (Transportation) to 9.9% (Clothing) of the total effect. Except for transportation and personal expenses, the relative importance of the spillover effect is higher for the most recent sample.

[1]Calculated as the ratio between the coefficient estimate subtracted from the direct effect and the coefficient estimate.

Table 5.1: Traditional AIDS Estimation - Broad Categories POF 2008/2010

	Habitation		**Food**		**Transportation**		**Personal Expenses**		**Health**		**Clothing**		**Education**	
Variable	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value
Constant	**0.564**	0.000	**0.532**	0.000	**0.126**	0.001	**0.128**	0.000	**0.075**	0.021	0.005	0.818	**-0.429**	0.000
Log Price Hab	**0.023**	0.000	**-0.005**	0.033	**-0.007**	0.004	-0.003	0.173	**-0.006**	0.000	-0.001	0.548	-0.001	0.477
Log Price Food	**-0.005**	0.033	0.002	0.367	0.001	0.682	-0.004	0.055	**-0.003**	0.040	**0.003**	0.028	**0.004**	0.010
Log Price Transp	**-0.007**	0.004	0.001	0.682	**0.015**	0.000	-0.001	0.699	-0.001	0.729	**-0.004**	0.049	**-0.004**	0.021
Log Price Personal	-0.003	0.173	-0.004	0.055	-0.001	0.699	**0.011**	0.000	0.000	0.843	-0.002	0.172	-0.002	0.158
Log Price Health	**-0.006**	0.000	**-0.003**	0.040	-0.001	0.729	0.000	0.843	**0.010**	0.000	-0.001	0.324	0.000	0.736
Log Price Cloth	-0.001	0.548	**0.003**	0.028	**-0.004**	0.049	-0.002	0.172	-0.001	0.324	**0.007**	0.004	**-0.003**	0.024
Log Price Educ	-0.001	0.477	**0.004**	0.010	**-0.004**	0.021	-0.002	0.158	0.000	0.736	**-0.003**	0.024	**0.006**	0.002
Log Real Expenditure	**-0.035**	0.000	**-0.039**	0.000	**0.013**	0.008	-0.004	0.241	-0.007	0.063	**0.013**	0.000	**0.060**	0.000
HH Age	0.001	0.130	0.000	0.514	**-0.001**	0.000	0.000	0.361	**0.001**	0.000	**0.000**	0.029	0.000	0.167
HH Comp. Elem	-0.011	0.661	**-0.040**	0.013	0.003	0.855	0.013	0.372	0.028	0.075	0.016	0.101	-0.009	0.568
HH Comp. Junior	0.013	0.650	**-0.049**	0.003	-0.003	0.866	0.014	0.351	0.032	0.053	0.006	0.575	-0.012	0.481
HH Comp. High	-0.008	0.764	**-0.053**	0.002	0.001	0.948	**0.031**	0.044	0.026	0.118	0.013	0.237	-0.010	0.571
HH Incomp. College	-0.017	0.613	**-0.071**	0.001	0.007	0.762	0.014	0.449	0.032	0.106	0.010	0.430	0.024	0.246
HH Comp. College	0.022	0.454	**-0.082**	0.000	-0.007	0.736	0.027	0.099	**0.042**	0.016	-0.004	0.721	0.002	0.902
HH Female	0.015	0.173	-0.010	0.134	**-0.021**	0.004	-0.001	0.870	0.008	0.203	0.001	0.757	0.008	0.230
H Size	-0.008	0.105	**0.007**	0.012	**0.011**	0.000	0.002	0.472	**-0.011**	0.000	-0.001	0.610	-0.001	0.685
H Total Child	-0.013	0.266	**0.018**	0.008	-0.011	0.149	-0.008	0.239	0.013	0.067	-0.002	0.724	0.002	0.778
H Total Youngster	0.001	0.923	**0.014**	0.002	**-0.019**	0.000	-0.006	0.178	0.003	0.588	0.003	0.298	0.004	0.360
H Total Adults	-0.009	0.383	0.003	0.597	0.007	0.296	0.008	0.145	**-0.021**	0.000	0.002	0.523	0.009	0.126
H Total Eldery	-0.010	0.312	0.009	0.133	-0.004	0.543	**-0.011**	0.039	**0.031**	0.000	-0.007	0.080	-0.008	0.178
Mills	-0.029	0.095	**-0.076**	0.000	**-0.022**	0.000	**-0.017**	0.004	**-0.040**	0.000	**-0.045**	0.000	**0.229**	0.000
Demographics	Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Mills	Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Observations	1119		1119		1119		1119		1119		1119		1119	
Log Likelihood	6824.61		6824.61		6824.61		6824.61		6824.61		6824.61		6824.61	

Coefficients in bold are significant with $p < 0.05$.

Table 5.2: Traditional AIDS Estimation - Broad Categories POF 2011/2013

	Habitation		**Food**		**Transportation**		**Personal Expenses**		**Health**		**Clothing**		**Education**	
Variable	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value
Constant	**0.362**	0.000	**0.646**	0.000	**0.072**	0.003	**0.085**	0.000	0.030	0.201	**0.093**	0.000	**-0.288**	0.000
Log Price Hab	**0.022**	0.000	**-0.008**	0.000	-0.003	0.083	0.000	0.987	**-0.007**	0.000	**-0.003**	0.013	-0.001	0.271
Log Price Food	**-0.008**	0.000	0.000	0.830	**0.003**	0.015	**-0.003**	0.006	**-0.003**	0.004	**0.004**	0.002	**0.007**	0.000
Log Price Transp	-0.003	0.083	**0.003**	0.015	**0.012**	0.000	**-0.004**	0.001	0.000	0.820	**-0.006**	0.000	**-0.003**	0.022
Log Price Personal	0.000	0.987	**-0.003**	0.006	**-0.004**	0.001	**0.009**	0.000	0.001	0.102	-0.002	0.134	-0.001	0.384
Log Price Health	**-0.007**	0.000	**-0.003**	0.004	0.000	0.820	0.001	0.102	**0.007**	0.000	-0.001	0.253	0.001	0.068
Log Price Cloth	**-0.003**	0.013	**0.004**	0.002	**-0.006**	0.000	-0.002	0.134	-0.001	0.253	**0.018**	0.000	**-0.009**	0.000
Log Price Educ	-0.001	0.271	**0.007**	0.000	**-0.003**	0.022	-0.001	0.384	0.001	0.068	**-0.009**	0.000	**0.006**	0.000
Log Real Expenditure	-0.003	0.564	**-0.061**	0.000	**0.012**	0.001	**0.010**	0.003	-0.002	0.471	**0.007**	0.019	**0.038**	0.000
HH Age	0.000	0.464	0.000	0.378	0.000	0.172	**-0.001**	0.001	**0.001**	0.000	**-0.001**	0.000	0.000	0.071
HH Comp. Elem	0.019	0.195	-0.011	0.329	-0.007	0.482	0.006	0.473	**0.018**	0.045	-0.007	0.389	**-0.019**	0.028
HH Comp. Junior	0.020	0.204	**-0.032**	0.008	0.003	0.790	0.005	0.556	0.016	0.104	0.004	0.652	-0.016	0.059
HH Comp. High	0.005	0.755	**-0.035**	0.002	0.016	0.109	0.001	0.945	**0.024**	0.015	-0.007	0.446	-0.004	0.667
HH Incomp. College	0.023	0.243	**-0.067**	0.000	-0.003	0.841	-0.009	0.413	**0.029**	0.019	-0.013	0.228	**0.041**	0.000
HH Comp. College	0.007	0.678	**-0.043**	0.001	0.002	0.891	0.014	0.177	**0.039**	0.000	**-0.030**	0.002	0.011	0.198
HH Female	0.009	0.179	-0.003	0.589	**-0.019**	0.000	0.004	0.291	0.007	0.111	0.004	0.319	-0.003	0.498
H Size	**-0.021**	0.000	**0.014**	0.000	**0.009**	0.000	0.004	0.073	**-0.007**	0.000	-0.002	0.277	**0.004**	0.017
H Total Child	**0.026**	0.001	-0.001	0.875	**-0.019**	0.000	**-0.012**	0.012	0.008	0.124	0.000	0.938	-0.002	0.588
H Total Youngster	**0.013**	0.015	0.004	0.303	**-0.013**	0.000	**-0.010**	0.002	0.004	0.241	0.003	0.323	-0.001	0.665
H Total Adults	**-0.014**	0.027	-0.003	0.592	0.006	0.187	0.007	0.053	**-0.015**	0.000	**0.007**	0.045	**0.011**	0.001
H Total Eldery	0.002	0.710	**0.012**	0.021	**-0.015**	0.000	-0.002	0.685	**0.024**	0.000	0.000	0.961	**-0.022**	0.000
Mills	-0.032	0.121	**0.669**	0.000	**-0.030**	0.000	**-0.034**	0.003	**-0.039**	0.000	**-0.043**	0.000	**-0.491**	0.005
Demographics	Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Mills	Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Observations	1985		1985		1985		1985		1985		1985		1985	
Log Likelihood	13210.73		13210.73		13210.73		13210.73		13210.73		13210.73		13210.73	

Coefficients in bold are significant with $p < 0.05$.

Table 5.3: Spatial AIDS Estimation - Broad Categories POF 2008/2010

	Habitation		**Food**		**Transportation**		**Personal Expenses**		**Health**		**Clothing**		**Education**	
Variable	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value
Constant	**0.552**	0.000	**0.498**	0.000	**0.109**	0.008	**0.116**	0.001	0.058	0.089	-0.006	0.775	**-0.327**	0.000
Log Price Hab	**0.022**	0.000	-0.004	0.061	**-0.007**	0.014	-0.003	0.145	**-0.006**	0.001	-0.001	0.613	-0.001	0.520
Log Price Food	-0.004	0.061	0.003	0.318	0.001	0.744	-0.003	0.081	**-0.003**	0.048	**0.003**	0.048	**0.004**	0.024
Log Price Transp	**-0.007**	0.014	0.001	0.744	**0.015**	0.000	-0.001	0.738	0.000	0.793	-0.003	0.071	**-0.004**	0.020
Log Price Personal	-0.003	0.145	-0.003	0.081	-0.001	0.738	**0.011**	0.000	0.000	0.827	-0.002	0.218	-0.002	0.229
Log Price Health	**-0.006**	0.001	**-0.003**	0.048	0.000	0.793	0.000	0.827	**0.010**	0.000	-0.001	0.330	0.001	0.643
Log Price Cloth	-0.001	0.613	**0.003**	0.048	-0.003	0.071	-0.002	0.218	-0.001	0.330	**0.007**	0.009	**-0.003**	0.022
Log Price Educ	-0.001	0.520	**0.004**	0.024	**-0.004**	0.020	-0.002	0.229	0.001	0.643	**-0.003**	0.022	**0.006**	0.002
Log Real Expenditure	**-0.034**	0.000	**-0.036**	0.000	**0.014**	0.008	-0.005	0.244	-0.006	0.130	**0.014**	0.000	**0.054**	0.000
HH Age	0.001	0.154	0.000	0.549	**-0.001**	0.000	0.000	0.423	**0.002**	0.000	**0.000**	0.045	0.000	0.161
HH Comp. Elem	-0.012	0.660	**-0.040**	0.024	0.003	0.865	0.013	0.394	0.028	0.089	0.016	0.130	-0.008	0.565
HH Comp. Junior	0.012	0.666	**-0.050**	0.009	-0.003	0.866	0.014	0.379	0.032	0.067	0.006	0.592	-0.011	0.474
HH Comp. High	-0.009	0.754	**-0.053**	0.006	0.002	0.938	0.030	0.063	0.026	0.134	0.012	0.262	-0.008	0.582
HH Incomp. College	-0.017	0.610	**-0.072**	0.003	0.007	0.769	0.013	0.491	0.032	0.127	0.010	0.465	0.027	0.161
HH Comp. College	0.021	0.476	**-0.083**	0.000	-0.006	0.761	0.025	0.135	**0.043**	0.025	-0.004	0.735	0.004	0.824
HH Female	0.015	0.189	-0.009	0.189	**-0.021**	0.010	-0.001	0.847	0.008	0.218	0.001	0.737	0.007	0.250
H Size	-0.008	0.124	**0.007**	0.034	**0.011**	0.002	0.002	0.463	**-0.011**	0.001	-0.001	0.616	-0.001	0.832
H Total Child	-0.013	0.281	**0.019**	0.017	-0.011	0.166	-0.009	0.192	0.013	0.080	-0.002	0.719	0.003	0.647
H Total Youngster	0.001	0.931	**0.014**	0.007	**-0.019**	0.002	-0.006	0.197	0.003	0.575	0.003	0.328	0.004	0.316
H Total Adults	-0.009	0.395	0.003	0.620	0.007	0.290	0.008	0.170	**-0.021**	0.002	0.002	0.576	0.009	0.101
H Total Eldery	-0.010	0.328	0.009	0.152	-0.004	0.544	-0.011	0.054	**0.032**	0.000	-0.007	0.084	-0.009	0.119
Mills	-0.023	0.162	**-0.068**	0.000	**-0.017**	0.003	**-0.015**	0.012	**-0.032**	0.000	**-0.040**	0.000	**0.195**	0.000
λ_{slm}	0.038	0.248	0.064	0.065	0.063	0.095	**0.109**	0.010	0.032	0.362	0.065	0.136	**-0.371**	0.003
Demographics	Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Mills	Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Observations	1119		1119		1119		1119		1119		1119		1119	
Log Likelihood	-6840.96		-6840.96		-6840.96		-6840.96		-6840.96		-6840.96		-6840.96	

Coefficients in bold are significant with $p < 0.05$.

Table 5.4: Spatial AIDS Estimation - Broad Categories POF 2011/2013

	Habitation		**Food**		**Transportation**		**Personal Expenses**		**Health**		**Clothing**		**Education**	
Variable	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value
Constant	**0.342**	0.000	**0.619**	0.000	**0.065**	0.016	**0.076**	0.002	0.026	0.278	**0.077**	0.002	**-0.205**	0.000
Log Price Hab	**0.022**	0.000	**-0.008**	0.000	-0.003	0.104	0.000	0.942	**-0.007**	0.000	**-0.003**	0.027	-0.001	0.298
Log Price Food	**-0.008**	0.000	0.001	0.702	**0.003**	0.026	**-0.003**	0.012	**-0.003**	0.006	**0.004**	0.006	**0.007**	0.000
Log Price Transp	-0.003	0.104	**0.003**	0.026	**0.012**	0.000	**-0.004**	0.005	0.000	0.804	**-0.006**	0.001	**-0.003**	0.030
Log Price Personal	0.000	0.942	**-0.003**	0.012	**-0.004**	0.005	**0.009**	0.000	0.001	0.114	-0.002	0.175	-0.001	0.365
Log Price Health	**-0.007**	0.000	**-0.003**	0.006	0.000	0.804	0.001	0.114	**0.008**	0.000	-0.001	0.235	0.001	0.058
Log Price Cloth	**-0.003**	0.027	**0.004**	0.006	**-0.006**	0.001	-0.002	0.175	-0.001	0.235	**0.017**	0.000	**-0.009**	0.000
Log Price Educ	-0.001	0.298	**0.007**	0.000	**-0.003**	0.030	-0.001	0.365	0.001	0.058	**-0.009**	0.000	**0.006**	0.000
Log Real Expenditure	-0.004	0.514	**-0.060**	0.000	**0.012**	0.002	**0.009**	0.007	-0.003	0.395	**0.008**	0.017	**0.037**	0.000
HH Age	0.000	0.534	0.000	0.496	0.000	0.184	**-0.001**	0.003	**0.001**	0.000	**-0.001**	0.000	0.000	0.099
HH Comp. Elem	0.018	0.225	-0.012	0.318	-0.007	0.492	0.006	0.520	0.018	0.061	-0.006	0.477	**-0.018**	0.041
HH Comp. Junior	0.019	0.244	**-0.031**	0.014	0.003	0.788	0.006	0.552	0.015	0.140	0.005	0.588	-0.015	0.075
HH Comp. High	0.003	0.848	**-0.034**	0.007	0.016	0.122	0.000	0.963	**0.023**	0.028	-0.005	0.541	-0.003	0.693
HH Incomp. College	0.021	0.301	**-0.064**	0.000	-0.003	0.850	-0.010	0.382	**0.028**	0.036	-0.012	0.304	**0.040**	0.001
HH Comp. College	0.005	0.761	**-0.039**	0.005	0.002	0.885	0.013	0.218	**0.036**	0.003	**-0.028**	0.008	0.011	0.216
HH Female	0.009	0.202	-0.003	0.573	**-0.019**	0.000	0.004	0.329	0.007	0.135	0.004	0.289	-0.002	0.547
H Size	**-0.020**	0.000	**0.013**	0.000	**0.009**	0.000	0.004	0.080	**-0.007**	0.002	-0.002	0.268	**0.004**	0.021
H Total Child	**0.026**	0.003	-0.001	0.935	**-0.020**	0.001	**-0.012**	0.019	0.008	0.134	0.000	0.956	-0.003	0.541
H Total Youngster	**0.013**	0.026	0.004	0.300	**-0.013**	0.001	**-0.010**	0.005	0.004	0.277	0.003	0.319	-0.001	0.711
H Total Adults	**-0.014**	0.037	-0.003	0.606	0.006	0.194	0.007	0.064	**-0.015**	0.002	0.007	0.052	**0.011**	0.003
H Total Eldery	0.003	0.679	**0.011**	0.037	**-0.015**	0.002	-0.002	0.638	**0.024**	0.000	0.000	0.920	**-0.021**	0.000
Mills	-0.031	0.141	**0.622**	0.002	**-0.029**	0.000	**-0.032**	0.008	**-0.037**	0.000	**-0.040**	0.000	**-0.453**	0.015
λ_{slm}	**0.080**	0.001	**0.081**	0.001	0.040	0.145	**0.075**	0.015	**0.086**	0.002	**0.101**	0.001	**-0.462**	0.000
Demographics	Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Mills	Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Observations	1985		1985		1985		1985		1985		1985		1985	
Log Likelihood	-13224.47		-13224.47		-13224.47		-13224.47		-13224.47		-13224.47		-13224.47	

Coefficients in bold are significant with $p < 0.05$.

Table 5.5: Average feedback and spillover effects - Broad Categories

	Habitation	Food	Transp.	Personal Exp.	Health	Clothing	Education
Feedback relative to coefficient estimate							
POF 2008-2010	0.90%	0.08%	0.04%	0.83%	1.35%	0.69%	1.64%
POF 2011-2013	3.39%	0.83%	1.80%	1.54%	1.75%	4.01%	0.37%
Spillover relative to total impact							
POF 2008-2010	4.00%	6.33%	6.39%	10.82%	3.34%	6.53%	59.03%
POF 2011-2013	7.91%	8.08%	4.04%	7.17%	8.59%	9.90%	84.54%

Percentages are in absolute value.

5.2 Second-stage results - Food Categories

As in the first-stage estimation, the first step consisted of estimating equations using the probit model for each subcategory. The probit results for the food categories are presented in the Tables A.2 and A.3 found in the Appendix.

The results reveal that an increase in income causes an increase in Fruits and Poultry and eggs in the POF 2008-2010 sample and an increase in all categories expenditure probability except for Cereal, Flour products, and Vegetables in the most recent sample. The age of the head of household causes an increase in Fruits expenditure probability for both samples and causes an increase in Dairy products and a decrease in Flour Products expenditure probabilities for the last sample. In the POF 2008-2010 sample, education level shows to be positively relevant for expenditure with Dairy Products. In the last sample, households with head of households with complete college education decrease the expenditure probability with Meat and Fish and Poultry and egg. Bigger households increase the purchase probability of Flour products, Poultry and egg, and Oil and Fats in the first sample and increase the purchase probability of Vegetables, Sugar and Sweets, Poultry and egg, and Dairy products in the last sample.

In terms of household composition, in the first sample, a higher number of youngsters increase the probability of purchasing Sugar and Sweets, while a higher number of elders increase the probability of purchasing Oil and Fats. In the POF 2011-2013, households with a higher number of adults have a lower probability of purchasing Fruits, while households with a higher number of elders tend to purchase fewer Sugar and Sweets and Dairy products. In the POF 2011-2013, female head of household has a positive effect on the purchase of Vegetables which is consistent with the expectation that women have greater concern with health issues than men. The geographic location of households plays a relevant role in Vegetable and Poultry and egg expenditures for the first sample and all categories except for Cereals and Poultry and egg in the last sample. There seem to be specific zone differences in consumption concerning the default zone (Center).

Education level shows to be positively relevant for expenditure with Dairy Products for the first sample and households with heads with complete college education decreases the expenditure probability with Meat and Fish and Poultry and egg in the last sample. Female head of household has a positive effect on expenditure with Vegetables in the 2011-2013 sample. In the 2008-2010 sample, the size of the household presents a significant and positive coefficient on the expenditure probability on Flour products, Poultry and egg, and oil and fats. In the 2011-2013 sample, household size increases the expenditure probability on Vegetables, Sugar and sweets, Poultry and egg, and Dairy products.

Now to the demand estimation results, as in the first stage of the two-staged budget model, we estimated the traditional AIDS model without the spatial component and the spatial AIDS model for each sample period. The parameter estimates of the coefficients obtained in the demand estimation are found, respectively, in Tables 5.6 and 5.8 for POF 2008-2010 and in Tables 5.7 and 5.9 for POF 2011-2013. The $Mills$ coefficient for the censoring term is significant at the 5% level for all food groups in the traditional demand system for both samples and loses significance for some categories in the spatial demand systems suggesting that accounting for censoring is relevant.

The socio-demographic variables in the demand model estimation are found to have statistically significant impacts on the intercepts of some of the food categories. In the 2008-2010 sample, the size of the household increases the expenditure share with cereals, flour products and reduces expenditure share with Vegetables, Fruits, and Poultry and eggs. In the same sample, households with older heads spend smaller shares on cereals and larger shares on fruits, and a higher number of children in the households reduce expenditure shares on Cereals, Meat and fish and increases expenditure shares on Sugar and sweets and Dairy products. Furthermore, the higher the level of education of the household head, the smaller the share spend on Cereals and Poultry and eggs.

In the 2011-2013 sample, the size of the household increases the expenditure share with Flour products and reduces expenditure share with Fruits, and households with older heads spend smaller shares on cereals and larger shares on fruits and on vegetables. Furthermore, the higher the level of education of the household head, the smaller the share spend on Cereals and Meat and fish, and the more significant share spend on fruits and dairy products. For both samples, households with female heads spend larger shares on vegetables and smaller shares on meat and fish.

The spatial lag in the spatial demand systems is significant for all categories except for Poultry and eggs in the POF 2008-2010 sample. All coefficients indicate a positive influence of neighbor's demand except the Oils and Fats variable. The negative spatial effect for the excluded equation occurs naturally as the adding-up restriction recovers it. Again, this may indicate that the results are not invariant to the choice for the excluded equation.

The average impact effects for food categories presented in Tables A.10, A.11 and

A.12 for sample POF 2008-2010 and in Tables A.13, A.14 and A.15 for sample POF 2011-2013 are found in the Appendix. Over all, the impacts are small in magnitude. In the 2008-2010 sample, indirect impacts are not significant for the poultry and eggs demand. To understand the importance of the impacts relative to the coefficients estimates, Table 5.10 shows summary statistics for the feedback and spillover impacts.

In the 2008-2010 sample, the highest relative feedback effect is observed for the Poultry and eggs demand, where the feedback effects correspond in average to 6.37% of the coefficients estimates. In the 2011-2013 sample, the highest relative feedback effect is observed for the Cereals demand (6.37%). The spillover is expressive given the high and negative lag effect found for the Oil and fats demand. Disregarding the excluded equation, in the 2008-2010 sample, the spillover effect corresponds from 4.27% (Poultry and eggs) to 8.75% (Cereals) of the total effect, while in the 2011-2013 sample, the spillover effect corresponds from 4.73% (Poultry and eggs) to 10.56% (Fruits) of the total effect. Except for Cereals and Flour products, the relative importance of the spillover effect is higher for the most recent sample.

Table 5.6: Traditional AIDS Estimation - Food Categories POF 2008/2010

	Cereals		**Flour Products**		**Vegetables**		**Sugar and Sweets**		**Fruits**		**Meat and Fish**		**Poultry and Eggs**		**Dairy products**		**Oil and Fats**	
Variable	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value
Constant	**0.275**	0.000	**0.324**	0.000	**0.097**	0.000	**0.107**	0.000	**0.200**	0.000	0.052	0.206	**0.166**	0.000	**0.183**	0.000	**-0.404**	0.000
Log Price Cereals	**0.016**	0.025	-0.001	0.891	**0.010**	0.031	**-0.021**	0.000	-0.003	0.458	0.000	0.969	0.003	0.388	0.004	0.371	-0.009	0.089
Log Price Flour	-0.001	0.891	0.014	0.159	0.007	0.213	0.006	0.301	-0.002	0.694	**-0.018**	0.043	-0.001	0.896	0.000	0.983	-0.005	0.447
Log Price Vegetables	**0.010**	0.031	0.007	0.213	-0.009	0.167	-0.007	0.076	0.003	0.386	-0.009	0.183	-0.006	0.098	0.007	0.157	0.004	0.426
Log Price Sugar	**-0.021**	0.000	0.006	0.301	-0.007	0.076	**0.012**	0.039	-0.006	0.146	**0.028**	0.000	-0.004	0.244	-0.001	0.850	-0.008	0.127
Log Price Fruits	-0.003	0.458	-0.002	0.694	0.003	0.386	-0.006	0.146	0.002	0.726	-0.005	0.399	0.002	0.515	0.003	0.445	0.005	0.271
Log Price Meat & Fish	0.000	0.969	**-0.018**	0.043	-0.009	0.183	**0.028**	0.000	-0.005	0.399	0.012	0.427	0.000	0.946	**-0.017**	0.034	0.009	0.273
Log Price Poultry	0.003	0.388	-0.001	0.896	-0.006	0.098	-0.004	0.244	0.002	0.515	0.000	0.946	0.007	0.065	**-0.008**	0.040	0.006	0.112
Log Price Dairy	0.004	0.371	0.000	0.983	0.007	0.157	-0.001	0.850	0.003	0.445	**-0.017**	0.034	**-0.008**	0.040	**0.016**	0.044	-0.005	0.360
Log Price Fat & Oils	-0.009	0.089	-0.005	0.447	0.004	0.426	-0.008	0.127	0.005	0.271	0.009	0.273	0.006	0.112	-0.005	0.360	0.002	0.783
Log Real Expenditure	**-0.025**	0.000	**-0.051**	0.000	0.003	0.378	-0.005	0.175	**-0.023**	0.000	**0.046**	0.000	-0.005	0.076	-0.004	0.354	**0.065**	0.000
HH Age	**-0.001**	0.004	0.001	0.135	0.000	0.622	0.000	0.216	**0.001**	0.000	0.000	0.757	0.000	0.624	-0.001	0.053	0.000	0.814
HH Comp. Elementery	-0.009	0.410	0.015	0.400	0.010	0.399	0.004	0.749	-0.006	0.656	-0.010	0.632	**-0.018**	0.042	-0.005	0.755	0.019	0.224
HH Comp. Junior	**-0.025**	0.022	0.023	0.206	0.009	0.477	0.013	0.373	0.010	0.526	-0.024	0.250	-0.018	0.066	0.005	0.745	0.007	0.657
HH Comp. High School	**-0.023**	0.038	0.029	0.111	0.010	0.411	0.013	0.354	0.010	0.508	-0.028	0.191	**-0.025**	0.008	0.001	0.975	0.013	0.453
HH Incomp. College	**-0.028**	0.041	0.005	0.826	0.021	0.167	0.009	0.612	0.011	0.544	-0.026	0.328	**-0.031**	0.009	0.001	0.955	0.037	0.072
HH Comp. College	**-0.037**	0.001	**0.042**	0.026	**0.028**	0.026	0.016	0.286	**0.049**	0.002	**-0.064**	0.004	**-0.039**	0.000	0.014	0.413	-0.009	0.604
HH Female	-0.002	0.649	-0.004	0.614	**0.015**	0.001	0.005	0.353	-0.011	0.061	**-0.021**	0.013	0.001	0.879	**0.014**	0.037	0.003	0.627
H Size	**0.006**	0.003	**0.016**	0.000	**-0.004**	0.035	-0.004	0.092	**-0.006**	0.038	0.004	0.254	**-0.004**	0.021	-0.005	0.086	-0.003	0.305
H Total Child	**-0.011**	0.017	-0.001	0.909	-0.005	0.284	**0.013**	0.027	0.008	0.195	**-0.024**	0.006	0.001	0.721	**0.015**	0.033	0.004	0.573
H Total Youngster	0.000	0.894	0.003	0.578	**-0.010**	0.003	0.006	0.143	-0.007	0.112	-0.010	0.090	0.001	0.617	0.006	0.184	**0.010**	0.028
H Total Adults	0.008	0.059	0.010	0.125	-0.006	0.203	0.009	0.068	-0.004	0.420	-0.013	0.098	-0.006	0.096	0.006	0.345	-0.004	0.466
H Total Eldery	-0.003	0.398	**0.015**	0.019	**0.009**	0.045	-0.007	0.195	0.004	0.467	**-0.023**	0.002	0.002	0.639	-0.002	0.738	0.005	0.363
Mills	**-0.047**	0.000	**-0.040**	0.000	**-0.032**	0.000	**-0.018**	0.000	**-0.038**	0.000	**-0.024**	0.000	**-0.045**	0.000	**-0.031**	0.000	**0.276**	0.000
Demographics	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Mills	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Observations	1078		1078		1078		1078		1078		1078		1078		1078		1078	
Log Likelihood	10326.57		10326.57		10326.57		10326.57		10326.57		10326.57		10326.57		10326.57		10326.57	

Coefficients in bold are significant with $p < 0.05$.

Table 5.7: Traditional AIDS Estimation - Food Categories POF 2011/2013

	Cereals		**Flour Products**		**Vegetables**		**Sugar and Sweets**		**Fruits**		**Meat and Fish**		**Poultry and Eggs**		**Dairy products**		**Oil and Fats**	
Variable	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value
Constant	**0.246**	0.000	**0.385**	0.000	**0.074**	0.000	**0.152**	0.000	**0.075**	0.001	**0.093**	0.002	**0.170**	0.000	**0.079**	0.000	**-0.274**	0.000
Log Price Cereals	0.004	0.415	-0.002	0.634	**0.009**	0.000	**-0.012**	0.000	0.002	0.627	0.004	0.438	0.004	0.177	0.001	0.764	**-0.009**	0.027
Log Price Flour	-0.002	0.634	**0.019**	0.003	**-0.007**	0.026	**-0.009**	0.016	0.006	0.177	0.006	0.291	0.002	0.523	**-0.015**	0.000	-0.001	0.812
Log Price Vegetables	**0.009**	0.000	**-0.007**	0.026	**-0.024**	0.000	**0.011**	0.000	**-0.027**	0.000	**0.011**	0.011	0.002	0.360	**0.019**	0.000	0.006	0.081
Log Price Sugar	**-0.012**	0.000	**-0.009**	0.016	**0.011**	0.000	**0.011**	0.009	0.000	0.912	0.002	0.767	0.002	0.533	-0.004	0.229	0.001	0.905
Log Price Fruits	0.002	0.627	0.006	0.177	**-0.027**	0.000	0.000	0.912	**0.018**	0.010	-0.003	0.639	-0.004	0.182	0.000	0.957	0.008	0.099
Log Price Meat & Fish	0.004	0.438	0.006	0.291	**0.011**	0.011	0.002	0.767	-0.003	0.639	0.007	0.523	**-0.012**	0.007	-0.008	0.133	-0.008	0.238
Log Price Poultry	0.004	0.177	0.002	0.523	0.002	0.360	0.002	0.533	-0.004	0.182	**-0.012**	0.007	**0.007**	0.021	-0.003	0.266	0.003	0.334
Log Price Dairy	0.001	0.764	**-0.015**	0.000	**0.019**	0.000	-0.004	0.229	0.000	0.957	-0.008	0.133	-0.003	0.266	**0.014**	0.002	-0.005	0.194
Log Price Fat & Oils	**-0.009**	0.027	-0.001	0.812	0.006	0.081	0.001	0.905	0.008	0.099	-0.008	0.238	0.003	0.334	-0.005	0.194	0.005	0.466
Log Real Expenditure	**-0.020**	0.000	**-0.050**	0.000	-0.004	0.153	**-0.006**	0.037	**-0.011**	0.001	**0.044**	0.000	**-0.007**	0.002	0.004	0.228	**0.050**	0.000
HH Age	**-0.001**	0.000	0.000	0.321	**0.000**	0.007	0.000	0.351	**0.001**	0.000	**-0.001**	0.036	**0.000**	0.009	0.000	0.609	0.000	0.605
HH Comp. Elementery	-0.007	0.239	-0.006	0.496	0.010	0.209	-0.009	0.303	**0.030**	0.001	-0.023	0.060	-0.011	0.050	0.016	0.067	0.000	0.964
HH Comp. Junior	-0.009	0.178	-0.018	0.072	0.002	0.852	0.002	0.845	**0.029**	0.003	-0.025	0.056	-0.008	0.219	**0.020**	0.030	0.007	0.482
HH Comp. High School	**-0.017**	0.007	-0.010	0.330	0.010	0.237	-0.004	0.691	**0.047**	0.000	**-0.031**	0.017	**-0.014**	0.016	**0.021**	0.022	-0.003	0.801
HH Incomp. College	**-0.029**	0.000	-0.007	0.600	0.005	0.640	0.011	0.304	**0.051**	0.000	**-0.053**	0.001	-0.013	0.094	**0.040**	0.001	-0.005	0.683
HH Comp. College	**-0.037**	0.000	0.002	0.836	**0.018**	0.039	0.003	0.729	**0.066**	0.000	**-0.055**	0.000	**-0.020**	0.002	**0.047**	0.000	**-0.025**	0.016
HH Female	-0.002	0.587	-0.004	0.437	**0.016**	0.000	-0.004	0.336	0.000	0.970	**-0.022**	0.000	0.003	0.296	0.008	0.075	0.005	0.295
H Size	0.002	0.113	**0.010**	0.000	-0.002	0.295	0.003	0.148	**-0.005**	0.023	-0.004	0.117	-0.002	0.132	0.000	0.856	-0.002	0.478
H Total Child	0.002	0.643	-0.004	0.444	-0.007	0.102	0.006	0.173	-0.005	0.301	**-0.013**	0.042	-0.003	0.295	**0.020**	0.000	0.004	0.396
H Total Youngster	-0.001	0.538	0.006	0.068	-0.003	0.371	0.000	0.967	-0.001	0.845	-0.001	0.888	0.001	0.817	-0.004	0.217	0.002	0.521
H Total Adults	0.000	0.981	**0.011**	0.010	**-0.012**	0.000	-0.001	0.724	**-0.014**	0.001	**0.014**	0.011	-0.001	0.848	0.001	0.756	0.002	0.652
H Total Eldery	0.000	0.924	**0.013**	0.002	0.006	0.091	**-0.011**	0.001	0.003	0.392	-0.003	0.516	0.002	0.376	-0.005	0.205	-0.004	0.299
Mills	**-0.044**	0.000	**-0.022**	0.000	**-0.034**	0.000	**-0.018**	0.000	**-0.018**	0.000	**-0.011**	0.015	**-0.042**	0.000	**-0.027**	0.000	**0.216**	0.000
Demographics	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Mills	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Observations	1965		1965		1965		1965		1965		1965		1965		1965		1965	
Log Likelihood	19951.54		19951.54		19951.54		19951.54		19951.54		19951.54		19951.54		19951.54		19951.54	

Coefficients in bold are significant with $p < 0.05$.

Table 5.8: Spatial AIDS Estimation - Food Categories POF 2008/2010

	Cereals		**Flour Products**		**Vegetables**		**Sugar and Sweets**		**Fruits**		**Meat and Fish**		**Poultry and Eggs**		**Dairy products**		**Oil and Fats**	
Variable	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value
Constant	**0.197**	0.000	**0.278**	0.000	**0.056**	0.028	**0.076**	0.012	**0.131**	0.000	-0.013	0.772	**0.086**	0.000	**0.124**	0.001	**0.064**	0.004
Log Price Cereals	0.013	0.098	-0.003	0.675	**0.011**	0.045	**-0.023**	0.000	-0.002	0.699	0.002	0.770	0.003	0.370	0.003	0.637	-0.005	0.097
Log Price Flour	-0.003	0.675	0.013	0.216	0.007	0.253	0.007	0.254	0.001	0.817	**-0.021**	0.033	0.000	0.958	0.001	0.885	**-0.005**	0.037
Log Price Vegetables	**0.011**	0.045	0.007	0.253	-0.008	0.239	-0.007	0.122	0.004	0.371	-0.007	0.370	-0.004	0.315	0.005	0.346	-0.001	0.804
Log Price Sugar	**-0.023**	0.000	0.007	0.254	-0.007	0.122	0.010	0.104	-0.006	0.183	**0.029**	0.001	-0.003	0.330	-0.002	0.744	**-0.005**	0.012
Log Price Fruits	-0.002	0.699	0.001	0.817	0.004	0.371	-0.006	0.183	0.002	0.724	-0.006	0.386	0.002	0.489	0.004	0.418	0.000	0.969
Log Price Meat & Fish	0.002	0.770	**-0.021**	0.033	-0.007	0.370	**0.029**	0.001	-0.006	0.386	0.013	0.423	0.000	0.965	-0.016	0.063	0.006	0.115
Log Price Poultry	0.003	0.370	0.000	0.958	-0.004	0.315	-0.003	0.330	0.002	0.489	0.000	0.965	0.006	0.142	-0.007	0.073	0.003	0.092
Log Price Dairy	0.003	0.637	0.001	0.885	0.005	0.346	-0.002	0.744	0.004	0.418	-0.016	0.063	-0.007	0.073	0.013	0.138	0.000	0.993
Log Price Fat & Oils	-0.005	0.097	**-0.005**	0.037	-0.001	0.804	**-0.005**	0.012	0.000	0.969	0.006	0.115	0.003	0.092	0.000	0.993	**0.007**	0.006
Log Real Expenditure	**-0.014**	0.000	**-0.046**	0.000	**0.010**	0.012	-0.002	0.707	**-0.015**	0.003	**0.054**	0.000	**0.006**	0.048	0.002	0.709	**0.005**	0.006
HH Age	**-0.001**	0.005	0.001	0.139	0.000	0.905	0.000	0.236	**0.001**	0.000	0.000	0.692	0.000	0.926	-0.001	0.083	0.000	0.972
HH Comp. Elementery	-0.005	0.646	0.020	0.291	0.008	0.517	0.003	0.821	-0.004	0.792	-0.008	0.706	-0.016	0.121	0.003	0.881	0.000	0.995
HH Comp. Junior	-0.025	0.057	0.026	0.193	0.009	0.509	0.011	0.471	0.014	0.394	-0.024	0.296	-0.018	0.091	0.013	0.470	-0.006	0.240
HH Comp. High School	-0.022	0.081	0.033	0.099	0.006	0.637	0.012	0.441	0.015	0.361	-0.028	0.228	**-0.023**	0.033	0.010	0.571	-0.002	0.598
HH Incomp. College	-0.023	0.153	0.008	0.733	0.021	0.202	0.010	0.609	0.015	0.474	-0.021	0.468	-0.023	0.089	0.011	0.625	0.002	0.777
HH Comp. College	**-0.040**	0.004	**0.044**	0.037	0.023	0.103	0.013	0.403	**0.054**	0.003	**-0.068**	0.008	**-0.040**	0.001	0.020	0.276	-0.006	0.224
HH Female	-0.003	0.568	-0.004	0.596	**0.015**	0.009	0.005	0.383	-0.010	0.148	**-0.020**	0.033	0.003	0.438	**0.015**	0.044	-0.001	0.485
H Size	**0.005**	0.047	**0.016**	0.000	**-0.005**	0.030	-0.004	0.115	**-0.006**	0.030	0.004	0.376	**-0.004**	0.048	-0.005	0.146	0.000	0.722
H Total Child	-0.007	0.202	0.000	0.980	-0.005	0.319	**0.014**	0.041	0.006	0.393	**-0.022**	0.027	0.001	0.855	**0.016**	0.034	-0.003	0.178
H Total Youngster	0.003	0.423	0.004	0.415	**-0.010**	0.013	0.007	0.105	-0.006	0.178	-0.008	0.197	0.002	0.459	0.007	0.138	0.000	0.881
H Total Adults	0.009	0.052	0.011	0.144	-0.007	0.133	0.009	0.101	-0.006	0.317	-0.013	0.125	-0.007	0.077	0.005	0.462	-0.001	0.713
H Total Eldery	-0.001	0.855	**0.016**	0.026	**0.010**	0.033	-0.008	0.155	0.005	0.424	**-0.023**	0.008	0.000	0.918	-0.002	0.711	0.003	0.065
Mills	-0.002	0.140	**-0.005**	0.046	-0.003	0.131	0.004	0.068	-0.003	0.085	**0.008**	0.001	**-0.010**	0.000	-0.001	0.543	**0.013**	0.002
λ_{slm}	**0.087**	0.001	**0.062**	0.007	**0.079**	0.003	**0.075**	0.003	**0.056**	0.021	**0.069**	0.002	0.049	0.082	**0.069**	0.004	**-0.546**	0.001
Demographics	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Mills	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Observations	1078		1078		1078		1078		1078		1078		1078		1078		1078	
Log Likelihood	-11104.32		-11104.32		-11104.32		-11104.32		-11104.32		-11104.32		-11104.32		-11104.32		-11104.32	

Coefficients in bold are significant with $p < 0.05$.

Table 5.9: Spatial AIDS Estimation - Food Categories POF 2011/2013

	Cereals		**Flour Products**		**Vegetables**		**Sugar and Sweets**		**Fruits**		**Meat and Fish**		**Poultry and Eggs**		**Dairy products**		**Oil and Fats**	
Variable	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value
Constant	**0.173**	0.000	**0.359**	0.000	0.022	0.251	**0.120**	0.000	0.035	0.124	0.049	0.122	**0.110**	0.000	0.035	0.112	**0.097**	0.000
Log Price Cereals	-0.003	0.495	-0.002	0.669	**0.009**	0.002	**-0.013**	0.000	0.005	0.215	0.003	0.558	0.005	0.067	0.000	0.957	**-0.005**	0.024
Log Price Flour	-0.002	0.669	**0.017**	0.013	**-0.007**	0.045	**-0.008**	0.040	0.007	0.182	0.004	0.517	0.003	0.402	**-0.013**	0.004	-0.001	0.762
Log Price Vegetables	**0.009**	0.002	**-0.007**	0.045	**-0.023**	0.000	**0.012**	0.000	**-0.026**	0.000	**0.011**	0.030	0.002	0.298	**0.019**	0.000	**0.003**	0.014
Log Price Sugar	**-0.013**	0.000	**-0.008**	0.040	**0.012**	0.000	**0.011**	0.016	0.002	0.684	0.001	0.826	0.003	0.300	-0.005	0.156	-0.003	0.066
Log Price Fruits	0.005	0.215	0.007	0.182	**-0.026**	0.000	0.002	0.684	**0.017**	0.027	-0.002	0.773	-0.004	0.298	0.002	0.571	-0.001	0.567
Log Price Meat & Fish	0.003	0.558	0.004	0.517	**0.011**	0.030	0.001	0.826	-0.002	0.773	0.005	0.708	**-0.012**	0.015	-0.009	0.127	-0.001	0.735
Log Price Poultry	0.005	0.067	0.003	0.402	0.002	0.298	0.003	0.300	-0.004	0.298	**-0.012**	0.015	0.005	0.150	-0.003	0.250	0.001	0.487
Log Price Dairy	0.000	0.957	**-0.013**	0.004	**0.019**	0.000	-0.005	0.156	0.002	0.571	-0.009	0.127	-0.003	0.250	**0.011**	0.030	-0.003	0.123
Log Price Fat & Oils	**-0.005**	0.024	-0.001	0.762	**0.003**	0.014	-0.003	0.066	-0.001	0.567	-0.001	0.735	0.001	0.487	-0.003	0.123	**0.009**	0.000
Log Real Expenditure	**-0.011**	0.000	**-0.047**	0.000	0.002	0.455	-0.002	0.582	**-0.007**	0.038	**0.049**	0.000	0.003	0.158	**0.009**	0.014	**0.004**	0.007
HH Age	**-0.001**	0.001	0.000	0.184	**0.001**	0.014	0.000	0.523	**0.001**	0.000	**-0.001**	0.032	**0.000**	0.013	0.000	0.531	0.000	0.709
HH Comp. Elementery	-0.005	0.497	-0.006	0.526	0.012	0.150	-0.010	0.270	**0.030**	0.004	-0.024	0.079	**-0.016**	0.015	0.016	0.093	0.002	0.459
HH Comp. Junior	-0.005	0.515	-0.019	0.091	0.003	0.753	0.001	0.887	**0.028**	0.008	-0.027	0.065	-0.011	0.107	**0.023**	0.029	0.005	0.105
HH Comp. High School	**-0.016**	0.028	-0.011	0.309	0.011	0.213	-0.005	0.625	**0.047**	0.000	**-0.033**	0.025	**-0.018**	0.011	**0.023**	0.031	0.002	0.551
HH Incomp. College	**-0.029**	0.004	-0.009	0.508	0.005	0.651	0.013	0.263	**0.050**	0.000	**-0.056**	0.003	-0.016	0.067	**0.040**	0.003	0.001	0.862
HH Comp. College	**-0.040**	0.000	0.001	0.964	0.014	0.132	0.001	0.931	**0.064**	0.000	**-0.058**	0.000	**-0.026**	0.001	**0.048**	0.000	-0.003	0.430
HH Female	-0.002	0.584	-0.004	0.397	**0.019**	0.000	-0.004	0.413	0.000	0.972	**-0.022**	0.002	0.004	0.171	0.007	0.136	0.001	0.563
H Size	0.001	0.439	**0.010**	0.000	-0.002	0.365	0.003	0.174	**-0.005**	0.031	-0.004	0.137	-0.002	0.224	0.000	0.971	-0.001	0.171
H Total Child	0.006	0.092	-0.005	0.387	-0.008	0.102	0.006	0.196	-0.006	0.260	-0.013	0.079	-0.003	0.366	**0.020**	0.001	0.001	0.488
H Total Youngster	-0.001	0.681	0.007	0.077	-0.002	0.472	0.000	0.907	0.000	0.921	0.000	0.938	0.002	0.521	-0.004	0.265	0.000	0.934
H Total Adults	0.002	0.487	**0.012**	0.011	**-0.014**	0.001	-0.001	0.804	**-0.016**	0.001	**0.015**	0.019	0.000	0.926	0.002	0.580	0.000	0.928
H Total Eldery	0.000	0.988	**0.014**	0.004	0.005	0.152	**-0.013**	0.002	0.002	0.572	-0.003	0.550	0.002	0.463	-0.007	0.110	0.000	0.875
Mills	**-0.004**	0.001	**0.005**	0.010	**-0.006**	0.002	0.002	0.184	0.000	0.876	**0.010**	0.000	**-0.010**	0.000	-0.003	0.061	0.006	0.058
λ_{slm}	**0.080**	0.000	**0.088**	0.000	**0.105**	0.000	**0.055**	0.005	**0.105**	0.000	**0.093**	0.000	**0.047**	0.033	**0.098**	0.000	**-0.670**	0.000
Demographics	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Mills	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Observations	1965		1965		1965		1965		1965		1965		1965		1965		1965	
Log Likelihood	-21247.30		-21247.30		-21247.30		-21247.30		-21247.30		-21247.30		-21247.30		-21247.30		-21247.30	

Coefficients in bold are significant with $p < 0.05$.

Table 5.10: Average feedback and spillover effects - Food Categories

	Cereals	Flour P.	Vegetables	Sugar & S.	Fruits	Meat & F.	Poultry & E.	Dairy P.	Oil & Fats
Feedback relative to coefficient estimate									
POF 2008-2010	1.28%	0.76%	1.37%	1.51%	2.62%	5.34%	6.37%	1.21%	2.16%
POF 2011-2013	6.25%	0.76%	0.01%	2.91%	1.28%	0.83%	2.04%	0.30%	1.03%
Spillover relative to total impact									
POF 2008-2010	8.75%	6.34%	7.85%	7.34%	5.71%	6.96%	4.27%	7.27%	103.17%
POF 2011-2013	7.97%	8.75%	10.30%	5.48%	10.56%	9.21%	4.73%	9.75%	206.99%

Percentages are in absolute value.

5.3 Elasticities

Results from demand systems are more commonly interpreted by analyzing the elasticities. Here I will analyze the elasticities calculated for the standard AIDS model and the spatial AIDS model. For the last model, the elasticities considering direct, indirect, and total impacts will be presented and compared. The elasticities for the first-stage estimation for broad categories are presented first, and the unconditional elasticities for the second-stage estimation for food subcategories will be presented next. Elasticities calculated at means by income and head of the household age quintiles will also be presented.

A price change in one good generates a substitution effect and an income effect that together will result in a change in demand. The substitution effect captures how when the relative price of one good increases, the consumer substitutes away from this good towards other goods. The income effect considers the effect of an increase (decrease) in the purchasing power of a consumer as a result of a price decrease (increase); the consumer can (cannot) now afford better products or more of the same products and will reoptimize its entire bundle and

With the Hicksian demand, the pure substitution effect in response to a price change is isolated. It is known as compensated due to the idea that, after a price change, the consumer will be given an amount of wealth (the “compensation”) sufficient to maintain the same utility level as experienced before the price change. The substitution or compensated or Hicksian elasticity is defined as the percentage change in the demand for a good in response to a change in a price that ignores the income effect. The uncompensated or Marshallian elasticity is composed of the substitution elasticity and the income effect that depends on the income elasticity.

Uncompensated price elasticities are used to measure the impact of a price rise on consumption when consumers’ monetary income is held constant. For some purposes, it is helpful to know the response when consumers’ real income remains unchanged. This is the case when a tax is imposed on the consumption of a specific good, and the revenue from the tax is redistributed back to consumers as a lump sum. This keeps real income unchanged, and the impact of a 1% rise in the price of the good in the demand of other goods will be given by compensated elasticity.

The average indirect effect elasticities capture the average impact on the expected demand of household of location i given a change in expenditure or price for households in location j. The average indirect effect measures the proportion of the impact of expenditure or price that spills over to other locations. The average direct effect elasticities capture the average impact on the expected demand of household of location i given a change in expenditure or price for households in the same location i. This impact includes the effect of feedback loops where a change in prices or income for i will affect the expected value of the dependent variable in i, which affects the neighbors of i, which also affects observation i.

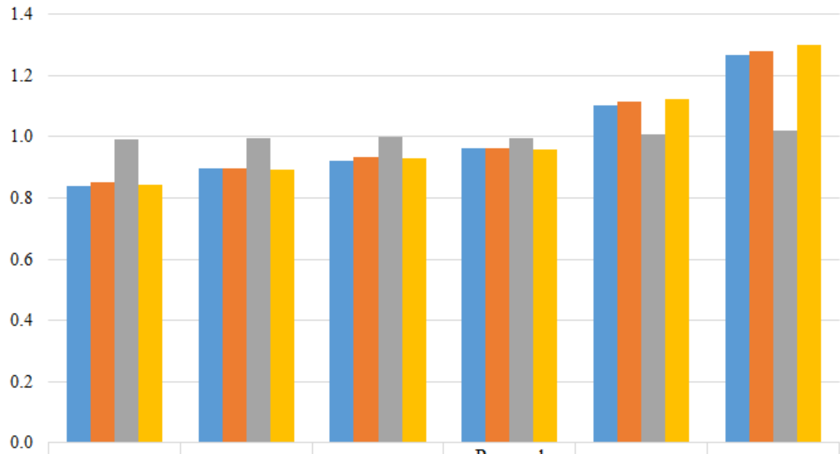
Broad Categories

Based on the parameters of the demand system estimation, the income, own-price and cross-price elasticities were calculated following the adaption of the Green and Alston (1990) method by Buse (1994) described by in Section 4.2. All elasticities are considered at means of the samples. The figures 5.1, 5.7 and 5.9 show respectively, the expenditure, uncompensated and compensated own-price elasticities for broad categories using the POF 2008-2010 and the figures 5.2, 5.8 and 5.10 show the elasticities for broad categories using the POF 2011-2013 sample. Tables with the complete price elasticities are in the Appendix (Tables A.17, A.16, A.19 and A.18).

In all figures, the elasticities for the traditional demand estimation and spatial estimation are shown. All expenditure elasticities are of the expected sign and are significant at the 5% level. Food, Habitation, and Health categories are necessities for both samples, while Transportation, Habitation, and Education are luxury categories (expenditure higher than one). Personal Expenses are also luxurious in the most recent sample. Food is the most inelastic category, and Clothing the most elastic category in both samples. Food and Clothing present higher expenditure elasticities in the 2008-2010 sample compared to the most recent sample, which presents higher Health, Habitation, and Personal expenses elasticities.

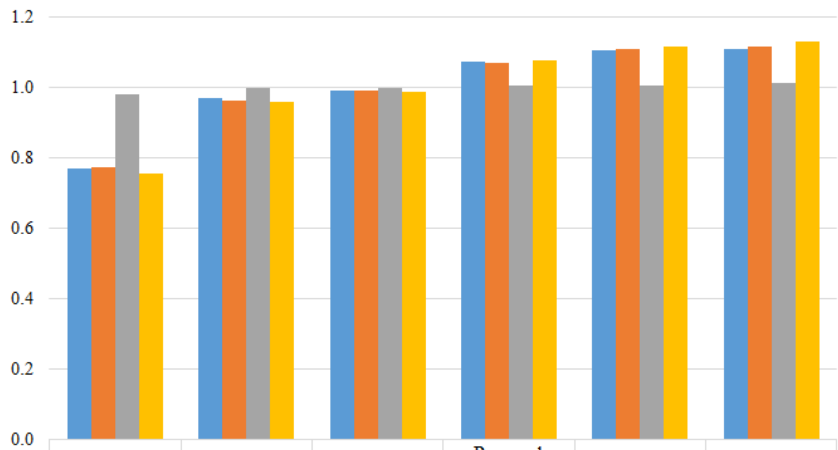
Although the direct and indirect impact effects are smaller than the total effects by definition, direct and indirect elasticities are not necessarily smaller than the total effect elasticities because of the elasticity formula for the linear demand system. For both samples, direct and total effect expenditure elasticities are similar to the traditional elasticity. The indirect effect elasticity for Food stands out in both samples and indicates that the spillover effect for this category is relatively significant. In both samples, the Transportation and Clothing indirect expenditure elasticities are smaller than the respective traditional, direct, and total effects, which may reveal lower spillover effects.

Figure 5.1: Expenditure elasticities - Broad categories POF 2008-2010



	Food	Habitation	Health	Personal Expenses	Transportation	Clothing
Traditional	0.839	0.897	0.923	0.963	1.102	1.265
Direct	0.851	0.897	0.932	0.963	1.114	1.280
Indirect	0.990	0.996	0.998	0.996	1.008	1.020
Total	0.841	0.892	0.930	0.959	1.121	1.300

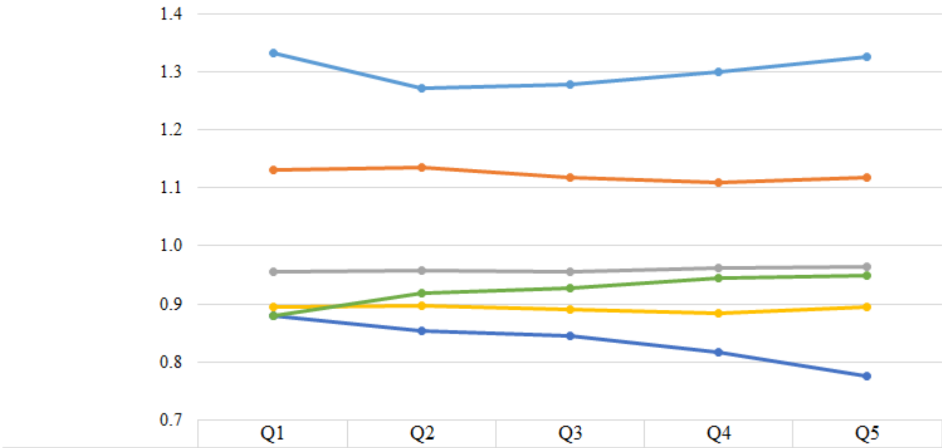
Figure 5.2: Expenditure elasticities - Broad categories POF 2011-2013



	Food	Health	Habitation	Personal Expenses	Transportation	Clothing
Traditional	0.770	0.970	0.990	1.073	1.105	1.107
Direct	0.773	0.963	0.989	1.070	1.109	1.117
Indirect	0.980	0.996	0.999	1.006	1.005	1.013
Total	0.754	0.960	0.988	1.076	1.114	1.130

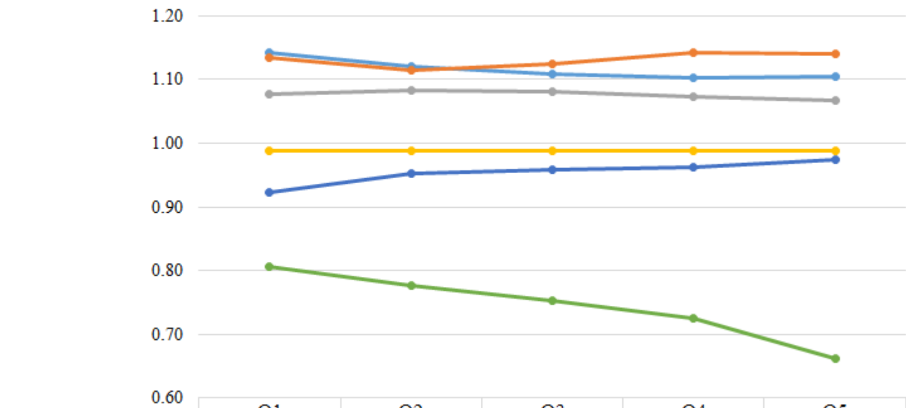
Figures 5.3 and 5.4 shows total impact expenditure elasticities according to per capita monthly households income quintiles respectively for POF 2008-2010 and POF 2011-2013. For both samples, Food categories expenditure elasticities are lower for the highest income group; that is, food products are viewed as more necessities by lower-income households as expected. Health category elasticities are higher for higher-income groups, although the difference is less expressive than the food category. For the first sample, clothing presents the highest elasticities for the first and last income quintile. For the last sample, the poorest group presents the highest elasticity for Transportation.

Figure 5.3: Total impact expenditure elasticities by income quintile - POF 2008-2010



	Q1	Q2	Q3	Q4	Q5
Clothing	1.333	1.272	1.278	1.300	1.326
Transportation	1.131	1.134	1.118	1.109	1.118
Personal Expenses	0.956	0.957	0.955	0.961	0.964
Habitation	0.894	0.898	0.890	0.885	0.895
Food	0.880	0.854	0.845	0.817	0.775
Health	0.879	0.920	0.927	0.944	0.948

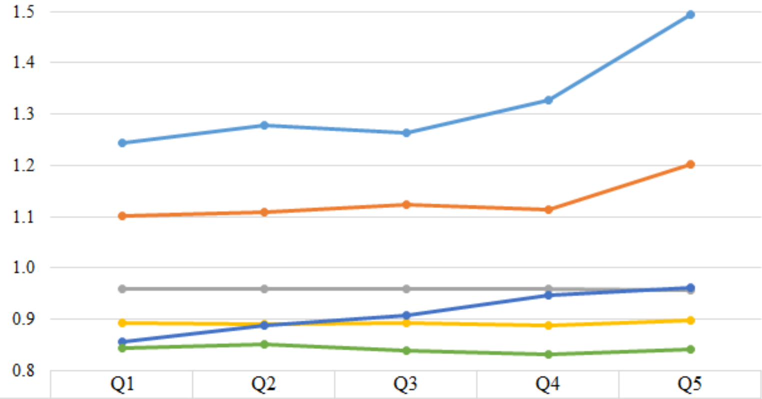
Figure 5.4: Total impact expenditure elasticities by income quintile - POF 2011-2013



	Q1	Q2	Q3	Q4	Q5
Transportation	1.143	1.120	1.108	1.103	1.104
Clothing	1.134	1.114	1.124	1.142	1.141
Personal Expenses	1.077	1.084	1.081	1.074	1.067
Habitation	0.989	0.988	0.988	0.988	0.988
Health	0.922	0.953	0.959	0.962	0.974
Food	0.807	0.776	0.753	0.726	0.662

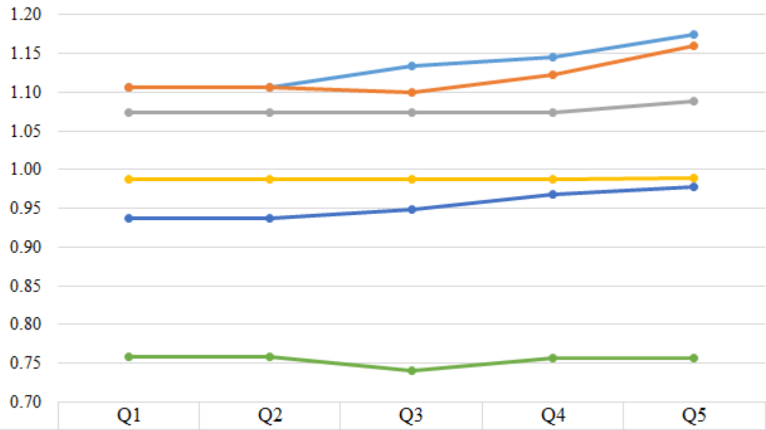
Figures 5.5 and 5.6 presents the total impact expenditure elasticities according to the age of the head of the household quintiles respectively for POF 2008-2010 and POF 2011-2013. For both samples, Clothing, Transportation, and Health expenditure elasticities are higher for household groups with older heads. Habitation's expenditure elasticity does not present significant variation by age group. Personal expenses' expenditure elasticity presents a higher value for the fifth quintile in the 2011-2013 sample.

Figure 5.5: Total impact expenditure elasticities by age quintile - POF 2008-2010



	Q1	Q2	Q3	Q4	Q5
Clothing	1.243	1.278	1.262	1.328	1.495
Transportation	1.100	1.108	1.124	1.114	1.201
Personal Expenses	0.959	0.959	0.960	0.960	0.957
Habitation	0.894	0.890	0.894	0.887	0.897
Health	0.856	0.888	0.907	0.947	0.962
Food	0.842	0.852	0.839	0.830	0.842

Figure 5.6: Total impact expenditure elasticities by age quintile - POF 2011-2013

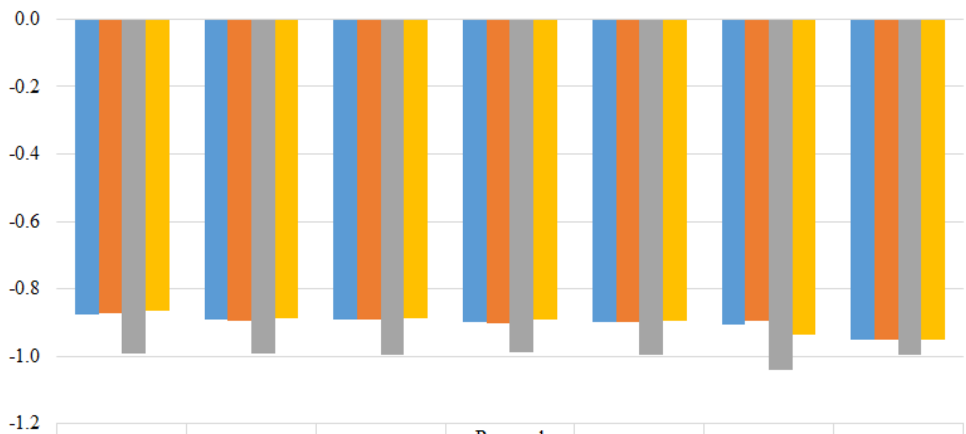


	Q1	Q2	Q3	Q4	Q5
Clothing	1.106	1.106	1.134	1.145	1.174
Transportation	1.106	1.106	1.099	1.123	1.160
Personal Expenses	1.074	1.074	1.074	1.073	1.089
Habitation	0.988	0.988	0.988	0.988	0.989
Health	0.937	0.937	0.949	0.968	0.979
Food	0.758	0.758	0.740	0.756	0.756

All own-price elasticities are negative, and most are statistically significant. All categories are inelastic, being the Clothing category the most inelastic for both periods. Food and Personal expenses are the categories with the highest uncompensated price elasticities, respectively, for the 2008-2010 sample and the 2011-2013 sample. Clothing is the less-price elastic for both samples. Price elasticities for all categories except for education and food are higher in the most recent sample.

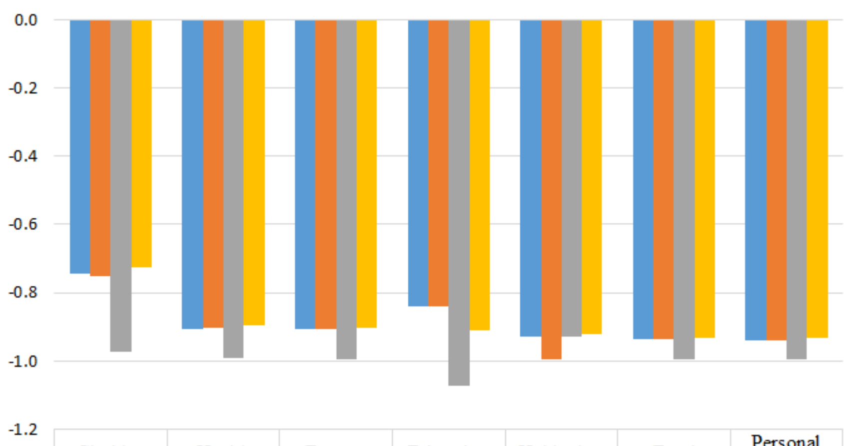
Traditional, direct, and total elasticities are similar for most of the categories. The indirect price elasticity is larger than the traditional, direct, and total elasticities for almost all categories. The exception is the Habitation category in the 2011-2013 sample, for which the direct price elasticity is the highest. In the most recent sample, indirect effect elasticity for clothing and education stands out relatively.

Figure 5.7: Uncompensated price elasticities - Broad categories POF 2008-2010



	Clothing	Transportation	Health	Personal Expenses	Habitation	Education	Food
Traditional	-0.875	-0.890	-0.891	-0.900	-0.898	-0.906	-0.951
Direct	-0.874	-0.894	-0.892	-0.903	-0.899	-0.895	-0.953
Indirect	-0.991	-0.993	-0.996	-0.988	-0.996	-1.039	-0.997
Total	-0.865	-0.887	-0.888	-0.892	-0.895	-0.934	-0.949

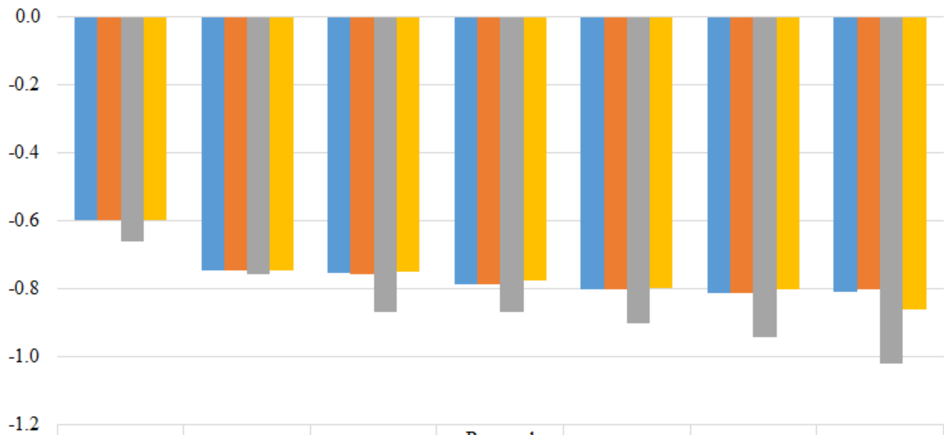
Figure 5.8: Uncompensated price elasticities - Broad categories POF 2011-2013



	Clothing	Health	Transp.	Education	Habitation	Food	Personal Expenses
Traditional	-0.746	-0.905	-0.905	-0.840	-0.929	-0.938	-0.939
Direct	-0.752	-0.904	-0.908	-0.838	-0.996	-0.937	-0.939
Indirect	-0.973	-0.991	-0.996	-1.074	-0.929	-0.994	-0.995
Total	-0.725	-0.895	-0.904	-0.912	-0.923	-0.932	-0.934

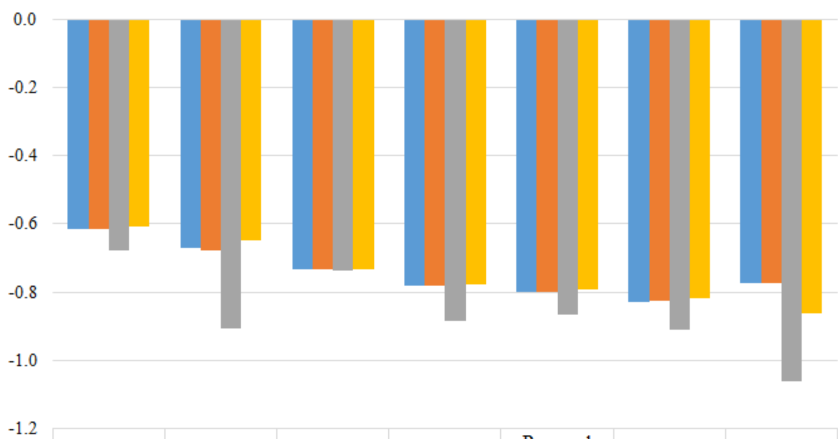
The compensated price elasticities provide the pure price effect on demand, that is, the price effect disregarding the income effect. The size of the income effect depends on the relative importance of the category in the budget share and the expenditure elasticity. Habitation and Food present the highest income effects for both samples and consequently the lowest compensated price elasticities. Compared with the 2008-2010 sample, the most recent sample presents higher income effects for Habitation, Personal expenses, and Clothing.

Figure 5.9: Compensated price elasticities - Broad categories POF 2008-2010



	Habitation	Food	Transportation	Personal Expenses	Health	Clothing	Education
Traditional	-0.598	-0.748	-0.755	-0.786	-0.803	-0.814	-0.808
Direct	-0.600	-0.746	-0.758	-0.789	-0.802	-0.812	-0.802
Indirect	-0.663	-0.757	-0.870	-0.870	-0.901	-0.942	-1.020
Total	-0.597	-0.745	-0.750	-0.778	-0.799	-0.802	-0.862

Figure 5.10: Compensated price elasticities - Broad categories POF 2011-2013

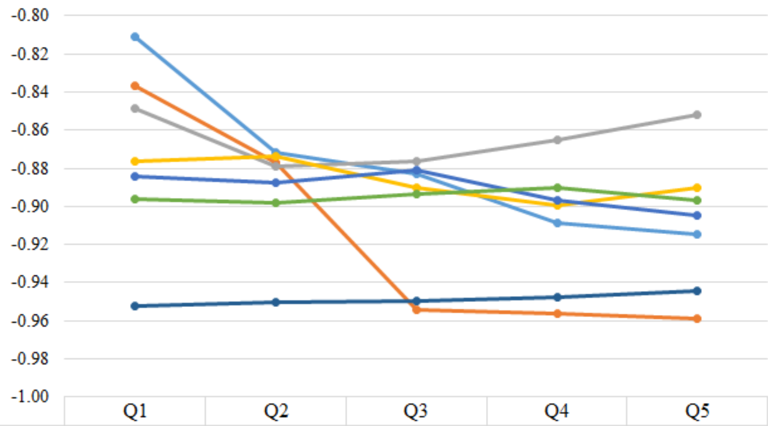


	Habitation	Clothing	Food	Transp.	Personal Expenses	Health	Education
Traditional	-0.614	-0.671	-0.734	-0.780	-0.799	-0.827	-0.772
Direct	-0.615	-0.677	-0.733	-0.782	-0.799	-0.827	-0.772
Indirect	-0.679	-0.905	-0.735	-0.883	-0.864	-0.911	-1.061
Total	-0.609	-0.649	-0.733	-0.778	-0.794	-0.818	-0.863

Figures 5.11 and 5.12 shows total impact uncompensated price elasticities according to per capita monthly households income quintiles respectively for POF 2008-2010 and POF 2011-2013. For both samples, Health, Education, Transportation, and Personal expenses are most inelastic for the group with the lowest income per capita with the elasticity increasing (in absolute value) with rising income. This can be explained by the limited accessibility of lower-income households to substitutes alternatives. On the other hand, compared to the first

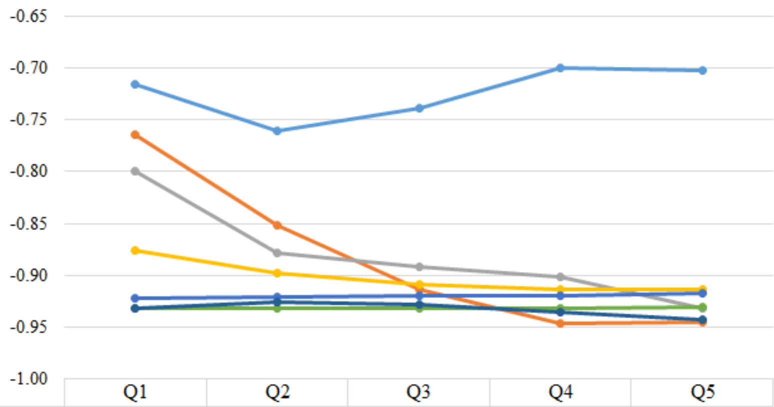
quintile, the last quintile presents a smaller sensibility to price for the food category in the POF 2008-2010 sample. In both samples, the clothing category is the most elastic for the second quintile and most inelastic for the richest group for the most recent sample.

Figure 5.11: Total impact uncompensated price elasticities by income quintile - POF 2008-2010



	Q1	Q2	Q3	Q4	Q5
Health	-0.811	-0.872	-0.883	-0.909	-0.915
Education	-0.837	-0.877	-0.954	-0.956	-0.959
Clothing	-0.849	-0.879	-0.876	-0.865	-0.852
Transportation	-0.876	-0.873	-0.890	-0.900	-0.890
Personal Expenses	-0.884	-0.887	-0.881	-0.897	-0.905
Habitation	-0.896	-0.898	-0.894	-0.890	-0.897
Food	-0.952	-0.950	-0.950	-0.947	-0.944

Figure 5.12: Total impact uncompensated price elasticities by income quintile - POF 2011-2013

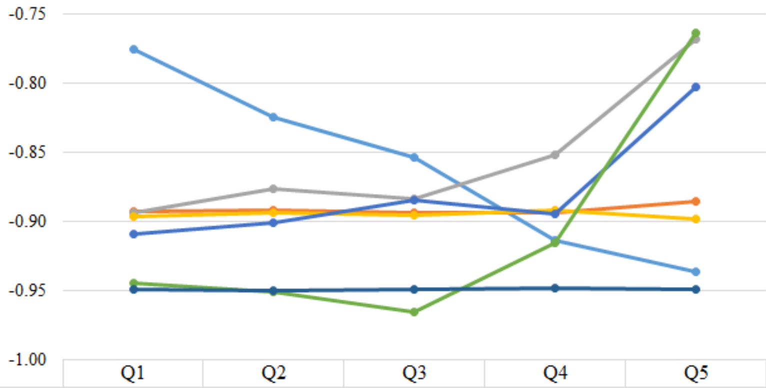


	Q1	Q2	Q3	Q4	Q5
Clothing	-0.715	-0.760	-0.738	-0.699	-0.702
Education	-0.764	-0.851	-0.914	-0.947	-0.945
Health	-0.800	-0.878	-0.892	-0.901	-0.932
Transportation	-0.876	-0.898	-0.909	-0.914	-0.913
Habitation	-0.923	-0.921	-0.921	-0.920	-0.918
Food	-0.933	-0.932	-0.932	-0.932	-0.931
Personal Expenses	-0.933	-0.927	-0.929	-0.936	-0.943

Figures 5.13 and 5.14 illustrates the total impact uncompensated price elasticities according to the age of the head of the household quintiles respectively for POF 2008-2010 and POF 2011-2013. For both samples, Health category presents higher elasticity (in absolute values) and lower elasticities (more inelastic) for Clothing, Education, and Transportation for

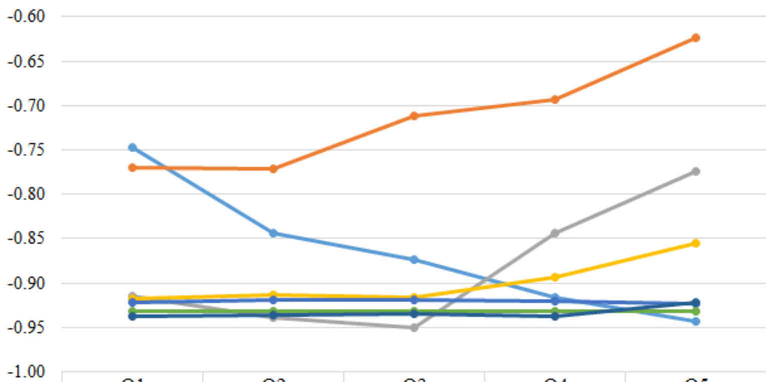
households with older heads. The expressive difference in the Health elasticities between the lowest and highest age quintiles are consistent with elasticities calculated by Kim et al. (2015).

Figure 5.13: Total impact uncompensated price elasticities by age quintile - POF 2008-2010



	Q1	Q2	Q3	Q4	Q5
Health	-0.775	-0.825	-0.853	-0.914	-0.937
Personal Expenses	-0.893	-0.891	-0.893	-0.894	-0.886
Clothing	-0.894	-0.876	-0.884	-0.851	-0.768
Habitation	-0.896	-0.894	-0.896	-0.892	-0.898
Transportation	-0.909	-0.901	-0.884	-0.894	-0.802
Education	-0.945	-0.951	-0.965	-0.915	-0.763
Food	-0.949	-0.950	-0.949	-0.948	-0.949

Figure 5.14: Total impact uncompensated price elasticities by age quintile - POF 2011-2013



	Q1	Q2	Q3	Q4	Q5
Health	-0.747	-0.844	-0.874	-0.916	-0.944
Clothing	-0.770	-0.771	-0.712	-0.693	-0.624
Education	-0.914	-0.939	-0.950	-0.844	-0.774
Transportation	-0.918	-0.913	-0.916	-0.894	-0.855
Habitation	-0.922	-0.919	-0.919	-0.920	-0.924
Food	-0.932	-0.932	-0.932	-0.932	-0.932
Personal Expenses	-0.938	-0.936	-0.935	-0.937	-0.921

The results can be broadly compared to the studies of Asano and Fiuza (2003) and Menezes et al. (2008) which are the few ones that have estimated demand systems for broad categories in the Brazilian context. Both studies estimate demand systems using the national household survey, the first study for the years of 1987/88 and 1996/97 and the second study for the years of 1987/88 and 1995/96. The expenditure elasticities found for the Food group using data from 2008-2010 and 2011-2013 (0.841 and 0.754) are higher than the ones found by both studies but still similar to the ones found by Asano and Fiuza (2003) (0.749 and 0.712). Both studies presented only uncompensated price elasticities, and they are more inelastic than the values we found.

Food Categories

From a multistage budgeting perspective, a change in the price of one subcategory of Food will not only directly affect the demand for other subcategories within the food category but will also modify the price index for Food and consequently the expenditure allocation to Food and the other broad categories from the previous budgeting stage which in turn will cause further indirect effects within the food category (Klonaris and Hallam, 2003). Most empirical studies focus on the conditional elasticities estimated within one stage of the demand system, that is, computed for a given amount spent on a specific category, such as Food. For policy purposes and welfare analysis, the unconditional elasticities are more relevant and, therefore, will be the focus of this analysis.

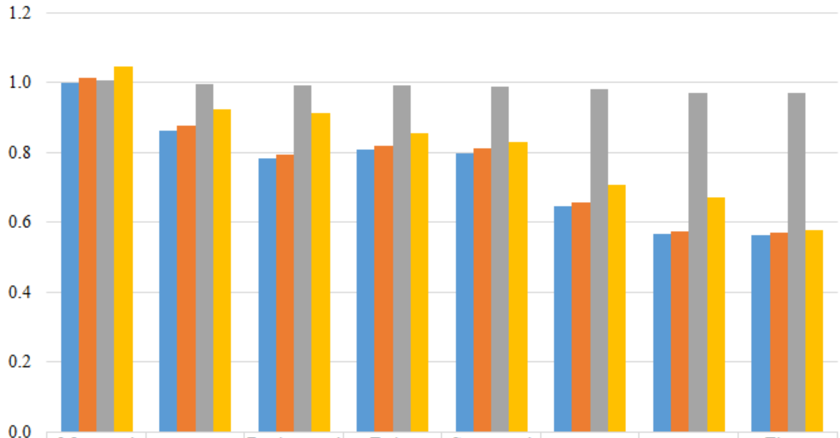
Figures 5.15 and 5.16 illustrates the unconditional expenditure elasticities for respectively, POF 2008-2010 and POF 2011-2013. All food subcategories are normal, and all can be classified as necessities except for the meat and fish category, which presents an elasticity higher and close to one in the most recent sample. For both samples, the last category mentioned has the highest expenditure elasticity while cereals and flour products present the lowest elasticities as expected.

The total impact expenditure elasticity is higher than the traditional elasticity for all categories except flour products in the most recent sample. The indirect impact expenditure elasticity is higher than traditional, direct, indirect, and total effects for almost all categories and is close to one. Compared to the POF 2008-2010 sample, the direct effect elasticities are more expressively higher than the traditional model, revealing higher feedback effects in the most recent sample.

To understand heterogeneity in consumption behaviors, figures 5.17 and 5.18 presents the unconditional total effects expenditure elasticities by per capita income quintiles. For simplicity, the same coefficients from the demand system were considered for all groups, and the elasticities were obtained considering the mean value at each sample. Except for fruits in the POF 2008-2010 sample, the expenditure elasticities of all categories are smaller for the group with the highest income. Cereals and Flour products were the categories with the largest difference between the highest and lowest income classes, which is a consistent result as these categories are considered basic necessity food products.

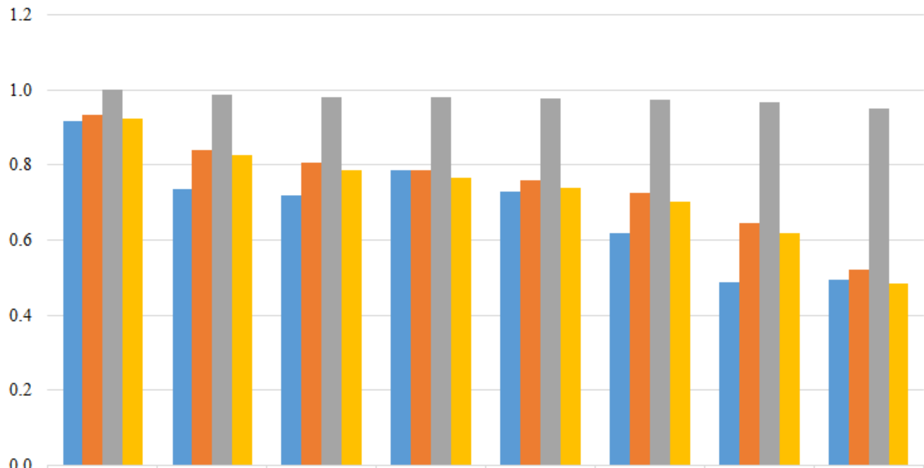
Figures 5.19 and 5.20 illustrates the unconditional uncompensated elasticities for respectively, POF 2008-2010 and POF 2011-2013. Vegetables for both samples and Cereals for the most recent sample are the only price-elastic categories. In the 2008-2010 sample,

Figure 5.15: Unconditional expenditure elasticities - Food categories POF 2008-2010



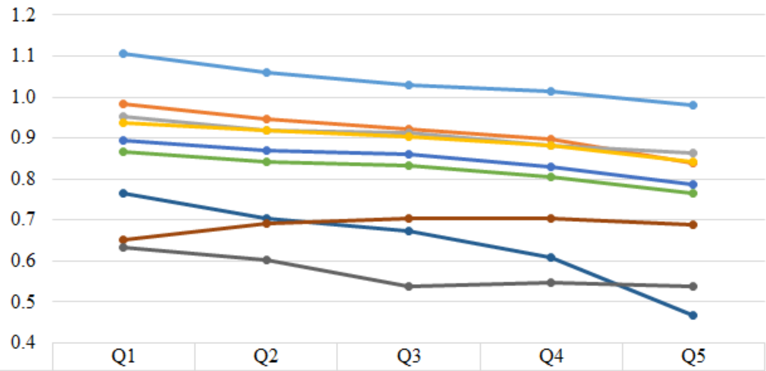
	Meat and Fish	Vegetables	Poultry and Eggs	Dairy products	Sugar and Sweets	Fruits	Cereals	Flour Products
Traditional	0.999	0.863	0.783	0.807	0.799	0.646	0.567	0.562
Direct	1.014	0.876	0.794	0.819	0.810	0.655	0.575	0.570
Indirect	1.006	0.998	0.994	0.991	0.989	0.981	0.972	0.971
Total	1.046	0.924	0.913	0.856	0.829	0.707	0.671	0.579

Figure 5.16: Unconditional expenditure elasticities - Food categories POF 2011-2013



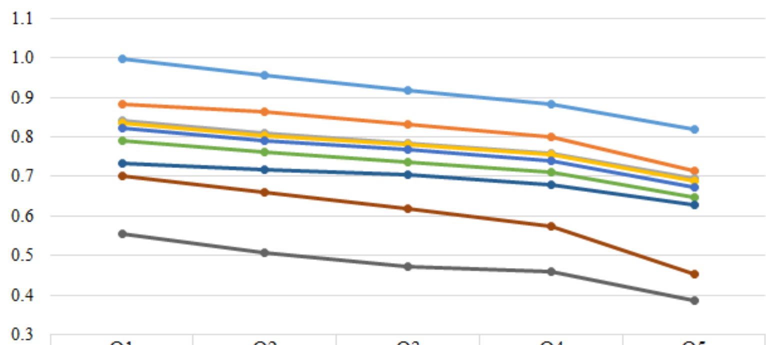
	Meat and Fish	Dairy products	Poultry and Eggs	Vegetables	Sugar and Sweets	Fruits	Cereals	Flour Products
Traditional	0.916	0.737	0.718	0.788	0.729	0.617	0.488	0.495
Direct	0.933	0.841	0.807	0.786	0.759	0.727	0.646	0.520
Indirect	1.001	0.989	0.982	0.982	0.979	0.973	0.966	0.949
Total	0.925	0.826	0.788	0.767	0.739	0.703	0.619	0.483

Figure 5.17: Unconditional Total impact expenditure elasticities by income quintile - POF 2008-2010



	Q1	Q2	Q3	Q4	Q5
Meat and Fish	1.108	1.061	1.028	1.013	0.981
Vegetables	0.984	0.947	0.923	0.896	0.840
Poultry and Eggs	0.954	0.920	0.912	0.882	0.862
Oil and Fats	0.936	0.918	0.905	0.881	0.843
Dairy products	0.895	0.868	0.860	0.831	0.788
Sugar and Sweets	0.868	0.841	0.832	0.805	0.765
Cereals	0.764	0.705	0.674	0.607	0.468
Fruits	0.652	0.691	0.703	0.705	0.688
Flour Products	0.633	0.603	0.537	0.548	0.538

Figure 5.18: Unconditional Total impact expenditure elasticities by income quintile - POF 2011-2013

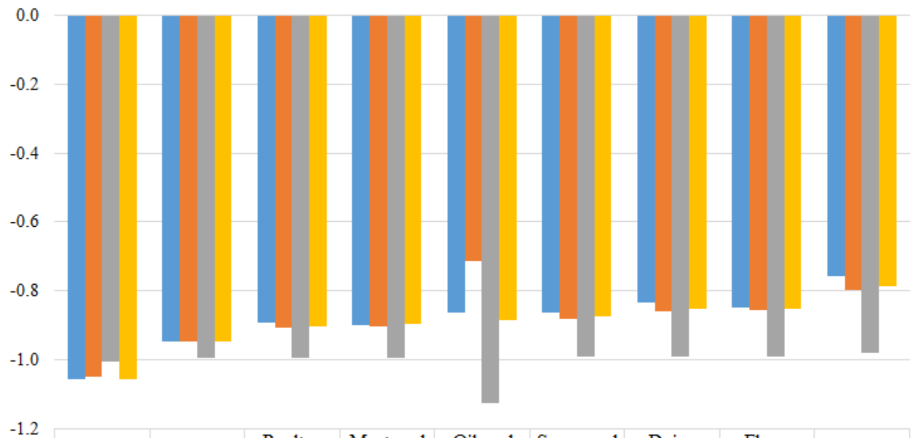


	Q1	Q2	Q3	Q4	Q5
Meat and Fish	0.998	0.955	0.918	0.884	0.818
Dairy products	0.881	0.862	0.833	0.800	0.714
Poultry and Eggs	0.842	0.809	0.785	0.760	0.696
Oil and Fats	0.836	0.804	0.781	0.754	0.689
Vegetables	0.823	0.790	0.767	0.739	0.673
Sugar and Sweets	0.791	0.762	0.738	0.712	0.649
Fruits	0.732	0.717	0.703	0.680	0.628
Cereals	0.701	0.661	0.620	0.575	0.454
Flour Products	0.557	0.507	0.471	0.461	0.386

Cereals is the most inelastic category, while Fruits is the most inelastic in the most recent sample. Vegetables, Cereals, and Oil and fats are more price elastic in the 2011-2013 sample. Fruits and Cereals are the categories with the most elasticity variation between samples.

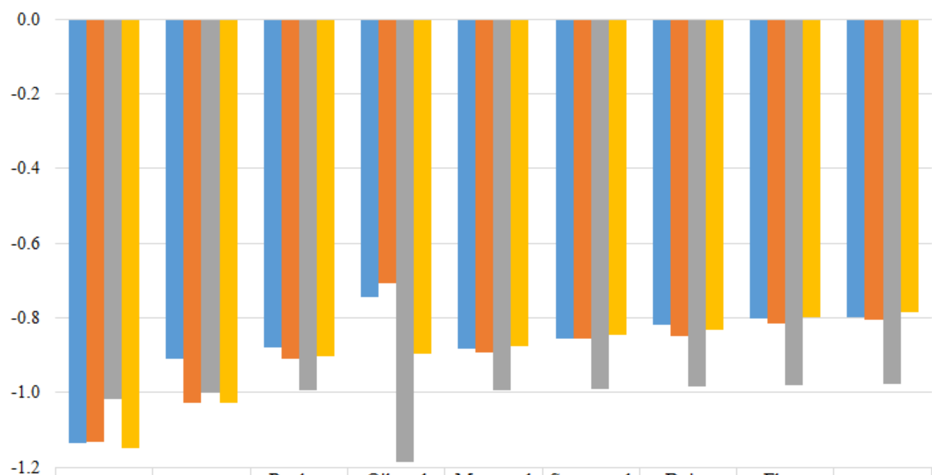
Vegetables present a less elastic indirect effect in both samples compared to the traditional, direct, and total elasticities. This is also the case of cereals in the most recent sample. For the remaining categories, the indirect effect elasticities are the more elastic ones. Direct effect elasticities are higher in absolute value than the traditional elasticities for all categories except Oil and fats.

Figure 5.19: Unconditional uncompensated elasticities - Food categories POF 2008-2010



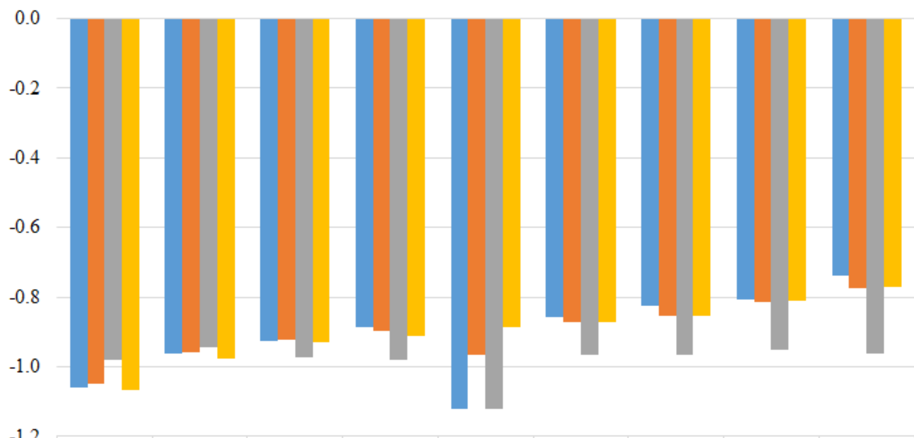
	Vegetables	Fruits	Poultry and Eggs	Meat and Fish	Oil and Fats	Sugar and Sweets	Dairy products	Flour Products	Cereals
Traditional	-1.056	-0.948	-0.892	-0.901	-0.863	-0.865	-0.833	-0.850	-0.759
Direct	-1.050	-0.946	-0.906	-0.904	-0.713	-0.882	-0.861	-0.858	-0.797
Indirect	-1.005	-0.997	-0.996	-0.995	-1.128	-0.991	-0.990	-0.990	-0.981
Total	-1.056	-0.947	-0.904	-0.895	-0.886	-0.874	-0.853	-0.853	-0.785

Figure 5.20: Unconditional uncompensated elasticities - Food categories POF 2011-2013



	Vegetables	Cereals	Poultry and Eggs	Oil and Fats	Meat and Fish	Sugar and Sweets	Dairy products	Flour Products	Fruits
Traditional	-1.136	-0.911	-0.881	-0.744	-0.881	-0.855	-0.820	-0.803	-0.798
Direct	-1.134	-1.026	-0.910	-0.707	-0.893	-0.855	-0.850	-0.814	-0.806
Indirect	-1.017	-1.002	-0.995	-1.188	-0.995	-0.991	-0.986	-0.981	-0.979
Total	-1.149	-1.029	-0.904	-0.896	-0.876	-0.845	-0.833	-0.798	-0.785

Figure 5.21: Unconditional compensated elasticities - Food categories POF 2008-2010



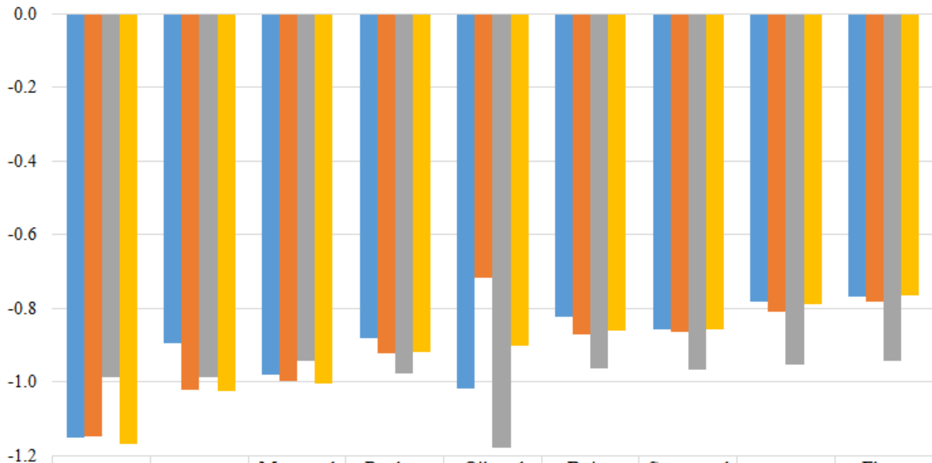
	Vegetables	Meat and Fish	Fruits	Poultry and Eggs	Oil and Fats	Sugar and Sweets	Dairy products	Flour Products	Cereals
Traditional	-1.059	-0.963	-0.926	-0.886	-1.121	-0.857	-0.826	-0.807	-0.739
Direct	-1.050	-0.958	-0.923	-0.898	-0.966	-0.873	-0.853	-0.814	-0.776
Indirect	-0.982	-0.944	-0.973	-0.979	-1.120	-0.965	-0.965	-0.952	-0.963
Total	-1.068	-0.977	-0.930	-0.911	-0.888	-0.871	-0.854	-0.811	-0.770

Figures 5.21 and 5.22 shows the unconditional compensated elasticities for respectively, POF 2008-2010 and POF 2011-2013. The difference between the uncompensated and compensated effect (income effect) is not expressive given the small expenditure share of the food subcategories. For both samples, the Meat and fish category presents the highest income effect and oil and fats the lowest. Dairy products and Poultry and eggs have higher income effects in the most recent sample.

The uncompensated and compensated cross-price elasticities in tables A.21, A.23, A.20 and A.22 in the Appendix reveal whether categories are substitutes or complements. Positive cross-price elasticities indicate that categories are substitutes, while negative values indicate complementary.

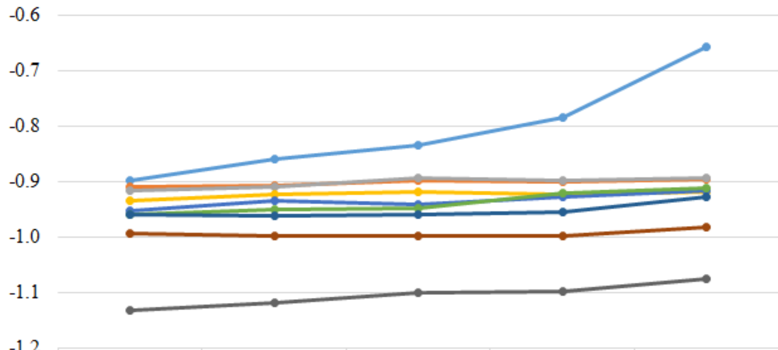
Figures 5.23 and 5.24 presents the unconditional total effect price elasticities by income per capita quintiles for respectively, POF 2008-2010 and POF 2011-2013. In the first sample, Cereals, Poultry and eggs, and Vegetables are more inelastic for the group with the highest income. In the most recent sample, Cereals' price elasticity presents an opposite behavior gaining elasticity as income increases. Fruits also present the lowest elasticity for the group with the highest income. The remaining categories are more inelastic as income increases.

Figure 5.22: Unconditional compensated elasticities - Food categories POF 2011-2013



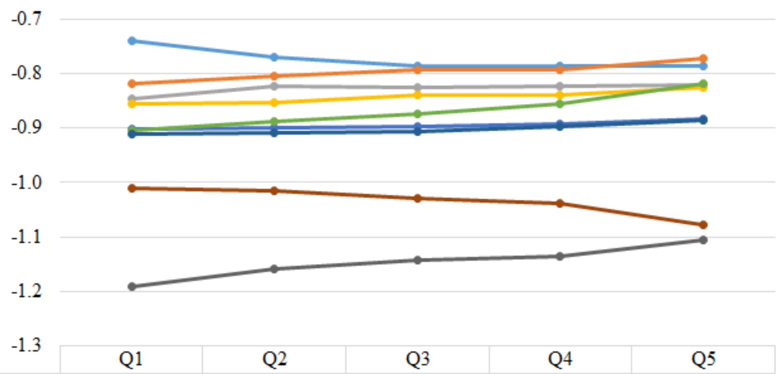
	Vegetables	Cereals	Meat and Fish	Poultry and Eggs	Oil and Fats	Dairy products	Sugar and Sweets	Fruits	Flour Products
Traditional	-1.152	-0.895	-0.979	-0.881	-1.018	-0.824	-0.857	-0.783	-0.769
Direct	-1.148	-1.019	-0.996	-0.921	-0.715	-0.871	-0.862	-0.808	-0.782
Indirect	-0.987	-0.985	-0.942	-0.977	-1.179	-0.963	-0.966	-0.951	-0.944
Total	-1.169	-1.023	-1.002	-0.918	-0.901	-0.860	-0.855	-0.789	-0.766

Figure 5.23: Unconditional total impact uncompensated price elasticities by income quintile - POF 2008-2010



	Q1	Q2	Q3	Q4	Q5
Cereals	-0.849	-0.810	-0.785	-0.734	-0.607
Dairy products	-0.860	-0.856	-0.848	-0.850	-0.845
Flour Products	-0.865	-0.858	-0.842	-0.847	-0.843
Sugar and Sweets	-0.884	-0.873	-0.868	-0.872	-0.867
Oil and Fats	-0.902	-0.885	-0.890	-0.877	-0.866
Meat and Fish	-0.908	-0.901	-0.897	-0.872	-0.862
Poultry and Eggs	-0.909	-0.912	-0.909	-0.904	-0.876
Fruits	-0.944	-0.948	-0.948	-0.947	-0.932
Vegetables	-1.082	-1.069	-1.050	-1.048	-1.025

Figure 5.24: Unconditional total impact uncompensated price elasticities by income quintile - POF 2011-2013



	Q1	Q2	Q3	Q4	Q5
Fruits	-0.740	-0.770	-0.785	-0.786	-0.786
Flour Products	-0.818	-0.804	-0.794	-0.793	-0.772
Dairy products	-0.846	-0.822	-0.824	-0.822	-0.822
Sugar and Sweets	-0.855	-0.853	-0.840	-0.840	-0.827
Oil and Fats	-0.902	-0.900	-0.898	-0.892	-0.882
Meat and Fish	-0.905	-0.889	-0.874	-0.856	-0.818
Poultry and Eggs	-0.912	-0.909	-0.906	-0.898	-0.885
Cereals	-1.011	-1.016	-1.028	-1.039	-1.078
Vegetables	-1.191	-1.158	-1.142	-1.135	-1.106

Overall, the elasticities found are at the same range as the values found by the literature on food demand estimation for the Brazilian context (Menezes et al., 2008; Pintos-Payeras, 2009; Leifert and Lucinda, 2015). However, our results are not directly comparable due to differences in data (most of the studies are based on national data from different periods), demand function, and definition of product categories.

5.4 Robustness tests

I consider some robustness exercises to understand if the spatial effect found significant is, in fact, peer effects, that is, if a household's expenditure decision is affected by their neighbor's demand. First, I estimate the spatial demand system limiting the samples to only 95% households closest to the center. Second, we estimate the spatial demand system using a weight matrix that gives weight to households that are far away "neighbors". Third, I estimate a spatial demand system in which the neighbor's demographics are also considered as explanatory variables for demand. In spatial econometric terms, we estimate a Spatial Durbin Model.

In the first exercise, we remove the 5% households most distant from the center and potentially isolated. With this, I avoid cases of isolated neighbors with geographically distant nearest neighbors. The results from the demand estimation without outliers are similar to the main results, and the spatial effects remain significant.

For the second robustness exercise, I expect that household demand will not be affected by the demands of others that are geographically distant. Specifically, we consider the five nearest neighbors counting from the fifth percentile most distant neighbor for each sample; that is, I give weight to the 55th to 60th nearest neighbors for the 2008-2010 sample and 99th to 104th nearest neighbor for the 2010-2103 sample. The results of the estimations for broad categories and food categories using both samples are presented in the Tables A.24, A.25, A.26 and A.27 in the Appendix. The results reveal that the spatial effects are not present anymore as expected in the POF 2008-2010 sample but are persistent in some equations for the POF 2011-2013 sample.

In the last robustness exercise, I estimated demand systems also controlling for spatial effects in the demographic variables of neighbors. The coefficients of the spatial lag controls for estimations with broad categories and food categories for each sample are presented respectively in Tables 5.11, 5.12, 5.13 and 5.14. The third robustness exercise was important to reveal that the correlation between neighbor demands is not caused by the demographics characteristics of one's neighbors.

The result for broad categories in sample POF 2008-2010 presented in Table 5.11 reveals that neighbor's head of household age positively affects expenditure on Habitation and negatively expenditure on Health. Neighbor's total number of children positively affects expenditure on Personal expenses. Neighbors' education level positively affects Clothing expenditure, while having neighbors with female head of household has a negative effect. Compared to the spatial lag model, the spatial lag in the Spatial Durbin Model component remains significant only for the Personal Expenses and Education equations.

The result for broad categories in sample POF 2011-13 in Table 5.12 reveals that neighbors' expenditure and the total number of youngsters negatively affect Clothing expenditure. Neighbor's total number of youngsters also effects negatively expenditure with food. Neighbor's head of households age and incomplete college level of education positively affects expenditure with Habitation. Compared to the spatial lag estimation, the spatial lag remains significant for Habitation, Food, Clothing, and Education and loses significance in Personal expenses and Health equations.

The results for Food categories in sample POF 2008-2010 presented in Table 5.13 show that in most of the equations, the demographics of neighbors were not significant in explaining demand; still, compared to the spatial lag estimation, the spatial lag coefficients for Cereals, Flour products, and Fruits loses significance. The results for Food categories in sample POF 2011-13 presented in Table 5.14 show that in most of the equations, the demographics of neighbors were not significant in explaining demand while neighbor's demand effect remained significant for all equations except for Poultry and eggs.

Table 5.11: SDM AIDS Estimation - Broad Categories POF 2008/2010

	Habitation		**Food**		**Transportation**		**Personal Expenses**		**Health**		**Clothing**		**Education**	
Variable	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value
w.Log Real Expend	**0.026**	0.046	0.001	0.885	-0.008	0.365	0.008	0.280	-0.002	0.769	-0.010	0.054	-0.014	0.088
w.HH Age	**0.002**	0.043	-0.001	0.101	0.001	0.526	0.000	0.571	**-0.001**	0.044	0.000	0.455	-0.001	0.152
w.HH Co. Elem	-0.091	0.106	-0.027	0.457	0.025	0.516	0.018	0.559	-0.007	0.838	**0.054**	0.013	0.027	0.389
w.HH Co. Junior	-0.069	0.261	-0.029	0.458	0.043	0.313	0.017	0.628	-0.033	0.377	0.043	0.071	0.029	0.397
w.HH Co. High	-0.057	0.347	-0.060	0.116	0.015	0.726	0.035	0.306	0.008	0.829	**0.061**	0.010	0.000	0.992
w.HH In. College	-0.017	0.815	-0.036	0.424	-0.010	0.847	0.011	0.794	0.016	0.719	**0.064**	0.022	-0.027	0.495
w.HH Co. College	-0.062	0.319	-0.044	0.263	-0.001	0.982	0.048	0.165	-0.005	0.897	**0.049**	0.043	0.015	0.661
w.HH Female	-0.014	0.562	0.002	0.869	-0.012	0.452	0.006	0.627	0.025	0.074	**-0.020**	0.028	0.011	0.380
w.H Size	-0.007	0.487	-0.003	0.631	0.010	0.168	-0.005	0.410	0.002	0.775	0.002	0.595	0.001	0.818
w.H Total Child	0.004	0.869	-0.011	0.466	-0.019	0.276	**0.046**	0.001	-0.020	0.191	0.001	0.903	-0.002	0.894
w.H Total Youngster	-0.009	0.596	0.019	0.079	0.009	0.432	0.009	0.355	-0.019	0.061	0.007	0.283	-0.016	0.097
w.H Total Adults	0.020	0.389	0.022	0.137	-0.018	0.260	0.000	0.996	-0.019	0.174	0.002	0.839	-0.006	0.627
w.H Total Eldery	-0.016	0.466	0.011	0.437	-0.017	0.262	0.008	0.535	0.011	0.396	0.001	0.886	0.002	0.875
w.Mills	0.010	0.785	-0.010	0.427	0.009	0.472	**0.029**	0.016	-0.005	0.720	-0.010	0.418	-0.023	0.580
λ_{slm}	0.026	0.432	0.034	0.371	0.045	0.234	**0.092**	0.020	-0.006	0.874	0.042	0.333	**-0.234**	0.050
Demographics	Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Mills	Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Observations	1119		1119		1119		1119		1119		1119		1119	
Log Likelihood	-6909.70		-6909.70		-6909.70		-6909.70		-6909.70		-6909.70		-6909.70	

Coefficients in bold are significant with $p < 0.05$.

Table 5.12: SDM AIDS Estimation - Broad Categories POF 2011/2013

	Habitation		**Food**		**Transportation**		**Personal Expenses**		**Health**		**Clothing**		**Education**	
Variable	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value
w.Log Real Expend	0.006	0.537	0.014	0.064	-0.009	0.157	0.001	0.831	0.009	0.163	**-0.011**	0.044	-0.010	0.078
w.HH Age	**0.002**	0.007	-0.001	0.147	0.000	0.485	0.000	0.261	0.000	0.399	0.000	0.769	0.000	0.635
w.HH Co. Elem	0.014	0.644	0.030	0.210	-0.025	0.216	0.020	0.266	0.003	0.875	-0.027	0.112	-0.016	0.373
w.HH Co. Junior	0.032	0.350	0.022	0.394	-0.018	0.415	-0.018	0.375	0.010	0.628	-0.010	0.592	-0.018	0.315
w.HH Co. High	0.056	0.103	0.001	0.981	-0.026	0.247	0.000	0.990	0.008	0.721	-0.021	0.270	-0.017	0.330
w.HH In. College	**0.090**	0.034	-0.022	0.480	-0.037	0.185	0.025	0.323	-0.017	0.520	-0.024	0.319	-0.014	0.504
w.HH Co. College	0.059	0.098	-0.010	0.706	-0.033	0.158	0.009	0.670	0.041	0.068	-0.032	0.107	-0.034	0.071
w.HH Female	-0.001	0.954	0.013	0.249	-0.010	0.291	0.012	0.166	0.004	0.642	-0.009	0.283	-0.010	0.238
w.H Size	-0.008	0.308	0.005	0.325	0.008	0.114	-0.005	0.228	-0.007	0.158	0.006	0.150	0.000	0.914
w.H Total Child	-0.009	0.585	0.004	0.775	0.007	0.537	0.006	0.525	-0.004	0.743	0.000	0.980	-0.004	0.626
w.H Total Youngster	0.019	0.121	**-0.019**	0.031	-0.007	0.374	0.003	0.674	0.012	0.116	**-0.015**	0.024	0.008	0.206
w.H Total Adults	-0.002	0.916	0.005	0.639	-0.005	0.638	0.005	0.551	0.011	0.256	-0.014	0.100	-0.001	0.864
w.H Total Eldery	-0.011	0.406	0.014	0.204	-0.011	0.224	0.015	0.060	-0.001	0.914	0.001	0.917	-0.007	0.407
w.Mills	0.023	0.734	0.298	0.381	-0.002	0.807	-0.007	0.815	-0.005	0.440	0.003	0.754	-0.310	0.362
λ_{slm}	**0.068**	0.003	**0.094**	0.000	0.015	0.587	0.045	0.127	0.042	0.127	**0.096**	0.001	**-0.359**	0.000
Demographics	Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Mills	Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Observations	1985		1985		1985		1985		1985		1985		1985	
Log Likelihood	-13300.85		-13300.85		-13300.85		-13300.85		-13300.85		-13300.85		-13300.85	

Coefficients in bold are significant with $p < 0.05$.

Table 5.13: SDM AIDS Estimation - Food Categories POF 2008/2010

	Cereals		**Flour Products**		**Vegetables**		**Sugar and Sweets**		**Fruits**		**Meat and Fish**		**Poultry and Eggs**		**Dairy products**		**Oil and Fats**	
Variable	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value
w.Log Real Expend	-0.002	0.758	-0.006	0.641	0.012	0.115	-0.001	0.949	0.007	0.504	-0.007	0.622	0.003	0.604	-0.002	0.832	-0.005	0.162
w.HH Age	0.000	0.563	0.000	0.765	0.000	0.432	0.000	0.536	-0.001	0.432	0.000	0.627	0.000	0.912	0.000	0.803	**0.000**	0.020
w.HH Co. Elem	-0.005	0.842	-0.030	0.452	0.019	0.472	0.016	0.609	-0.028	0.409	0.035	0.461	0.014	0.522	-0.036	0.321	0.015	0.108
w.HH Co. Junior	-0.015	0.583	-0.005	0.912	0.010	0.719	0.022	0.516	-0.016	0.665	0.009	0.855	0.013	0.574	-0.042	0.279	**0.023**	0.023
w.HH Co. High	-0.040	0.149	-0.015	0.724	0.022	0.442	0.042	0.214	0.004	0.911	0.021	0.682	0.009	0.711	-0.057	0.148	0.014	0.176
w.HH In. College	-0.025	0.446	-0.010	0.841	0.039	0.247	0.028	0.488	0.043	0.311	0.031	0.608	0.012	0.672	**-0.124**	0.007	0.006	0.625
w.HH Co. College	-0.028	0.312	0.010	0.818	0.031	0.276	0.022	0.508	0.016	0.656	-0.008	0.871	-0.015	0.515	-0.041	0.293	0.013	0.228
w.HH Female	0.005	0.636	0.014	0.393	-0.003	0.772	0.006	0.668	-0.011	0.425	-0.008	0.696	-0.001	0.901	-0.004	0.785	0.002	0.545
w.H Size	0.001	0.900	-0.001	0.854	-0.005	0.354	-0.001	0.878	-0.005	0.445	0.014	0.097	0.001	0.885	-0.005	0.451	0.001	0.534
w.H Total Child	0.019	0.099	-0.003	0.871	-0.010	0.422	-0.002	0.899	0.006	0.674	-0.021	0.320	0.001	0.892	0.008	0.614	0.000	0.925
w.H Total Youngster	0.012	0.100	0.008	0.483	0.011	0.152	-0.005	0.581	-0.003	0.755	-0.009	0.498	-0.002	0.761	-0.015	0.170	0.002	0.420
w.H Total Adults	-0.007	0.509	-0.002	0.921	-0.015	0.176	0.004	0.733	-0.008	0.588	0.024	0.217	0.016	0.066	-0.014	0.354	0.000	0.939
w.H Total Eldery	-0.005	0.617	0.008	0.621	-0.007	0.480	0.011	0.363	0.002	0.860	0.004	0.843	-0.004	0.636	-0.002	0.900	-0.007	0.067
w.Mills	-0.001	0.743	0.004	0.449	**0.009**	0.013	-0.007	0.115	0.001	0.756	-0.003	0.537	-0.001	0.832	0.005	0.169	-0.009	0.283
λ_{slm}	0.041	0.079	0.033	0.127	**0.077**	0.002	**0.046**	0.047	0.022	0.360	**0.043**	0.038	0.028	0.316	**0.047**	0.033	**-0.336**	0.017
Demographics	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Mills	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Observations	1078		1078		1078		1078		1078		1078		1078		1078		1078	
Log Likelihood	-11162.59		-21247.30		-21247.30		-21247.30		-21247.30		-21247.30		-21247.30		-21247.30		-21247.30	

Coefficients in bold are significant with $p < 0.05$.

Table 5.14: SDM AIDS Estimation - Food Categories POF 2011/2013

	Cereals		**Flour Products**		**Vegetables**		**Sugar and Sweets**		**Fruits**		**Meat and Fish**		**Poultry and Eggs**		**Dairy products**		**Oil and Fats**	
Variable	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value
w.Log Real Expend	-0.008	0.122	0.011	0.119	0.005	0.444	**-0.014**	0.032	**0.017**	0.011	-0.005	0.620	-0.001	0.879	-0.004	0.604	-0.003	0.237
w.HH Age	0.000	0.175	0.000	0.934	0.000	0.691	-0.001	0.182	0.000	0.860	0.000	0.471	0.000	0.180	0.001	0.061	0.000	0.490
w.HH Co. Elem	-0.025	0.086	0.003	0.870	0.011	0.539	-0.011	0.561	0.024	0.235	-0.022	0.431	-0.006	0.629	0.025	0.199	0.000	0.996
w.HH Co. Junior	-0.010	0.527	-0.013	0.588	0.014	0.478	-0.023	0.264	0.006	0.791	0.011	0.723	0.007	0.620	0.001	0.962	0.007	0.333
w.HH Co. High	-0.005	0.753	-0.020	0.380	0.016	0.399	-0.009	0.651	0.029	0.187	-0.043	0.154	0.003	0.835	0.022	0.316	0.008	0.275
w.HH In. College	-0.014	0.467	-0.013	0.643	-0.020	0.416	0.018	0.479	0.023	0.398	-0.050	0.180	0.008	0.640	0.040	0.143	0.009	0.298
w.HH Co. College	-0.023	0.129	-0.015	0.486	0.015	0.416	0.001	0.960	0.021	0.308	-0.037	0.198	-0.012	0.407	**0.048**	0.021	0.002	0.820
w.HH Female	-0.011	0.105	0.011	0.304	0.013	0.137	**-0.020**	0.031	0.013	0.167	-0.007	0.602	0.005	0.442	0.001	0.891	-0.005	0.085
w.H Size	0.000	0.986	-0.001	0.921	-0.001	0.913	0.003	0.475	0.001	0.805	-0.006	0.377	-0.004	0.188	0.005	0.287	0.002	0.287
w.H Total Child	-0.005	0.535	-0.008	0.478	0.000	0.967	0.003	0.793	-0.004	0.721	0.019	0.215	**0.015**	0.037	-0.014	0.182	-0.005	0.122
w.H Total Youngster	0.008	0.171	-0.008	0.364	-0.004	0.571	0.003	0.678	-0.002	0.850	0.010	0.366	0.001	0.911	-0.007	0.399	-0.002	0.525
w.H Total Adults	0.002	0.725	-0.004	0.707	0.000	0.971	0.002	0.863	0.001	0.922	0.002	0.882	0.006	0.354	-0.007	0.463	-0.002	0.471
w.H Total Eldery	0.009	0.179	0.001	0.880	-0.009	0.277	**0.022**	0.009	-0.001	0.909	-0.024	0.055	0.007	0.209	-0.007	0.444	0.001	0.679
w.Mills	0.002	0.352	0.008	0.092	-0.002	0.610	-0.001	0.666	**0.007**	0.029	-0.002	0.666	**-0.010**	0.001	0.003	0.411	-0.005	0.403
λ_{slm}	**0.065**	0.000	**0.077**	0.000	**0.087**	0.000	**0.044**	0.015	**0.101**	0.000	**0.074**	0.000	0.004	0.849	**0.078**	0.000	**-0.530**	0.000
Demographics	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Mills	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Observations	1965		1965		1965		1965		1965		1965		1965		1965		1965	
Log Likelihood	-21315.45		-21315.45		-21315.45		-21315.45		-21315.45		-21315.45		-21315.45		-21315.45		-21315.45	

Coefficients in bold are significant with $p < 0.05$.

6 FINAL CONSIDERATIONS

Literature has long acknowledged theoretically and empirically the importance of peer effects in consumption. However, due to data limitations, there still is a lot to understand, especially for countries in development. This thesis adds to this literature by estimating a spatial demand model using Brazilian disaggregated data on consumption that has not been applied to this purpose before. Two main challenges were involved in this study. The first was to theoretically adapt the traditional demand estimation model based on the classical demand theory to incorporate social interaction. The second was to develop estimation routines that allowed spatial seemingly unrelated regressions method to be applied to the demand estimation context.

The main contribution of the thesis was to provide the calculation and analysis of a complete set of elasticities including expenditure, uncompensated, compensated, and unconditional elasticities for the spatial model from which direct, indirect and total effects can be specified. Other contributions of the thesis consist of presenting a summarized overview of the theoretical and empirical literature on demand estimation and social interactions in consumption; developing a theoretically and empirically well-specified spatial demand system; and providing empirical results for categories in a multistage budgeting model, that is, considering first the demand for broad categories and in the second stage demand for food subcategories within the general group of food items.

Although this study seeks to attend to most of the problems involving demand estimation and social interactions in consumption pointed out by the literature, several caveats indicate room for improvement. First, in the demand estimation model, the Heien and Wesseils (1990) method used for censoring has been criticized for not providing consistent estimates. Although the Shonkwiler and Yen (1999) method was shown to be inefficient, it is the most popular method used by the recent literature and will be applied to improve the study further. Second, the model developed and estimated was a spatial linear almost ideal demand system. As discussed in the thesis, the linear approximation of the demand estimation can impose several limitations in the estimated coefficients and, consequently, the elasticities. The next step of the research will be to estimate a spatial version of the nonlinear demand system.

From the results of the empirical investigation, it can be concluded that neighbors cause a small but not negligible effect on a household's consumption behaviors. Peers effects were found more relevant for Food categories and the 2011-2013 sample. Consequently, the resulting elasticities derived from demand estimations must now consider spillover and feedback effects provoked by the social interaction. Given that demand elasticities are important economic parameters used for tax simulation policies with welfare outcomes and the calibration of computable general equilibrium models analysis, its precise computation is of great relevance.

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APPENDIX

Appendix I - Constraints for AIDS

This appendix presents the derivation of the implied restrictions for a theoretically well behaved AIDS model discussed in Section 2.2.

I.a. Adding-up restriction for AIDS

The AIDS demand system is given by

$$s_i = \alpha_i + \sum_j \gamma_{ij} \log(p_j) + \beta_i \log\left(w - \alpha_0 - \sum_i \alpha_i \log(p_i) - \frac{1}{2} \sum_i \sum_j \gamma_{ij} \log(p_i) \log(p_j) \right) \quad \forall i = 1, ..., G \tag{6.1}$$

When summed over all goods $i = 1, ..., G$

$$\begin{aligned}\sum_i s_i &= \sum_i \alpha_i + \sum_i \sum_j \gamma_{ij} \log(p_j) + \\ &+ \sum_i \beta_i \log\left(w - \alpha_0 - \sum_i \alpha_i \log(p_i) - \frac{1}{2} \sum_i \sum_j \gamma_{ij} \log(p_i) \log(p_j) \right) = 1\end{aligned}$$

$$\begin{aligned}&\Rightarrow \sum_i \alpha_i + \sum_j \log(p_j) \sum_i \gamma_{ij} + \\ &+ \log\left(w - \alpha_0 - \sum_i \alpha_i \log(p_i) - \frac{1}{2} \sum_i \sum_j \gamma_{ij} \log(p_i) \log(p_j) \right) \sum_i \beta_i = 1\end{aligned} \tag{6.2}$$

If Equation 6.2 is true for any real numbers $\sum_j \log(p_j)$ and $\log(w - g(\mathbf{p}))$ then for $\sum_j \log(p_j) = 0$ and $\log(w - g(\mathbf{p})) = 0$, $\sum_i \alpha_i$ must be equal to 1. And if $\sum_i \alpha_i = 1$, for $\sum_j \log(p_j) = 1$ or $\log(w - g(\mathbf{p})) = 1$, then $\sum_i \gamma_{ij} = \sum_i \beta_i = 0$ must be true. Therefore, $\sum_i s_i = 1$ implies the restrictions $\sum_i \alpha_i = 1$ and $\sum_i \gamma_{ij} = \sum_i \beta_i = 0$.

I.b. Homogeneity restriction for AIDS

Homogeneity restrictions imply that the budget shares will not change if all prices and expenditures changes in the same proportion. The restrictions can be written as

$$\sum_j \frac{\partial s_i}{\partial \log p_j} + \frac{\partial s_i}{\partial \log w} = 0 \quad \forall i \tag{6.3}$$

$$\Rightarrow \sum_j \left(\gamma_{ij} - \beta_i \frac{\partial \log g(\mathbf{p})}{\partial \log p_j} \right) + \beta_i = \sum_j \gamma_{ij} - \beta_i \sum_j \frac{\partial \log g(p)}{\partial \log p_j} + \beta_i = 0 \quad \forall i \tag{6.4}$$

For Equation 6.4 to be true, $\sum_j \gamma_{ij} = 0$ must hold for all i once that if $\beta_i = 0$ or $\beta_i \neq 0$ and $\sum_j \frac{\partial \log g(\mathbf{p})}{\partial \log p_j} = 1$, then $\sum_j \gamma_{ij} = 0$.

I.c. Symmetry restriction for AIDS

The symmetry restrictions require compensated demand effects to be symmetric, which from the Slutsky equation means

$$\frac{\partial q_i}{\partial p_j} + q_j \frac{\partial q_i}{\partial w} = \frac{\partial q_j}{\partial p_i} + q_i \frac{\partial q_j}{\partial w} \quad \forall i, j \tag{6.5}$$

where q_i and q_j are the Marshallian demands. By multiplying the equation by $p_i p_j / w$ and using the following identities

$$\frac{\partial p_i}{\partial \log p_i} = p_i, \quad \frac{\partial s_i}{\partial p_j} = \frac{\partial q_i}{\partial p_j} \frac{p_i}{w}, \quad \frac{\partial w}{\partial \log w} = w, \quad \frac{\partial s_i}{\partial w} = \frac{\partial q_i}{\partial w} \frac{p_i}{w} - \frac{s_i}{w}$$

the following symmetry restrictions for the derivatives of the budget shares are found

$$\frac{\partial s_i}{\partial \log(p_j)} + s_j \frac{\partial s_i}{\partial \log(w)} = \frac{\partial s_j}{\partial \log(p_i)} + s_i \frac{\partial s_j}{\partial \log(w)} \quad \forall i, j \tag{6.6}$$

By replacing the derivates of equation s_i into the symmetry condition above follows

$$\begin{aligned} &\gamma_{ij} - \beta_i \frac{\partial \log g(\mathbf{p})}{\partial \log(p_j)} + \beta_i \left\{ \alpha_j + \sum_k \gamma_{jk} \log(p_k) + \beta_j \left(\log w - \log g(\mathbf{p}) \right) \right\} \\ &= \gamma_{ji} - \beta_j \frac{\partial \log(g(\mathbf{p}))}{\partial \log(p_i)} + \beta_j \left\{ \alpha_i + \sum_k \gamma_{ik} \log(p_k) + \beta_i \left(\log w - \log g(\mathbf{p}) \right) \right\} \end{aligned}$$

$$\Rightarrow \gamma_{ij} - \beta_i \left\{ \frac{\partial \log g(\mathbf{p})}{\partial \log(p_j)} - \alpha_j - \sum_k \gamma_{jk} \log(p_k) \right\} = \gamma_{ji} - \beta_j \left\{ \frac{\partial \log(g(\mathbf{p}))}{\partial \log(p_i)} - \alpha_i - \sum_k \gamma_{ik} \log(p_k) \right\} \quad \forall i, j \tag{6.7}$$

With the definition of $\log g(\mathbf{p})$,

$$\frac{\partial \log g(\mathbf{p})}{\partial \log(p_j)} = \alpha_j + \frac{1}{2} \sum_k (\gamma_{kj} + \gamma_{jk}) \log p_k \tag{6.8}$$

equation 6.7 is

$$\gamma_{ij} - \beta_i \left\{ \frac{1}{2} \sum_k (\gamma_{kj} - \gamma_{jk}) \log p_k \right\} = \gamma_{ji} - \beta_j \left\{ \frac{1}{2} \sum_k (\gamma_{ik} - \gamma_{ki}) \log p_k \right\} \quad \forall i, j \tag{6.9}$$

which leads to the restriction

$$\gamma_{ij} = \gamma_{ji} \tag{6.10}$$

I.d. Negativity restriction for AIDS

The terms of the Slutsky matrix are given by

$$\frac{\partial^2 c(\mathbf{p}, u)}{\partial p_i \partial p_j} = S_{ij} = \frac{w}{p_i p_j} \left(s_i s_j + \frac{\partial s_i}{\partial \log p_j} + \delta_{ij} s_i \right) \tag{6.11}$$

where $\delta_{ij} = 1$ if $i = j$, $\delta_{ij} = 0$, otherwise. These compensated derivates, therefore the s_i is given by Equation 2.30 from which

$$\frac{\partial s_i}{\partial \log p_j} = \gamma_{ij} + \beta_i \beta_j u \beta_0 \prod_i p_i^{\beta_i} \tag{6.12}$$

Replacing u with the indirect utility in Equation 2.31 gives

$$\frac{\partial s_i}{\partial \log p_j} = \gamma_{ij} + \beta_i \beta_j \log \frac{w}{p} \tag{6.13}$$

The Slutsky term will be

$$\frac{\partial^2 c(\mathbf{p}, u)}{\partial p_i \partial p_j} = S_{ij} = \frac{w}{p_i p_j} \left(s_i s_j + \gamma_{ij} + \beta_i \beta_j \log \frac{w}{p} + \delta_{ij} s_i \right) \tag{6.14}$$

S_{ij} depends on each point separately and cannot be ensured by any restrictions on the parameters alone.

Appendix II - Supplementary Tables

This section presents supplementary result tables.

Table A.1: Probit Models - Broad Categories

	Habitation	Food	Transportation	Personal	Health	Clothing	Education
HH Log Income	0.730**	0.188	0.733***	0.254**	0.429***	0.467***	0.588***
	(0.225)	(0.107)	(0.058)	(0.097)	(0.045)	(0.041)	(0.044)
HH Age	0.012	-0.008	-0.020***	-0.012	0.013***	-0.006*	-0.002
	(0.012)	(0.007)	(0.003)	(0.007)	(0.003)	(0.002)	(0.003)
HH Female	0.151	0.148	-0.085	0.142	0.157**	0.156**	0.072
	(0.400)	(0.151)	(0.076)	(0.160)	(0.061)	(0.055)	(0.057)
H Size	0.060	-0.027	0.149***	0.060	0.026	0.032	0.063*
	(0.209)	(0.069)	(0.041)	(0.080)	(0.029)	(0.026)	(0.026)
H Total Child	-0.172	-0.069	-0.162	-0.257	-0.031	-0.017	0.102
	(0.324)	(0.151)	(0.093)	(0.158)	(0.063)	(0.061)	(0.060)
H Total Youngster	-0.299	0.068	-0.111	0.013	-0.038	0.012	0.122**
	(0.254)	(0.119)	(0.067)	(0.130)	(0.044)	(0.042)	(0.041)
H Total Adults and Elders	0.233						
	(0.400)						
H Total Adults		-0.060	0.415***	0.056	-0.036	0.004	0.103
		(0.136)	(0.071)	(0.144)	(0.055)	(0.050)	(0.053)
H Total Elders		0.217	-0.267***	0.263	0.155**	-0.104*	-0.269***
		(0.149)	(0.068)	(0.166)	(0.059)	(0.049)	(0.052)
HH Comp. Elem.		0.322	0.088		0.353**	0.131	0.071
		(0.285)	(0.133)		(0.123)	(0.113)	(0.146)
HH Incomp. High		0.203	0.101		0.245	0.129	-0.003
		(0.309)	(0.150)		(0.132)	(0.123)	(0.154)
HH Comp. High.		0.093	0.098		0.326*	0.083	0.144
		(0.309)	(0.153)		(0.134)	(0.123)	(0.153)
HH Incomp. College		-0.251	0.101		0.293	0.039	0.388*
		(0.360)	(0.226)		(0.170)	(0.157)	(0.179)
HH Comp. College		0.001	0.104		0.418**	0.054	0.285
		(0.352)	(0.181)		(0.153)	(0.137)	(0.164)
Price Habitation	-0.001						
	(0.002)						
Price Food		0.003					
		(0.004)					
Price Transportation			0.001				
			(0.002)				
Price Personal Exp.				0.000			
				(0.001)			
Price Health					-0.000		
					(0.000)		
Price Clothing						-0.001	
						(0.001)	
Price Education							-0.001***
							(0.000)
Constant	-3.147	0.979	-3.871***	0.624	-3.781***	-3.174***	-5.369***
	(1.687)	(0.784)	(0.423)	(0.766)	(0.338)	(0.304)	(0.342)
Number of Obs.	3109	3109	3109	3109	3109	3109	3109

Source: Authors' Computations. Standard Error in Parentheses. * p<0.05, ** p<0.01, *** p<0.001

Table A.2: Probit Models - Food Categories POF 2008-2010

	Cereals	Flour Products	Vegetables	Sugar	Fruits	Meat & Fish	Poultry & Egg	Dairy products	Oil & Fats
HH Age	-0.002	0.010	-0.001	0.007	0.014*	0.001	0.009	0.007	-0.003
	(0.005)	(0.009)	(0.006)	(0.006)	(0.006)	(0.007)	(0.005)	(0.006)	(0.005)
HH Comp. Elem.	0.157	0.606	-0.031	-0.044	0.184	0.215	0.178	0.603**	0.099
	(0.241)	(0.377)	(0.325)	(0.316)	(0.274)	(0.306)	(0.258)	(0.233)	(0.229)
HH Incomp. High	0.071	0.390	0.152	-0.015	0.315	0.113	-0.029	0.658*	-0.009
	(0.257)	(0.401)	(0.349)	(0.340)	(0.293)	(0.330)	(0.272)	(0.257)	(0.244)
HH Comp. High.	0.090	0.627	-0.126	0.154	0.371	0.115	0.157	0.895***	0.254
	(0.261)	(0.420)	(0.344)	(0.350)	(0.297)	(0.337)	(0.280)	(0.267)	(0.250)
HH Incomp. College	0.261	0.394	0.193	0.372	0.223	0.681	0.495	0.749*	0.132
	(0.340)	(0.526)	(0.469)	(0.474)	(0.366)	(0.534)	(0.388)	(0.351)	(0.310)
HH Comp. College	-0.055	0.651	0.016	0.193	0.385	-0.031	0.058	0.791**	0.032
	(0.285)	(0.487)	(0.384)	(0.386)	(0.346)	(0.366)	(0.309)	(0.300)	(0.273)
HH Female	-0.152	-0.237	-0.111	-0.086	0.070	-0.030	0.071	-0.012	-0.123
	(0.106)	(0.202)	(0.132)	(0.136)	(0.124)	(0.142)	(0.114)	(0.121)	(0.099)
H Size	0.061	0.233*	0.038	0.118	-0.007	0.132	0.123*	0.117	0.163***
	(0.049)	(0.113)	(0.063)	(0.068)	(0.057)	(0.073)	(0.057)	(0.061)	(0.048)
H Total Child	0.220	0.181	0.035	0.022	-0.080	0.345	0.023	0.198	-0.091
	(0.129)	(0.286)	(0.154)	(0.169)	(0.122)	(0.235)	(0.133)	(0.159)	(0.108)
H Total Youngster	0.141	0.374	0.058	0.268*	0.081	0.241	0.087	0.153	0.115
	(0.081)	(0.223)	(0.103)	(0.130)	(0.088)	(0.139)	(0.092)	(0.104)	(0.076)
H Total Adults	0.109	0.121	-0.127	0.033	-0.098	0.012	-0.045	-0.051	-0.109
	(0.098)	(0.195)	(0.128)	(0.127)	(0.116)	(0.133)	(0.106)	(0.113)	(0.091)
H Total Elders	0.152	0.342	0.172	-0.129	0.124	0.016	-0.101	-0.021	0.223*
	(0.099)	(0.230)	(0.134)	(0.121)	(0.126)	(0.130)	(0.107)	(0.112)	(0.094)
HH Log Income	-0.027	-0.004	0.114	-0.112	0.303***	0.007	0.177*	0.084	-0.101
	(0.076)	(0.152)	(0.094)	(0.101)	(0.090)	(0.103)	(0.081)	(0.087)	(0.073)
East zone	-0.065	0.120	0.660**	0.041	0.326	-0.019	0.490*	0.080	-0.052
	(0.216)	(0.380)	(0.243)	(0.275)	(0.277)	(0.286)	(0.221)	(0.246)	(0.207)
North zone	-0.146	-0.402	0.248	-0.041	0.092	-0.243	0.266	0.016	0.034
	(0.224)	(0.375)	(0.250)	(0.283)	(0.291)	(0.291)	(0.230)	(0.256)	(0.214)
West zone	0.044	0.484	0.314	0.191	-0.167	-0.296	0.241	0.165	0.113
	(0.246)	(0.511)	(0.275)	(0.320)	(0.306)	(0.313)	(0.253)	(0.285)	(0.231)
South zone	0.223	0.398	0.706**	0.166	0.184	-0.031	0.496*	0.342	0.298
	(0.218)	(0.402)	(0.251)	(0.277)	(0.279)	(0.284)	(0.227)	(0.252)	(0.206)
Price Cereals	-0.008								
	(0.031)								
Price Flour Products		-0.029							
		(0.018)							
Price Vegetables			-0.092						
			(0.049)						
Price Sugar and Sweets				-0.001					
				(0.013)					
Price Fruits					0.020				
					(0.056)				
Price Meat and Fish						-0.009			
						(0.017)			
Price Poultry and Egg							-0.021		
							(0.037)		
Price Dairy products								-0.015*	
								(0.008)	
Price Oil and Fats									0.015
									(0.021)
Constant	0.879	0.283	0.308	1.572	-2.318**	0.979	-1.489*	-0.764	0.893
	(0.642)	(1.157)	(0.788)	(0.832)	(0.736)	(0.827)	(0.675)	(0.710)	(0.601)
Number of Obs.	1078	1078	1078	1078	1078	1078	1078	1078	1078

Source: Authors' Computations. Standard Error in Parentheses. * p<0.05, ** p<0.01, *** p<0.001

Table A.3: Probit Models - Food Categories POF 2011-2013

	Cereals	Flour Products	Vegetables	Sugar	Fruits	Meat & Fish	Poultry & Egg	Dairy products	Oil & Fats
HH Age	-0.000	-0.016*	0.008	0.007	0.013**	-0.003	-0.000	0.008*	0.002
	(0.003)	(0.007)	(0.005)	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)	(0.003)
HH Comp. Elem.	0.202	0.238	0.523*	-0.182	0.141	-0.038	-0.352	0.081	0.064
	(0.153)	(0.305)	(0.227)	(0.228)	(0.213)	(0.239)	(0.190)	(0.163)	(0.152)
HH Incomp. High	0.250	-0.089	0.361	-0.080	0.076	-0.151	-0.258	0.263	0.162
	(0.168)	(0.323)	(0.238)	(0.249)	(0.226)	(0.257)	(0.204)	(0.182)	(0.166)
HH Comp. High.	0.109	-0.212	0.453	-0.187	0.149	-0.247	-0.251	0.158	0.059
	(0.167)	(0.322)	(0.243)	(0.248)	(0.231)	(0.257)	(0.206)	(0.181)	(0.166)
HH Incomp. College	0.037	-0.484	0.220	0.289	-0.085	-0.546	-0.333	0.120	-0.066
	(0.217)	(0.400)	(0.305)	(0.370)	(0.288)	(0.316)	(0.259)	(0.241)	(0.214)
HH Comp. College	-0.087	-0.326	0.063	-0.445	-0.071	-0.656*	-0.555*	0.192	-0.288
	(0.186)	(0.360)	(0.266)	(0.272)	(0.262)	(0.279)	(0.225)	(0.210)	(0.184)
HH Female	-0.080	-0.058	0.431***	0.007	0.128	-0.074	0.088	-0.041	-0.006
	(0.078)	(0.154)	(0.125)	(0.107)	(0.107)	(0.115)	(0.088)	(0.088)	(0.077)
H Size	0.062	0.129	0.229***	0.155**	0.064	0.076	0.120**	0.097*	0.061
	(0.039)	(0.086)	(0.064)	(0.057)	(0.054)	(0.060)	(0.046)	(0.045)	(0.038)
H Total Child	0.205*	-0.285	-0.200	-0.007	-0.075	0.151	0.043	-0.039	0.041
	(0.101)	(0.190)	(0.147)	(0.138)	(0.119)	(0.172)	(0.109)	(0.103)	(0.091)
H Total Youngster	-0.002	0.041	-0.019	-0.110	-0.001	0.061	0.081	0.016	0.066
	(0.064)	(0.150)	(0.109)	(0.092)	(0.087)	(0.112)	(0.079)	(0.074)	(0.063)
H Total Adults	0.122	0.177	-0.206	0.021	-0.380***	0.147	0.010	0.065	-0.016
	(0.072)	(0.146)	(0.109)	(0.097)	(0.100)	(0.106)	(0.080)	(0.080)	(0.070)
H Total Elders	-0.016	0.117	-0.109	-0.233*	-0.152	-0.097	-0.023	-0.234**	-0.126
	(0.070)	(0.151)	(0.108)	(0.095)	(0.098)	(0.103)	(0.080)	(0.079)	(0.068)
HH Log Income	0.065	0.073	0.107	0.168*	0.234**	0.249**	0.241***	0.216***	0.150**
	(0.057)	(0.107)	(0.083)	(0.075)	(0.078)	(0.082)	(0.063)	(0.064)	(0.056)
East zone	0.275	0.636*	0.452*	0.399	-0.198	0.684***	0.158	0.017	0.292
	(0.164)	(0.283)	(0.216)	(0.208)	(0.268)	(0.201)	(0.183)	(0.203)	(0.168)
North zone	-0.311	-0.022	-0.151	-0.457*	-0.557*	0.158	-0.099	-0.553**	-0.310
	(0.168)	(0.269)	(0.214)	(0.205)	(0.276)	(0.200)	(0.189)	(0.205)	(0.170)
West zone	0.400*	0.881*	0.359	0.675**	-0.152	0.675**	0.103	0.340	0.480**
	(0.184)	(0.360)	(0.240)	(0.261)	(0.296)	(0.233)	(0.204)	(0.241)	(0.184)
South zone	0.395*	0.601*	0.734**	0.527*	0.202	0.826***	0.362	0.053	0.363*
	(0.161)	(0.270)	(0.230)	(0.207)	(0.274)	(0.199)	(0.187)	(0.202)	(0.162)
Price Cereals	-0.038								
	(0.026)								
Price Flour Products		0.020							
		(0.023)							
Price Vegetables			-0.078						
			(0.055)						
Price Sugar and Sweets				-0.010					
				(0.009)					
Price Fruits					0.088				
					(0.058)				
Price Meat and Fish						-0.009			
						(0.016)			
Price Poultry and Egg							-0.018		
							(0.022)		
Price Dairy products								-0.003	
								(0.003)	
Price Oil and Fats									0.002
									(0.017)
Constant	-0.002	1.405	-0.636	-0.407	-1.118	-0.579	-0.842	-1.152*	-0.820
	(0.469)	(0.878)	(0.674)	(0.621)	(0.663)	(0.676)	(0.526)	(0.531)	(0.457)
Number of Obs.	1965	1965	1965	1965	1965	1965	1965	1965	1965

Source: Authors' Computations. Standard Error in Parentheses. * p<0.05, ** p<0.01, *** p<0.001

Table A.4: Direct, Indirect and Total average impacts - Broad Categories POF 2008-2010

	Habitation						Food						Transportation					
	Direct Impact		Indirect Impact		Total Impact		Direct Impact		Indirect Impact		Total Impact		Direct Impact		Indirect Impact		Total Impact	
	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value
Constant	**0.553**	0.000	0.023	0.243	**0.576**	0.000	**0.498**	0.000	0.034	0.062	**0.531**	0.000	**0.109**	0.005	0.007	0.153	**0.116**	0.005
Log Price Hab	**0.022**	0.000	0.001	0.260	**0.023**	0.000	-0.004	0.054	0.000	0.205	-0.005	0.053	**-0.007**	0.006	0.000	0.174	**-0.007**	0.006
Log Price Food	**-0.004**	0.049	0.000	0.353	-0.005	0.051	0.003	0.303	0.000	0.418	0.003	0.302	0.001	0.735	0.000	0.782	0.001	0.736
Log Price Transp	**-0.007**	0.007	0.000	0.312	**-0.007**	0.007	0.001	0.765	0.000	0.825	0.001	0.767	**0.015**	0.000	0.001	0.118	**0.016**	0.000
Log Price Personal	-0.003	0.128	0.000	0.403	-0.003	0.127	-0.003	0.058	0.000	0.228	-0.004	0.060	-0.001	0.735	0.000	0.779	-0.001	0.735
Log Price Health	**-0.006**	0.000	0.000	0.290	**-0.006**	0.000	**-0.003**	0.037	0.000	0.199	**-0.003**	0.038	0.000	0.805	0.000	0.843	0.000	0.806
Log Price Cloth	-0.001	0.623	0.000	0.750	-0.001	0.626	**0.003**	0.033	0.000	0.205	**0.004**	0.034	-0.003	0.059	0.000	0.234	-0.004	0.059
Log Price Educ	-0.001	0.537	0.000	0.664	-0.001	0.538	**0.004**	0.015	0.000	0.149	**0.004**	0.015	**-0.004**	0.011	0.000	0.183	**-0.005**	0.011
Log Real Expend	**-0.034**	0.000	-0.001	0.258	**-0.036**	0.000	**-0.036**	0.000	-0.002	0.074	**-0.038**	0.000	**0.014**	0.004	0.001	0.161	**0.015**	0.004
HH Age	0.001	0.142	0.000	0.436	0.001	0.144	0.000	0.539	0.000	0.624	0.000	0.541	**-0.001**	0.000	0.000	0.121	**-0.002**	0.000
HH Comp. Elem	-0.012	0.653	0.000	0.753	-0.012	0.654	**-0.039**	0.015	-0.003	0.153	**-0.041**	0.015	0.003	0.876	0.000	0.898	0.003	0.877
HH Comp. Junior	0.012	0.672	0.001	0.737	0.012	0.671	**-0.049**	0.004	-0.003	0.126	**-0.052**	0.004	-0.004	0.853	0.000	0.874	-0.004	0.853
HH Comp. High	-0.009	0.734	0.000	0.822	-0.010	0.735	**-0.052**	0.002	-0.004	0.123	**-0.056**	0.002	0.002	0.932	0.000	0.940	0.002	0.932
HH Incomp. College	-0.017	0.622	-0.001	0.723	-0.017	0.622	**-0.071**	0.000	-0.005	0.106	**-0.076**	0.000	0.007	0.750	0.001	0.792	0.008	0.751
HH Comp. College	0.021	0.484	0.001	0.610	0.021	0.484	**-0.083**	0.000	-0.006	0.085	**-0.088**	0.000	-0.006	0.760	0.000	0.793	-0.007	0.760
HH Female	0.015	0.172	0.001	0.447	0.015	0.172	-0.009	0.162	-0.001	0.303	-0.010	0.162	**-0.021**	0.005	-0.001	0.166	**-0.023**	0.005
H Size	-0.008	0.104	0.000	0.385	-0.008	0.105	**0.007**	0.032	0.000	0.191	**0.007**	0.032	**0.011**	0.000	0.001	0.134	**0.012**	0.000
H Total Child	-0.013	0.272	-0.001	0.507	-0.013	0.273	**0.019**	0.009	0.001	0.156	**0.020**	0.010	-0.011	0.153	-0.001	0.323	-0.012	0.155
H Total Youngster	0.001	0.923	0.000	0.922	0.001	0.922	**0.014**	0.002	0.001	0.121	**0.015**	0.002	**-0.019**	0.000	-0.001	0.131	**-0.020**	0.001
H Total Adults	-0.009	0.369	0.000	0.555	-0.010	0.369	0.003	0.599	0.000	0.651	0.004	0.599	0.007	0.280	0.000	0.416	0.008	0.280
H Total Eldery	-0.010	0.297	0.000	0.520	-0.010	0.299	0.009	0.115	0.001	0.268	0.010	0.116	-0.004	0.537	0.000	0.605	-0.004	0.536
Mills	-0.023	0.130	-0.001	0.418	-0.024	0.131	**-0.068**	0.000	-0.005	0.072	**-0.073**	0.000	**-0.017**	0.001	-0.001	0.147	**-0.018**	0.001

Coefficients in bold are significant with $p < 0.05$.

Table A.5: Direct, Indirect and Total average impacts - Broad Categories POF 2008-2010 (Cont.)

	Personal Expenses						Health						Clothing					
	Direct Impact		Indirect Impact		Total Impact		Direct Impact		Indirect Impact		Total Impact		Direct Impact		Indirect Impact		Total Impact	
	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value
Constant	**0.115**	0.000	**0.014**	0.024	**0.129**	0.000	0.059	0.075	0.002	0.450	0.061	0.075	-0.006	0.797	0.000	0.810	-0.006	0.795
Log Price Hab	-0.003	0.135	0.000	0.215	-0.003	0.137	**-0.006**	0.000	0.000	0.370	**-0.006**	0.000	-0.001	0.604	0.000	0.690	-0.001	0.606
Log Price Food	-0.003	0.057	0.000	0.139	-0.004	0.057	**-0.003**	0.034	0.000	0.407	**-0.003**	0.035	**0.003**	0.034	0.000	0.243	**0.003**	0.035
Log Price Transp	-0.001	0.717	0.000	0.733	-0.001	0.717	0.000	0.819	0.000	0.887	0.000	0.819	-0.003	0.054	0.000	0.263	-0.004	0.055
Log Price Personal	**0.011**	0.000	**0.001**	0.021	**0.012**	0.000	0.000	0.822	0.000	0.888	0.000	0.822	-0.002	0.210	0.000	0.390	-0.002	0.211
Log Price Health	0.000	0.823	0.000	0.845	0.000	0.825	**0.010**	0.000	0.000	0.348	**0.010**	0.000	-0.001	0.307	0.000	0.453	-0.001	0.307
Log Price Cloth	-0.002	0.207	0.000	0.272	-0.002	0.207	-0.001	0.333	0.000	0.583	-0.001	0.333	**0.007**	0.004	0.000	0.206	**0.007**	0.004
Log Price Educ	-0.002	0.219	0.000	0.284	-0.002	0.219	0.001	0.636	0.000	0.775	0.001	0.637	**-0.003**	0.013	0.000	0.222	**-0.003**	0.014
Log Real Expend	-0.004	0.242	-0.001	0.327	-0.005	0.245	-0.006	0.109	0.000	0.459	-0.007	0.109	**0.014**	0.000	0.001	0.143	**0.014**	0.000
HH Age	0.000	0.412	0.000	0.462	0.000	0.413	**0.001**	0.000	0.000	0.369	**0.002**	0.000	**0.000**	0.031	0.000	0.239	**0.000**	0.032
HH Comp. Elem	0.013	0.369	0.002	0.434	0.015	0.371	0.029	0.069	0.001	0.451	0.030	0.070	0.016	0.116	0.001	0.313	0.017	0.116
HH Comp. Junior	0.014	0.343	0.002	0.410	0.016	0.345	0.032	0.059	0.001	0.446	0.033	0.059	0.006	0.592	0.000	0.685	0.006	0.594
HH Comp. High	**0.031**	0.048	0.004	0.138	**0.035**	0.050	0.027	0.113	0.001	0.479	0.028	0.113	0.012	0.248	0.001	0.408	0.013	0.248
HH Incomp. College	0.013	0.472	0.002	0.517	0.015	0.473	0.033	0.119	0.001	0.498	0.034	0.120	0.009	0.455	0.001	0.571	0.010	0.456
HH Comp. College	0.026	0.104	0.003	0.195	0.030	0.106	**0.043**	0.017	0.001	0.421	**0.045**	0.017	-0.004	0.724	0.000	0.763	-0.004	0.723
HH Female	-0.001	0.865	0.000	0.872	-0.001	0.865	0.008	0.192	0.000	0.506	0.009	0.191	0.001	0.731	0.000	0.807	0.002	0.734
H Size	0.002	0.468	0.000	0.510	0.002	0.468	**-0.011**	0.000	0.000	0.369	**-0.011**	0.000	-0.001	0.612	0.000	0.683	-0.001	0.613
H Total Child	-0.009	0.193	-0.001	0.264	-0.010	0.194	0.013	0.061	0.000	0.439	0.013	0.063	-0.002	0.702	0.000	0.778	-0.002	0.704
H Total Youngster	-0.006	0.177	-0.001	0.253	-0.006	0.178	0.003	0.533	0.000	0.671	0.003	0.531	0.003	0.333	0.000	0.468	0.003	0.334
H Total Adults	0.008	0.173	0.001	0.265	0.009	0.175	**-0.021**	0.000	-0.001	0.389	**-0.022**	0.000	0.002	0.574	0.000	0.654	0.002	0.574
H Total Eldery	**-0.011**	0.047	-0.001	0.130	**-0.012**	0.048	**0.031**	0.000	0.001	0.356	**0.033**	0.000	-0.007	0.080	0.000	0.302	-0.007	0.083
Mills	**-0.015**	0.007	-0.002	0.064	**-0.017**	0.007	**-0.033**	0.000	-0.001	0.359	**-0.034**	0.000	**-0.040**	0.000	-0.003	0.133	**-0.043**	0.000

Coefficients in bold are significant with $p < 0.05$.

Table A.6: Direct, Indirect and Total average impacts - Broad Categories POF 2008-2010 (Cont.)

	Education					
	Effect direct		Effect indirect		Effect total	
Variables	Coeff	p-value	Coeff	p-value	Coeff	p-value
Constant	**-0.329**	0.000	**0.120**	0.000	**-0.209**	0.000
Log Price Hab	-0.001	0.518	0.000	0.542	-0.001	0.527
Log Price Food	**0.004**	0.014	-0.001	0.055	**0.002**	0.029
Log Price Transp	**-0.004**	0.012	0.002	0.052	**-0.003**	0.025
Log Price Personal	-0.002	0.238	0.001	0.288	-0.001	0.256
Log Price Health	0.000	0.672	0.000	0.706	0.000	0.668
Log Price Cloth	**-0.003**	0.015	0.001	0.058	**-0.002**	0.029
Log Price Educ	**0.006**	0.000	**-0.002**	0.016	**0.004**	0.003
Log Real Expend	**0.054**	0.000	**-0.020**	0.002	**0.034**	0.000
HH Age	0.000	0.172	0.000	0.225	0.000	0.191
HH Comp. Elem	-0.008	0.556	0.003	0.571	-0.005	0.569
HH Comp. Junior	-0.011	0.483	0.004	0.502	-0.007	0.498
HH Comp. High	-0.008	0.590	0.003	0.607	-0.005	0.598
HH Incomp. College	0.027	0.139	-0.010	0.196	0.017	0.164
HH Comp. College	0.004	0.825	-0.001	0.835	0.002	0.827
HH Female	0.007	0.208	-0.003	0.259	0.004	0.225
H Size	-0.001	0.823	0.000	0.827	0.000	0.828
H Total Child	0.003	0.666	-0.001	0.686	0.002	0.669
H Total Youngster	0.004	0.280	-0.002	0.330	0.003	0.292
H Total Adults	0.009	0.090	-0.003	0.135	0.006	0.119
H Total Eldery	-0.009	0.114	0.003	0.173	-0.005	0.134
Mills	**0.195**	0.000	**-0.073**	0.002	**0.123**	0.000

Coefficients in bold are significant with $p < 0.05$.

Table A.7: Direct, Indirect and Total average impacts - Broad Categories POF 2011-2013

	Habitation						Food						Transportation					
	Direct Impact		Indirect Impact		Total Impact		Direct Impact		Indirect Impact		Total Impact		Direct Impact		Indirect Impact		Total Impact	
	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value
Constant	**0.343**	0.000	**0.029**	0.000	**0.372**	0.000	**0.619**	0.000	**0.054**	0.000	**0.674**	0.000	**0.065**	0.007	0.003	0.207	**0.067**	0.006
Log Price Hab	**0.022**	0.000	**0.002**	0.001	**0.024**	0.000	**-0.008**	0.000	**-0.001**	0.003	**-0.009**	0.000	-0.003	0.083	0.000	0.292	-0.003	0.083
Log Price Food	**-0.008**	0.000	**-0.001**	0.003	**-0.009**	0.000	0.001	0.671	0.000	0.672	0.001	0.670	**0.003**	0.017	0.000	0.254	**0.003**	0.017
Log Price Transp	-0.003	0.071	0.000	0.121	-0.003	0.071	**0.003**	0.017	**0.000**	0.049	**0.003**	0.017	**0.012**	0.000	0.000	0.162	**0.012**	0.000
Log Price Personal	0.000	0.965	0.000	0.967	0.000	0.965	**-0.003**	0.004	**0.000**	0.023	**-0.004**	0.004	**-0.004**	0.002	0.000	0.219	**-0.004**	0.002
Log Price Health	**-0.007**	0.000	**-0.001**	0.003	**-0.007**	0.000	**-0.003**	0.002	**0.000**	0.027	**-0.003**	0.002	0.000	0.828	0.000	0.868	0.000	0.829
Log Price Cloth	**-0.003**	0.018	**0.000**	0.049	**-0.004**	0.018	**0.004**	0.002	**0.000**	0.020	**0.004**	0.002	**-0.006**	0.000	0.000	0.188	**-0.006**	0.000
Log Price Educ	-0.001	0.305	0.000	0.353	-0.001	0.306	**0.007**	0.000	**0.001**	0.002	**0.007**	0.000	**-0.003**	0.018	0.000	0.240	**-0.003**	0.018
Log Real Expend	-0.003	0.519	0.000	0.537	-0.004	0.519	**-0.060**	0.000	**-0.005**	0.000	**-0.065**	0.000	**0.012**	0.000	0.001	0.192	**0.013**	0.000
HH Age	0.000	0.518	0.000	0.528	0.000	0.517	0.000	0.507	0.000	0.539	0.000	0.508	0.000	0.162	0.000	0.356	0.000	0.162
HH Comp. Elem	0.018	0.233	0.001	0.274	0.019	0.233	-0.012	0.295	-0.001	0.327	-0.013	0.295	-0.007	0.469	0.000	0.574	-0.007	0.469
HH Comp. Junior	0.018	0.258	0.002	0.306	0.020	0.258	**-0.032**	0.007	**-0.003**	0.038	**-0.035**	0.007	0.003	0.802	0.000	0.820	0.003	0.801
HH Comp. High	0.003	0.871	0.000	0.884	0.003	0.871	**-0.035**	0.002	**-0.003**	0.025	**-0.038**	0.003	0.016	0.117	0.001	0.334	0.017	0.118
HH Incomp. College	0.020	0.315	0.002	0.350	0.022	0.315	**-0.065**	0.000	**-0.006**	0.006	**-0.071**	0.000	-0.003	0.842	0.000	0.870	-0.003	0.842
HH Comp. College	0.005	0.786	0.000	0.798	0.005	0.787	**-0.040**	0.001	**-0.003**	0.018	**-0.043**	0.001	0.001	0.912	0.000	0.910	0.001	0.911
HH Female	0.009	0.204	0.001	0.239	0.010	0.204	-0.003	0.572	0.000	0.594	-0.003	0.573	**-0.019**	0.000	-0.001	0.181	**-0.020**	0.000
H Size	**-0.021**	0.000	**-0.002**	0.003	**-0.023**	0.000	**0.013**	0.000	**0.001**	0.002	**0.014**	0.000	**0.009**	0.000	0.000	0.181	**0.009**	0.000
H Total Child	**0.027**	0.000	**0.002**	0.018	**0.029**	0.000	-0.001	0.913	0.000	0.920	-0.001	0.913	**-0.020**	0.000	-0.001	0.185	**-0.020**	0.000
H Total Youngster	**0.013**	0.017	0.001	0.054	**0.014**	0.017	0.004	0.259	0.000	0.301	0.005	0.259	**-0.013**	0.000	-0.001	0.197	**-0.013**	0.000
H Total Adults	**-0.014**	0.026	-0.001	0.060	**-0.015**	0.026	-0.002	0.615	0.000	0.634	-0.003	0.615	0.006	0.185	0.000	0.394	0.006	0.187
H Total Eldery	0.003	0.664	0.000	0.687	0.003	0.665	**0.011**	0.030	0.001	0.068	**0.012**	0.030	**-0.015**	0.000	-0.001	0.202	**-0.015**	0.000
Mills	-0.030	0.131	-0.003	0.187	-0.033	0.132	**0.626**	0.000	**0.055**	0.011	**0.681**	0.000	**-0.029**	0.000	-0.001	0.163	**-0.030**	0.000

Coefficients in bold are significant with $p < 0.05$.

Table A.8: Direct, Indirect and Total average impacts - Broad Categories POF 2011-2013 (Cont.)

	Personal Expenses						Health						Clothing					
	Direct Impact		Indirect Impact		Total Impact		Direct Impact		Indirect Impact		Total Impact		Direct Impact		Indirect Impact		Total Impact	
	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value
Constant	**0.076**	0.001	**0.006**	0.034	**0.082**	0.001	0.026	0.258	0.002	0.304	0.029	0.259	**0.078**	0.000	**0.008**	0.010	**0.086**	0.000
Log Price Hab	0.000	0.935	0.000	0.937	0.000	0.935	**-0.007**	0.000	**-0.001**	0.003	**-0.007**	0.000	**-0.003**	0.020	0.000	0.065	**-0.004**	0.020
Log Price Food	**-0.003**	0.006	0.000	0.077	**-0.004**	0.006	**-0.003**	0.001	**0.000**	0.027	**-0.003**	0.001	**0.004**	0.002	**0.000**	0.027	**0.004**	0.002
Log Price Transp	**-0.004**	0.002	0.000	0.055	**-0.005**	0.002	0.000	0.787	0.000	0.783	0.000	0.786	**-0.006**	0.000	**-0.001**	0.013	**-0.007**	0.000
Log Price Personal	**0.009**	0.000	**0.001**	0.023	**0.010**	0.000	0.001	0.092	0.000	0.139	0.001	0.092	-0.002	0.162	0.000	0.218	-0.002	0.163
Log Price Health	0.001	0.083	0.000	0.173	0.001	0.083	**0.007**	0.000	**0.001**	0.002	**0.008**	0.000	-0.001	0.198	0.000	0.246	-0.001	0.199
Log Price Cloth	-0.002	0.138	0.000	0.235	-0.002	0.139	-0.001	0.199	0.000	0.238	-0.001	0.199	**0.017**	0.000	**0.002**	0.002	**0.019**	0.000
Log Price Educ	-0.001	0.351	0.000	0.421	-0.001	0.352	**0.001**	0.038	0.000	0.095	**0.001**	0.039	**-0.009**	0.000	**-0.001**	0.002	**-0.010**	0.000
Log Real Expend	**0.009**	0.004	0.001	0.077	**0.010**	0.004	-0.003	0.395	0.000	0.429	-0.003	0.396	**0.008**	0.010	0.001	0.052	**0.009**	0.010
HH Age	**-0.001**	0.001	0.000	0.055	**-0.001**	0.001	**0.001**	0.000	**0.000**	0.003	**0.001**	0.000	**-0.001**	0.000	**0.000**	0.010	**-0.001**	0.000
HH Comp. Elem	0.006	0.509	0.000	0.564	0.006	0.510	**0.018**	0.042	0.002	0.086	**0.020**	0.042	-0.006	0.469	-0.001	0.497	-0.007	0.469
HH Comp. Junior	0.006	0.515	0.000	0.560	0.006	0.515	0.015	0.118	0.001	0.165	0.017	0.118	0.005	0.559	0.001	0.578	0.006	0.559
HH Comp. High	0.000	0.959	0.000	0.981	0.000	0.961	**0.023**	0.021	0.002	0.061	**0.025**	0.021	-0.005	0.558	-0.001	0.586	-0.006	0.559
HH Incomp. College	-0.010	0.389	-0.001	0.448	-0.011	0.390	**0.028**	0.025	0.003	0.069	**0.031**	0.026	-0.011	0.299	-0.001	0.338	-0.012	0.299
HH Comp. College	0.013	0.197	0.001	0.273	0.014	0.197	**0.037**	0.001	**0.003**	0.017	**0.040**	0.001	**-0.027**	0.004	**-0.003**	0.030	**-0.030**	0.004
HH Female	0.004	0.329	0.000	0.401	0.004	0.330	0.007	0.117	0.001	0.179	0.008	0.119	0.004	0.275	0.000	0.321	0.005	0.275
H Size	0.004	0.063	0.000	0.148	0.004	0.063	**-0.007**	0.001	**-0.001**	0.016	**-0.008**	0.001	-0.002	0.282	0.000	0.326	-0.002	0.283
H Total Child	**-0.012**	0.014	-0.001	0.086	**-0.012**	0.015	0.007	0.155	0.001	0.205	0.008	0.155	0.000	0.991	0.000	0.990	0.000	0.991
H Total Youngster	**-0.010**	0.002	-0.001	0.056	**-0.010**	0.002	0.004	0.270	0.000	0.307	0.004	0.271	0.003	0.316	0.000	0.359	0.003	0.316
H Total Adults	**0.007**	0.044	0.001	0.130	**0.008**	0.043	**-0.015**	0.000	**-0.001**	0.013	**-0.016**	0.000	**0.007**	0.047	0.001	0.102	**0.008**	0.048
H Total Eldery	-0.002	0.652	0.000	0.688	-0.002	0.652	**0.024**	0.000	**0.002**	0.002	**0.027**	0.000	0.000	0.910	0.000	0.904	0.000	0.909
Mills	**-0.032**	0.003	-0.003	0.067	**-0.035**	0.003	**-0.037**	0.000	**-0.003**	0.001	**-0.041**	0.000	**-0.040**	0.000	**-0.004**	0.002	**-0.045**	0.000

Coefficients in bold are significant with $p < 0.05$.

Table A.9: Direct, Indirect and Total average impacts - Broad Categories POF 2011-2013 (Cont.)

	Education					
	Effect direct		Effect indirect		Effect total	
Variables	Coeff	p-value	Coeff	p-value	Coeff	p-value
Constant	**-0.204**	0.000	**0.092**	0.000	**-0.112**	0.000
Log Price Hab	-0.001	0.266	0.001	0.286	-0.001	0.276
Log Price Food	**0.007**	0.000	**-0.003**	0.000	**0.004**	0.000
Log Price Transp	**-0.003**	0.018	**0.001**	0.035	**-0.001**	0.026
Log Price Personal	-0.001	0.357	0.000	0.370	0.000	0.369
Log Price Health	0.001	0.052	-0.001	0.079	0.001	0.058
Log Price Cloth	**-0.009**	0.000	**0.004**	0.000	**-0.005**	0.000
Log Price Educ	**0.006**	0.000	**-0.003**	0.000	**0.003**	0.000
Log Real Expend	**0.037**	0.000	**-0.017**	0.000	**0.020**	0.000
HH Age	0.000	0.068	0.000	0.082	0.000	0.089
HH Comp. Elem	**-0.018**	0.029	**0.008**	0.045	**-0.010**	0.042
HH Comp. Junior	-0.016	0.059	0.007	0.083	-0.008	0.070
HH Comp. High	-0.003	0.681	0.002	0.684	-0.002	0.688
HH Incomp. College	**0.040**	0.000	**-0.018**	0.001	**0.022**	0.001
HH Comp. College	0.011	0.207	-0.005	0.230	0.006	0.220
HH Female	-0.002	0.547	0.001	0.555	-0.001	0.555
H Size	**0.004**	0.013	**-0.002**	0.029	**0.002**	0.020
H Total Child	-0.002	0.561	0.001	0.567	-0.001	0.570
H Total Youngster	-0.001	0.694	0.000	0.696	-0.001	0.702
H Total Adults	**0.011**	0.001	**-0.005**	0.004	**0.006**	0.003
H Total Eldery	**-0.021**	0.000	**0.010**	0.000	**-0.012**	0.000
Mills	**-0.466**	0.007	**0.212**	0.014	**-0.254**	0.016

Coefficients in bold are significant with $p < 0.05$.

Table A.10: Direct, Indirect and Total average impacts - Food Categories POF 2008-2010

	Cereals						Flour Products						Vegetables					
	Direct Impact		Indirect Impact		Total Impact		Direct Impact		Indirect Impact		Total Impact		Direct Impact		Indirect Impact		Total Impact	
	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value
Constant	**0.197**	0.000	**0.019**	0.000	**0.216**	0.000	**0.277**	0.000	**0.018**	0.007	**0.296**	0.000	**0.056**	0.018	0.005	0.071	**0.061**	0.018
Log Price Cereals	0.013	0.085	0.001	0.129	0.014	0.086	-0.002	0.668	0.000	0.685	-0.003	0.668	**0.010**	0.045	0.001	0.106	**0.011**	0.045
Log Price Flour	-0.003	0.626	0.000	0.639	-0.003	0.626	0.013	0.206	0.001	0.261	0.014	0.205	0.006	0.248	0.001	0.303	0.007	0.249
Log Price Vegetables	**0.011**	0.034	0.001	0.077	**0.012**	0.035	0.007	0.230	0.000	0.284	0.007	0.229	-0.008	0.241	-0.001	0.298	-0.008	0.242
Log Price Sugar	**-0.023**	0.000	**-0.002**	0.002	**-0.025**	0.000	0.007	0.247	0.000	0.309	0.007	0.247	-0.007	0.124	-0.001	0.190	-0.007	0.126
Log Price Fruits	-0.002	0.711	0.000	0.717	-0.002	0.711	0.001	0.791	0.000	0.807	0.001	0.791	0.003	0.373	0.000	0.410	0.004	0.373
Log Price Meat & Fish	0.002	0.780	0.000	0.791	0.002	0.780	**-0.021**	0.027	-0.001	0.088	**-0.022**	0.027	-0.007	0.371	-0.001	0.418	-0.007	0.372
Log Price Poultry	0.004	0.339	0.000	0.364	0.004	0.339	0.000	0.979	0.000	0.970	0.000	0.978	-0.004	0.258	0.000	0.319	-0.004	0.259
Log Price Dairy	0.002	0.651	0.000	0.666	0.003	0.651	0.001	0.887	0.000	0.895	0.001	0.888	0.005	0.323	0.000	0.370	0.005	0.323
Log Price Fat & Oils	-0.004	0.083	0.000	0.126	-0.005	0.083	**-0.005**	0.027	0.000	0.091	**-0.006**	0.027	-0.001	0.801	0.000	0.802	-0.001	0.801
Log Real Expenditure	**-0.014**	0.000	**-0.001**	0.005	**-0.015**	0.000	**-0.046**	0.000	**-0.003**	0.007	**-0.049**	0.000	**0.010**	0.006	**0.001**	0.040	**0.010**	0.006
HH Age	**-0.001**	0.002	**0.000**	0.018	**-0.001**	0.002	0.001	0.111	0.000	0.180	0.001	0.110	0.000	0.908	0.000	0.919	0.000	0.908
HH Comp. Elementery	-0.005	0.679	0.000	0.693	-0.005	0.680	0.020	0.267	0.001	0.331	0.021	0.268	0.008	0.538	0.001	0.568	0.008	0.538
HH Comp. Junior	**-0.025**	0.049	-0.002	0.091	**-0.027**	0.050	0.026	0.172	0.002	0.241	0.028	0.172	0.008	0.537	0.001	0.570	0.009	0.537
HH Comp. High School	-0.022	0.082	-0.002	0.127	-0.024	0.083	0.033	0.083	0.002	0.158	0.035	0.084	0.006	0.667	0.000	0.692	0.006	0.668
HH Incomp. College	-0.022	0.149	-0.002	0.192	-0.024	0.150	0.008	0.721	0.001	0.740	0.009	0.721	0.021	0.178	0.002	0.239	0.023	0.178
HH Comp. College	**-0.040**	0.002	**-0.004**	0.016	**-0.044**	0.002	**0.044**	0.022	0.003	0.087	**0.047**	0.022	0.022	0.109	0.002	0.171	0.024	0.110
HH Female	-0.003	0.545	0.000	0.568	-0.003	0.545	-0.004	0.611	0.000	0.652	-0.004	0.612	**0.015**	0.004	**0.001**	0.036	**0.016**	0.004
H Size	**0.004**	0.037	0.000	0.077	**0.005**	0.038	**0.016**	0.000	**0.001**	0.015	**0.017**	0.000	**-0.005**	0.022	0.000	0.072	**-0.006**	0.022
H Total Child	-0.006	0.218	-0.001	0.252	-0.007	0.218	0.000	0.977	0.000	0.981	0.000	0.978	-0.005	0.312	0.000	0.363	-0.006	0.312
H Total Youngster	0.003	0.394	0.000	0.419	0.003	0.394	0.004	0.374	0.000	0.416	0.005	0.374	**-0.010**	0.005	**-0.001**	0.039	**-0.010**	0.005
H Total Adults	**0.009**	0.037	0.001	0.073	**0.010**	0.037	0.010	0.144	0.001	0.223	0.011	0.145	-0.007	0.117	-0.001	0.192	-0.008	0.118
H Total Eldery	-0.001	0.803	0.000	0.812	-0.001	0.803	**0.016**	0.017	0.001	0.083	**0.017**	0.017	**0.010**	0.019	0.001	0.072	**0.011**	0.020
Mills	-0.002	0.115	0.000	0.167	-0.003	0.116	**-0.005**	0.038	0.000	0.117	**-0.006**	0.039	-0.003	0.119	0.000	0.181	-0.003	0.119

Coefficients in bold are significant with $p < 0.05$.

Table A.11: Direct, Indirect and Total average impacts - Food Categories POF 2008-2010 (Cont.)

	Sugar and Sweets						**Fruits**						**Meat and Fish**					
	Direct Impact		Indirect Impact		Total Impact		Direct Impact		Indirect Impact		Total Impact		Direct Impact		Indirect Impact		Total Impact	
	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value
Constant	**0.076**	0.006	**0.006**	0.039	**0.082**	0.006	**0.131**	0.000	**0.008**	0.041	**0.139**	0.000	-0.010	0.810	-0.001	0.776	-0.011	0.807
Log Price Cereals	**-0.023**	0.000	**-0.002**	0.007	**-0.025**	0.000	-0.002	0.687	0.000	0.721	-0.002	0.688	0.002	0.793	0.000	0.820	0.002	0.794
Log Price Flour	0.007	0.238	0.001	0.293	0.007	0.238	0.001	0.806	0.000	0.831	0.001	0.807	**-0.021**	0.021	-0.002	0.066	**-0.023**	0.021
Log Price Vegetables	-0.007	0.110	-0.001	0.162	-0.007	0.110	0.004	0.355	0.000	0.441	0.004	0.356	-0.006	0.415	0.000	0.451	-0.007	0.416
Log Price Sugar	0.010	0.091	0.001	0.154	0.011	0.092	-0.006	0.176	0.000	0.268	-0.006	0.176	**0.028**	0.000	**0.002**	0.015	**0.031**	0.000
Log Price Fruits	-0.006	0.194	0.000	0.254	-0.006	0.195	0.002	0.705	0.000	0.733	0.002	0.705	-0.006	0.377	0.000	0.408	-0.006	0.377
Log Price Meat & Fish	**0.029**	0.000	**0.002**	0.013	**0.031**	0.000	-0.006	0.410	0.000	0.492	-0.006	0.412	0.013	0.414	0.001	0.441	0.014	0.414
Log Price Poultry	-0.003	0.323	0.000	0.364	-0.003	0.324	0.002	0.491	0.000	0.539	0.002	0.491	0.000	0.991	0.000	0.992	0.000	0.991
Log Price Dairy	-0.002	0.748	0.000	0.760	-0.002	0.748	0.004	0.463	0.000	0.515	0.004	0.463	-0.016	0.060	-0.001	0.115	-0.017	0.060
Log Price Fat & Oils	**-0.005**	0.005	**0.000**	0.037	**-0.005**	0.005	0.000	0.974	0.000	0.976	0.000	0.974	0.005	0.117	0.000	0.176	0.006	0.116
Log Real Expenditure	-0.001	0.721	0.000	0.739	-0.002	0.722	**-0.015**	0.001	-0.001	0.064	**-0.016**	0.001	**0.054**	0.000	**0.004**	0.004	**0.058**	0.000
HH Age	0.000	0.212	0.000	0.267	0.000	0.212	**0.001**	0.000	**0.000**	0.045	**0.001**	0.000	0.000	0.681	0.000	0.704	0.000	0.682
HH Comp. Elementery	0.003	0.846	0.000	0.853	0.003	0.846	-0.005	0.775	0.000	0.786	-0.005	0.775	-0.008	0.694	-0.001	0.713	-0.009	0.694
HH Comp. Junior	0.011	0.494	0.001	0.528	0.011	0.494	0.013	0.420	0.001	0.487	0.014	0.421	-0.024	0.278	-0.002	0.330	-0.026	0.279
HH Comp. High School	0.011	0.447	0.001	0.484	0.012	0.448	0.015	0.371	0.001	0.447	0.016	0.372	-0.028	0.217	-0.002	0.270	-0.030	0.218
HH Incomp. College	0.008	0.644	0.001	0.658	0.009	0.644	0.015	0.463	0.001	0.530	0.016	0.463	-0.021	0.454	-0.002	0.480	-0.023	0.454
HH Comp. College	0.013	0.405	0.001	0.449	0.014	0.405	**0.054**	0.001	0.003	0.063	**0.057**	0.001	**-0.068**	0.003	**-0.005**	0.036	**-0.073**	0.003
HH Female	0.005	0.357	0.000	0.395	0.006	0.356	-0.009	0.142	-0.001	0.230	-0.010	0.141	**-0.020**	0.024	-0.002	0.081	**-0.022**	0.024
H Size	-0.004	0.082	0.000	0.147	-0.005	0.083	**-0.006**	0.022	0.000	0.121	**-0.007**	0.022	0.003	0.389	0.000	0.429	0.004	0.390
H Total Child	**0.014**	0.024	0.001	0.085	**0.015**	0.024	0.006	0.380	0.000	0.444	0.006	0.380	**-0.022**	0.015	-0.002	0.055	**-0.024**	0.015
H Total Youngster	0.007	0.083	0.001	0.149	0.008	0.083	-0.006	0.166	0.000	0.254	-0.006	0.165	-0.008	0.187	-0.001	0.245	-0.009	0.187
H Total Adults	0.009	0.088	0.001	0.156	0.010	0.089	-0.006	0.315	0.000	0.385	-0.006	0.315	-0.013	0.111	-0.001	0.180	-0.014	0.111
H Total Eldery	-0.008	0.130	-0.001	0.188	-0.009	0.130	0.004	0.436	0.000	0.482	0.005	0.435	**-0.023**	0.003	**-0.002**	0.035	**-0.025**	0.003
Mills	**0.004**	0.042	0.000	0.095	**0.004**	0.042	-0.003	0.082	0.000	0.189	-0.003	0.083	**0.008**	0.000	**0.001**	0.021	**0.008**	0.000

Coefficients in bold are significant with $p < 0.05$.

Table A.12: Direct, Indirect and Total average impacts - Food Categories POF 2008-2010 (Cont.)

	Poultry and Eggs						**Dairy products**						**Oil and Fats**					
	Direct Impact		Indirect Impact		Total Impact		Direct Impact		Indirect Impact		Total Impact		Direct Impact		Indirect Impact		Total Impact	
	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value
Constant	**0.086**	0.000	0.004	0.118	**0.090**	0.000	**0.124**	0.000	**0.009**	0.018	**0.133**	0.000	**0.064**	0.001	**-0.037**	0.045	**0.027**	0.000
Log Price Cereals	0.003	0.393	0.000	0.495	0.003	0.393	0.003	0.618	0.000	0.640	0.003	0.618	-0.004	0.078	0.002	0.119	-0.002	0.127
Log Price Flour	0.000	0.987	0.000	0.976	0.000	0.989	0.001	0.875	0.000	0.878	0.001	0.875	**-0.005**	0.023	0.003	0.054	-0.002	0.064
Log Price Vegetables	-0.003	0.324	0.000	0.452	-0.004	0.324	0.005	0.368	0.000	0.426	0.005	0.369	-0.001	0.780	0.000	0.787	0.000	0.789
Log Price Sugar	-0.003	0.344	0.000	0.449	-0.003	0.342	-0.002	0.705	0.000	0.730	-0.002	0.706	**-0.005**	0.007	**0.003**	0.031	**-0.002**	0.036
Log Price Fruits	0.002	0.460	0.000	0.554	0.002	0.460	0.004	0.421	0.000	0.459	0.004	0.421	0.000	0.930	0.000	0.936	0.000	0.928
Log Price Meat & Fish	0.000	0.969	0.000	0.947	0.000	0.968	-0.016	0.053	-0.001	0.118	-0.017	0.053	0.006	0.103	-0.003	0.139	0.003	0.148
Log Price Poultry	0.006	0.132	0.000	0.298	0.006	0.132	-0.007	0.064	-0.001	0.126	-0.008	0.064	0.003	0.102	-0.002	0.131	0.001	0.160
Log Price Dairy	-0.007	0.061	0.000	0.244	-0.008	0.061	0.013	0.139	0.001	0.196	0.013	0.139	0.000	0.998	0.000	0.987	0.000	0.989
Log Price Fat & Oils	0.003	0.080	0.000	0.256	0.003	0.080	0.000	0.995	0.000	0.989	0.000	0.995	**0.007**	0.002	**-0.004**	0.016	**0.003**	0.026
Log Real Expenditure	**0.006**	0.035	0.000	0.228	**0.006**	0.036	0.002	0.715	0.000	0.739	0.002	0.716	**0.005**	0.002	**-0.002**	0.016	**0.002**	0.020
HH Age	0.000	0.908	0.000	0.892	0.000	0.906	-0.001	0.078	0.000	0.150	-0.001	0.078	0.000	0.952	0.000	0.958	0.000	0.949
HH Comp. Elementery	-0.016	0.101	-0.001	0.270	-0.017	0.101	0.002	0.889	0.000	0.890	0.003	0.888	0.000	0.988	0.000	0.997	0.000	0.978
HH Comp. Junior	-0.019	0.072	-0.001	0.236	-0.020	0.071	0.013	0.474	0.001	0.509	0.014	0.474	-0.005	0.272	0.003	0.295	-0.002	0.322
HH Comp. High School	**-0.023**	0.021	-0.001	0.188	**-0.025**	0.021	0.010	0.560	0.001	0.582	0.011	0.560	-0.002	0.635	0.001	0.636	-0.001	0.664
HH Incomp. College	-0.023	0.067	-0.001	0.244	-0.024	0.067	0.010	0.642	0.001	0.673	0.011	0.643	0.002	0.779	-0.001	0.784	0.001	0.787
HH Comp. College	**-0.040**	0.000	-0.002	0.127	**-0.042**	0.000	0.020	0.264	0.002	0.317	0.022	0.265	-0.006	0.248	0.003	0.276	-0.003	0.297
HH Female	0.003	0.425	0.000	0.534	0.003	0.426	**0.015**	0.032	0.001	0.088	**0.016**	0.032	-0.001	0.440	0.001	0.458	-0.001	0.476
H Size	**-0.004**	0.037	0.000	0.220	**-0.004**	0.037	-0.004	0.126	0.000	0.192	-0.005	0.126	0.000	0.754	0.000	0.769	0.000	0.755
H Total Child	0.001	0.835	0.000	0.846	0.001	0.834	**0.017**	0.025	0.001	0.086	**0.018**	0.026	-0.003	0.176	0.001	0.213	-0.001	0.228
H Total Youngster	0.002	0.484	0.000	0.573	0.002	0.484	0.007	0.116	0.001	0.184	0.008	0.116	0.000	0.823	0.000	0.823	0.000	0.836
H Total Adults	-0.007	0.056	0.000	0.237	-0.007	0.056	0.005	0.405	0.000	0.440	0.006	0.405	-0.001	0.734	0.000	0.737	0.000	0.752
H Total Eldery	0.000	0.906	0.000	0.924	0.000	0.907	-0.002	0.712	0.000	0.723	-0.002	0.711	**0.003**	0.047	-0.002	0.079	0.001	0.092
Mills	**-0.010**	0.000	0.000	0.118	**-0.010**	0.000	-0.001	0.533	0.000	0.559	-0.001	0.533	**0.013**	0.001	**-0.007**	0.010	**0.006**	0.018

Coefficients in bold are significant with $p < 0.05$.

Table A.13: Direct, Indirect and Total average impacts - Food Categories POF 2011-2013

	Cereals						**Flour Products**						**Vegetables**					
	Direct Impact		Indirect Impact		Total Impact		Direct Impact		Indirect Impact		Total Impact		Direct Impact		Indirect Impact		Total Impact	
	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value
Constant	**0.173**	0.000	**0.015**	0.000	**0.187**	0.000	**0.359**	0.000	**0.035**	0.000	**0.394**	0.000	0.022	0.265	0.002	0.282	0.024	0.265
Log Price Cereals	-0.003	0.458	0.000	0.470	-0.004	0.457	-0.002	0.682	0.000	0.687	-0.002	0.682	**0.009**	0.001	**0.001**	0.005	**0.010**	0.001
Log Price Flour	-0.002	0.653	0.000	0.661	-0.002	0.653	**0.018**	0.006	**0.002**	0.014	**0.019**	0.006	**-0.007**	0.031	**-0.001**	0.049	**-0.008**	0.032
Log Price Vegetables	**0.009**	0.001	**0.001**	0.007	**0.010**	0.001	**-0.007**	0.034	-0.001	0.052	**-0.008**	0.034	**-0.023**	0.000	**-0.003**	0.000	**-0.026**	0.000
Log Price Sugar	**-0.013**	0.000	**-0.001**	0.002	**-0.014**	0.000	**-0.008**	0.030	**-0.001**	0.044	**-0.009**	0.030	**0.012**	0.000	**0.001**	0.001	**0.014**	0.000
Log Price Fruits	0.005	0.186	0.000	0.217	0.006	0.186	0.006	0.180	0.001	0.200	0.007	0.180	**-0.026**	0.000	**-0.003**	0.000	**-0.029**	0.000
Log Price Meat & Fish	0.003	0.536	0.000	0.550	0.004	0.536	0.004	0.517	0.000	0.530	0.004	0.517	**0.011**	0.016	**0.001**	0.025	**0.012**	0.016
Log Price Poultry	0.005	0.053	0.000	0.076	0.006	0.052	0.003	0.397	0.000	0.412	0.003	0.397	0.002	0.327	0.000	0.345	0.003	0.328
Log Price Dairy	0.000	0.987	0.000	0.982	0.000	0.987	**-0.013**	0.002	**-0.001**	0.008	**-0.015**	0.002	**0.019**	0.000	**0.002**	0.000	**0.021**	0.000
Log Price Fat & Oils	**-0.005**	0.017	**0.000**	0.039	**-0.005**	0.017	0.000	0.800	0.000	0.812	-0.001	0.800	**0.003**	0.009	**0.000**	0.020	**0.004**	0.009
Log Real Expenditure	**-0.011**	0.000	**-0.001**	0.001	**-0.012**	0.000	**-0.047**	0.000	**-0.005**	0.000	**-0.052**	0.000	0.002	0.452	0.000	0.463	0.002	0.452
HH Age	**-0.001**	0.000	**0.000**	0.003	**-0.001**	0.000	0.000	0.166	0.000	0.183	0.000	0.166	**0.000**	0.009	**0.000**	0.020	**0.001**	0.009
HH Comp. Elementery	-0.004	0.533	0.000	0.548	-0.004	0.533	-0.006	0.537	-0.001	0.549	-0.007	0.537	0.012	0.147	0.001	0.177	0.014	0.148
HH Comp. Junior	-0.004	0.547	0.000	0.573	-0.004	0.548	-0.018	0.095	-0.002	0.118	-0.020	0.095	0.003	0.734	0.000	0.736	0.003	0.734
HH Comp. High School	**-0.016**	0.020	**-0.001**	0.040	**-0.017**	0.020	-0.010	0.312	-0.001	0.333	-0.012	0.313	0.012	0.185	0.001	0.207	0.013	0.186
HH Incomp. College	**-0.028**	0.001	**-0.002**	0.009	**-0.031**	0.001	-0.008	0.517	-0.001	0.535	-0.009	0.517	0.005	0.644	0.001	0.648	0.006	0.643
HH Comp. College	**-0.039**	0.000	**-0.003**	0.000	**-0.042**	0.000	0.001	0.940	0.000	0.941	0.001	0.940	0.015	0.115	0.002	0.138	0.016	0.115
HH Female	-0.002	0.590	0.000	0.609	-0.002	0.591	-0.004	0.400	0.000	0.412	-0.004	0.400	**0.019**	0.000	**0.002**	0.000	**0.021**	0.000
H Size	0.001	0.425	0.000	0.450	0.001	0.426	**0.009**	0.000	**0.001**	0.001	**0.010**	0.000	-0.002	0.339	0.000	0.349	-0.002	0.338
H Total Child	0.006	0.075	0.001	0.107	0.007	0.075	-0.005	0.359	0.000	0.382	-0.005	0.360	-0.007	0.091	-0.001	0.116	-0.008	0.091
H Total Youngster	-0.001	0.679	0.000	0.683	-0.001	0.679	0.007	0.061	0.001	0.082	0.008	0.061	-0.002	0.470	0.000	0.483	-0.002	0.470
H Total Adults	0.002	0.519	0.000	0.531	0.002	0.519	**0.012**	0.006	**0.001**	0.018	**0.013**	0.006	**-0.014**	0.000	**-0.002**	0.003	**-0.016**	0.000
H Total Eldery	0.000	0.950	0.000	0.948	0.000	0.950	**0.013**	0.002	**0.001**	0.008	**0.015**	0.002	0.005	0.157	0.001	0.180	0.006	0.157
Mills	**-0.004**	0.000	**0.000**	0.006	**-0.004**	0.000	**0.005**	0.004	**0.001**	0.014	**0.006**	0.004	**-0.006**	0.000	**-0.001**	0.003	**-0.006**	0.000

Coefficients in bold are significant with $p < 0.05$.

Table A.14: Direct, Indirect and Total average impacts - Food Categories POF 2011-2013 (Cont.)

	Sugar and Sweets						**Fruits**						**Meat and Fish**					
	Direct Impact		Indirect Impact		Total Impact		Direct Impact		Indirect Impact		Total Impact		Direct Impact		Indirect Impact		Total Impact	
	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value
Constant	**0.121**	0.000	**0.007**	0.005	**0.128**	0.000	0.036	0.111	0.004	0.131	0.040	0.111	0.049	0.118	0.005	0.131	0.054	0.117
Log Price Cereals	**-0.013**	0.000	**-0.001**	0.018	**-0.014**	0.000	0.006	0.178	0.001	0.194	0.006	0.178	0.003	0.528	0.000	0.535	0.004	0.528
Log Price Flour	**-0.008**	0.030	0.000	0.095	**-0.009**	0.030	0.007	0.162	0.001	0.179	0.008	0.162	0.004	0.518	0.000	0.522	0.004	0.518
Log Price Vegetables	**0.012**	0.000	**0.001**	0.013	**0.013**	0.000	**-0.026**	0.000	**-0.003**	0.000	**-0.029**	0.000	**0.010**	0.023	**0.001**	0.037	**0.011**	0.023
Log Price Sugar	**0.011**	0.012	0.001	0.065	**0.012**	0.012	0.001	0.702	0.000	0.709	0.002	0.702	0.001	0.840	0.000	0.844	0.001	0.840
Log Price Fruits	0.002	0.664	0.000	0.679	0.002	0.664	**0.017**	0.017	**0.002**	0.031	**0.020**	0.018	-0.002	0.741	0.000	0.749	-0.002	0.742
Log Price Meat & Fish	0.001	0.803	0.000	0.802	0.001	0.802	-0.002	0.741	0.000	0.746	-0.003	0.741	0.005	0.686	0.000	0.695	0.005	0.687
Log Price Poultry	0.003	0.300	0.000	0.350	0.003	0.300	-0.004	0.280	0.000	0.301	-0.004	0.281	**-0.012**	0.008	**-0.001**	0.019	**-0.013**	0.008
Log Price Dairy	-0.005	0.126	0.000	0.192	-0.005	0.127	0.002	0.609	0.000	0.613	0.002	0.609	-0.009	0.128	-0.001	0.144	-0.009	0.128
Log Price Fat & Oils	-0.003	0.059	0.000	0.119	-0.003	0.059	-0.001	0.590	0.000	0.601	-0.001	0.591	-0.001	0.770	0.000	0.775	-0.001	0.770
Log Real Expenditure	-0.002	0.521	0.000	0.568	-0.002	0.522	**-0.007**	0.029	**-0.001**	0.046	**-0.008**	0.030	**0.049**	0.000	**0.005**	0.000	**0.054**	0.000
HH Age	0.000	0.529	0.000	0.552	0.000	0.529	**0.001**	0.000	**0.000**	0.000	**0.001**	0.000	**-0.001**	0.021	**0.000**	0.039	**-0.001**	0.022
HH Comp. Elementery	-0.010	0.268	-0.001	0.332	-0.010	0.269	**0.030**	0.001	**0.003**	0.004	**0.033**	0.001	-0.024	0.071	-0.002	0.089	-0.026	0.071
HH Comp. Junior	0.001	0.886	0.000	0.884	0.001	0.886	**0.028**	0.004	**0.003**	0.011	**0.031**	0.004	-0.027	0.056	-0.003	0.074	-0.030	0.056
HH Comp. High School	-0.005	0.623	0.000	0.652	-0.005	0.624	**0.047**	0.000	**0.005**	0.000	**0.052**	0.000	**-0.033**	0.022	**-0.003**	0.035	**-0.036**	0.022
HH Incomp. College	0.014	0.220	0.001	0.275	0.015	0.220	**0.049**	0.000	**0.006**	0.001	**0.055**	0.000	**-0.057**	0.001	**-0.006**	0.005	**-0.063**	0.001
HH Comp. College	0.001	0.923	0.000	0.911	0.001	0.922	**0.063**	0.000	**0.007**	0.000	**0.071**	0.000	**-0.059**	0.000	**-0.006**	0.001	**-0.065**	0.000
HH Female	-0.003	0.427	0.000	0.466	-0.004	0.427	0.000	0.982	0.000	0.978	0.000	0.981	**-0.022**	0.000	**-0.002**	0.003	**-0.024**	0.000
H Size	0.003	0.152	0.000	0.216	0.003	0.152	**-0.005**	0.025	**-0.001**	0.039	**-0.005**	0.025	-0.004	0.140	0.000	0.159	-0.005	0.140
H Total Child	0.006	0.203	0.000	0.261	0.006	0.203	-0.006	0.250	-0.001	0.268	-0.006	0.251	-0.013	0.065	-0.001	0.090	-0.014	0.065
H Total Youngster	0.000	0.894	0.000	0.906	0.000	0.895	0.000	0.931	0.000	0.933	0.000	0.931	0.000	0.948	0.000	0.950	0.000	0.948
H Total Adults	-0.001	0.779	0.000	0.794	-0.001	0.779	**-0.016**	0.000	**-0.002**	0.001	**-0.018**	0.000	**0.014**	0.017	**0.001**	0.029	**0.016**	0.017
H Total Eldery	**-0.013**	0.001	**-0.001**	0.030	**-0.013**	0.001	0.002	0.567	0.000	0.573	0.003	0.567	-0.003	0.564	0.000	0.573	-0.004	0.564
Mills	0.002	0.155	0.000	0.226	0.002	0.156	0.000	0.888	0.000	0.889	0.000	0.888	**0.009**	0.000	**0.001**	0.000	**0.010**	0.000

Coefficients in bold are significant with $p < 0.05$.

Table A.15: Direct, Indirect and Total average impacts - Food Categories POF 2011-2013 (Cont.)

	Poultry and Eggs						**Dairy products**						**Oil and Fats**					
	Direct Impact		Indirect Impact		Total Impact		Direct Impact		Indirect Impact		Total Impact		Direct Impact		Indirect Impact		Total Impact	
	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value
Constant	**0.109**	0.000	**0.005**	0.032	**0.115**	0.000	0.035	0.098	0.004	0.117	0.038	0.098	**0.097**	0.000	**-0.067**	0.000	**0.031**	0.000
Log Price Cereals	0.005	0.060	0.000	0.177	0.006	0.060	0.000	0.931	0.000	0.926	0.000	0.930	**-0.005**	0.013	**0.003**	0.021	-0.002	0.055
Log Price Flour	0.003	0.401	0.000	0.475	0.003	0.401	**-0.014**	0.001	**-0.001**	0.006	**-0.015**	0.001	-0.001	0.749	0.000	0.752	0.000	0.763
Log Price Vegetables	0.002	0.275	0.000	0.365	0.003	0.275	**0.019**	0.000	**0.002**	0.000	**0.021**	0.000	**0.003**	0.007	**-0.002**	0.016	**0.001**	0.037
Log Price Sugar	0.003	0.282	0.000	0.369	0.003	0.282	-0.005	0.146	-0.001	0.168	-0.005	0.146	-0.003	0.056	0.002	0.069	-0.001	0.112
Log Price Fruits	-0.004	0.298	0.000	0.397	-0.004	0.299	0.002	0.573	0.000	0.581	0.003	0.573	-0.001	0.578	0.001	0.580	0.000	0.608
Log Price Meat & Fish	**-0.012**	0.007	-0.001	0.102	**-0.013**	0.007	-0.008	0.119	-0.001	0.137	-0.009	0.119	-0.001	0.729	0.001	0.727	0.000	0.754
Log Price Poultry	0.005	0.148	0.000	0.258	0.005	0.149	-0.003	0.229	0.000	0.244	-0.004	0.229	0.001	0.504	-0.001	0.514	0.000	0.527
Log Price Dairy	-0.003	0.268	0.000	0.362	-0.003	0.268	**0.011**	0.020	**0.001**	0.034	**0.013**	0.020	-0.002	0.116	0.002	0.124	-0.001	0.177
Log Price Fat & Oils	0.001	0.490	0.000	0.550	0.001	0.490	-0.002	0.112	0.000	0.131	-0.003	0.112	**0.009**	0.000	**-0.006**	0.001	**0.003**	0.012
Log Real Expenditure	0.003	0.135	0.000	0.264	0.003	0.136	**0.009**	0.008	**0.001**	0.020	**0.010**	0.008	**0.004**	0.003	**-0.002**	0.007	**0.001**	0.037
HH Age	**0.000**	0.007	0.000	0.106	**0.000**	0.007	0.000	0.553	0.000	0.561	0.000	0.553	0.000	0.705	0.000	0.707	0.000	0.722
HH Comp. Elementery	**-0.016**	0.007	-0.001	0.106	**-0.017**	0.008	0.016	0.074	0.002	0.095	0.018	0.075	0.002	0.450	-0.002	0.460	0.001	0.472
HH Comp. Junior	-0.011	0.077	-0.001	0.196	-0.012	0.077	**0.023**	0.020	**0.002**	0.034	**0.026**	0.020	0.005	0.093	-0.004	0.104	0.002	0.151
HH Comp. High School	**-0.018**	0.004	-0.001	0.098	**-0.019**	0.004	**0.022**	0.021	**0.002**	0.035	**0.025**	0.021	0.002	0.531	-0.001	0.539	0.001	0.550
HH Incomp. College	**-0.016**	0.045	-0.001	0.167	**-0.017**	0.045	**0.040**	0.001	**0.004**	0.007	**0.044**	0.002	0.001	0.824	-0.001	0.829	0.000	0.827
HH Comp. College	**-0.027**	0.000	-0.001	0.058	**-0.028**	0.000	**0.048**	0.000	**0.005**	0.000	**0.053**	0.000	-0.003	0.453	0.002	0.459	-0.001	0.485
HH Female	0.004	0.136	0.000	0.252	0.005	0.137	0.007	0.107	0.001	0.125	0.008	0.106	0.001	0.579	-0.001	0.581	0.000	0.609
H Size	-0.002	0.201	0.000	0.311	-0.002	0.201	0.000	0.990	0.000	0.988	0.000	0.990	-0.001	0.143	0.001	0.158	0.000	0.197
H Total Child	-0.003	0.366	0.000	0.435	-0.003	0.366	**0.020**	0.000	**0.002**	0.001	**0.022**	0.000	0.001	0.485	-0.001	0.494	0.000	0.508
H Total Youngster	0.002	0.473	0.000	0.528	0.002	0.473	-0.004	0.259	0.000	0.284	-0.004	0.260	0.000	0.910	0.000	0.911	0.000	0.914
H Total Adults	0.000	0.896	0.000	0.919	0.000	0.897	0.003	0.560	0.000	0.568	0.003	0.560	0.000	0.945	0.000	0.947	0.000	0.944
H Total Eldery	0.002	0.456	0.000	0.530	0.002	0.457	-0.007	0.100	-0.001	0.123	-0.007	0.101	0.000	0.887	0.000	0.895	0.000	0.878
Mills	**-0.010**	0.000	**-0.001**	0.033	**-0.011**	0.000	**-0.003**	0.046	0.000	0.062	**-0.003**	0.046	**0.006**	0.043	-0.004	0.054	0.002	0.096

Coefficients in bold are significant with $p < 0.05$.

Table A.16: Uncompensated Elasticities - Broad Categories POF 2008-2010

Elasticity of	**With respect to price of**						
	Habitation	Food	Transp.	Personal Exp.	Health	Clothing	Education
Traditional model							
Habitation	-0.8976	0.0111	-0.0082	0.0040	-0.0082	0.0023	-0.0003
Food	0.0345	-0.9514	0.0231	0.0046	0.0051	0.0218	0.0230
Transportation	-0.0911	-0.0178	-0.8900	-0.0184	-0.0136	-0.0336	-0.0377
Personal Expenses	-0.0107	-0.0206	-0.0019	-0.8999	0.0017	-0.0155	-0.0162
Health	-0.0374	-0.0074	0.0045	0.0069	-0.8912	-0.0052	0.0070
Clothing	-0.1073	0.0059	-0.1047	-0.0738	-0.0429	-0.8748	-0.0675
Education	-0.5516	-0.2688	-0.2940	-0.2368	-0.1376	-0.1458	-0.9065
SAR Direct Effect							
Habitation	-0.8993	0.0118	-0.0071	0.0030	-0.0084	0.0027	0.0005
Food	0.0314	-0.9525	0.0207	0.0035	0.0033	0.0208	0.0213
Transportation	-0.0926	-0.0217	-0.8938	-0.0190	-0.0137	-0.0330	-0.0399
Personal Expenses	-0.0129	-0.0198	-0.0014	-0.9034	0.0014	-0.0139	-0.0133
Health	-0.0426	-0.0110	0.0050	0.0054	-0.8915	-0.0056	0.0080
Clothing	-0.1096	-0.0002	-0.1038	-0.0735	-0.0454	-0.8742	-0.0733
Education	-0.4953	-0.2435	-0.2819	-0.2102	-0.1219	-0.1449	-0.8953
SAR Indirect Effect							
Habitation	-0.9958	0.0005	-0.0003	0.0001	-0.0003	0.0001	0.0000
Food	0.0022	-0.9968	0.0014	0.0002	0.0002	0.0014	0.0015
Transportation	-0.0064	-0.0015	-0.9928	-0.0013	-0.0009	-0.0022	-0.0027
Personal Expenses	-0.0015	-0.0024	-0.0002	-0.9883	0.0002	-0.0017	-0.0016
Health	-0.0015	-0.0004	0.0002	0.0002	-0.9962	-0.0002	0.0003
Clothing	-0.0077	-0.0001	-0.0074	-0.0052	-0.0031	-0.9910	-0.0051
Education	0.1842	0.0905	0.1047	0.0783	0.0454	0.0539	-1.0388
SAR Total Effect							
Habitation	-0.8951	0.0123	-0.0074	0.0032	-0.0088	0.0028	0.0005
Food	0.0336	-0.9493	0.0221	0.0038	0.0035	0.0222	0.0227
Transportation	-0.0990	-0.0232	-0.8866	-0.0202	-0.0146	-0.0352	-0.0426
Personal Expenses	-0.0146	-0.0223	-0.0016	-0.8916	0.0017	-0.0156	-0.0149
Health	-0.0441	-0.0114	0.0052	0.0056	-0.8877	-0.0058	0.0082
Clothing	-0.1173	-0.0003	-0.1112	-0.0786	-0.0485	-0.8653	-0.0784
Education	-0.3111	-0.1530	-0.1773	-0.1320	-0.0765	-0.0910	-0.9344

Table A.17: Compensated and Expenditure Elasticities - Broad Categories POF 2008-2010

Elasticity of	**With respect to price of**							**Expenditure**
	Habitation	Food	Transp.	Personal Exp.	Health	Clothing	Education	**Elasticity**
Traditional model								
Habitation	-0.5979	0.2283	0.1012	0.1106	0.0776	0.0457	0.0346	0.8969
Food	0.3149	-0.7480	0.1255	0.1043	0.0853	0.0624	0.0556	0.8393
Transportation	0.2771	0.2492	-0.7555	0.1125	0.0918	0.0197	0.0051	1.1023
Personal Expenses	0.3110	0.2127	0.1156	-0.7856	0.0938	0.0311	0.0213	0.9630
Health	0.2709	0.2161	0.1171	0.1165	-0.8029	0.0395	0.0428	0.9228
Clothing	0.3153	0.3123	0.0497	0.0764	0.0781	-0.8136	-0.0184	1.2650
Education	0.2973	0.3467	0.0160	0.0650	0.1054	-0.0229	-0.8078	2.5409
SAR Direct Effect								
Habitation	-0.5997	0.2291	0.1023	0.1095	0.0773	0.0461	0.0353	0.8968
Food	0.3159	-0.7462	0.1246	0.1046	0.0848	0.0620	0.0543	0.8515
Transportation	0.2794	0.2481	-0.7579	0.1133	0.0929	0.0208	0.0034	1.1136
Personal Expenses	0.3089	0.2135	0.1161	-0.7890	0.0935	0.0327	0.0241	0.9634
Health	0.2690	0.2149	0.1188	0.1161	-0.8023	0.0395	0.0442	0.9325
Clothing	0.3180	0.3098	0.0524	0.0784	0.0770	-0.8123	-0.0236	1.2798
Education	0.3042	0.3362	0.0101	0.0740	0.1070	-0.0291	-0.8023	2.3931
SAR Indirect Effect								
Habitation	-0.6632	0.2417	0.1212	0.1184	0.0949	0.0483	0.0387	0.9957
Food	0.3329	-0.7570	0.1222	0.1178	0.0949	0.0493	0.0399	0.9898
Transportation	0.3303	0.2427	-0.8699	0.1183	0.0955	0.0466	0.0365	1.0079
Personal Expenses	0.3311	0.2388	0.1213	-0.8700	0.0954	0.0464	0.0371	0.9955
Health	0.3318	0.2413	0.1219	0.1186	-0.9008	0.0481	0.0391	0.9976
Clothing	0.3331	0.2470	0.1171	0.1159	0.0944	-0.9417	0.0345	1.0198
Education	0.3452	0.2072	0.1635	0.1355	0.0915	0.0772	-1.0201	0.4819
SAR Total Effect								
Habitation	-0.5969	0.2285	0.1015	0.1092	0.0766	0.0460	0.0352	0.8925
Food	0.3147	-0.7454	0.1248	0.1037	0.0840	0.0629	0.0554	0.8413
Transportation	0.2757	0.2485	-0.7498	0.1129	0.0927	0.0190	0.0010	1.1215
Personal Expenses	0.3058	0.2100	0.1154	-0.7778	0.0934	0.0308	0.0224	0.9589
Health	0.2667	0.2139	0.1187	0.1160	-0.7988	0.0392	0.0443	0.9301
Clothing	0.3169	0.3146	0.0474	0.0758	0.0758	-0.8024	-0.0279	1.2997
Education	0.3153	0.3012	0.0515	0.0907	0.1029	-0.0003	-0.8615	1.8750

Table A.18: Uncompensated Elasticities - Broad Categories POF 2011-2013

Elasticity of	**With respect to price of**						
	Habitation	Food	Transp.	Personal Exp.	Health	Clothing	Education
Traditional model							
Habitation	-0.9263	-0.0240	-0.0071	0.0012	-0.0205	-0.0100	-0.0037
Food	0.0410	-0.9377	0.0381	0.0170	0.0089	0.0302	0.0327
Transportation	-0.0562	0.0004	-0.9052	-0.0513	-0.0067	-0.0607	-0.0259
Personal Expenses	-0.0231	-0.0456	-0.0407	-0.9386	0.0039	-0.0197	-0.0088
Health	-0.0745	-0.0233	0.0059	0.0197	-0.9047	-0.0092	0.0164
Clothing	-0.0837	0.0296	-0.1022	-0.0427	-0.0219	-0.7456	-0.1404
Education	-0.4471	-0.1069	-0.2326	-0.1968	-0.0604	-0.3995	-0.8396
SAR Direct Effect							
Habitation	-0.9269	-0.0233	-0.0071	0.0012	-0.0202	-0.0096	-0.0034
Food	0.0401	-0.9374	0.0375	0.0170	0.0079	0.0299	0.0316
Transportation	-0.0569	-0.0008	-0.9076	-0.0507	-0.0070	-0.0598	-0.0266
Personal Expenses	-0.0230	-0.0450	-0.0401	-0.9388	0.0044	-0.0191	-0.0089
Health	-0.0720	-0.0240	0.0072	0.0215	-0.9038	-0.0100	0.0181
Clothing	-0.0844	0.0269	-0.1007	-0.0429	-0.0244	-0.7519	-0.1397
Education	-0.4338	-0.1066	-0.2285	-0.1932	-0.0538	-0.3934	-0.8382
SAR Indirect Effect							
Habitation	-0.9937	-0.0020	-0.0006	0.0001	-0.0017	-0.0008	-0.0003
Food	0.0035	-0.9945	0.0033	0.0015	0.0007	0.0026	0.0028
Transportation	-0.0023	0.0000	-0.9962	-0.0021	-0.0003	-0.0025	-0.0011
Personal Expenses	-0.0018	-0.0036	-0.0032	-0.9951	0.0003	-0.0015	-0.0007
Health	-0.0067	-0.0023	0.0006	0.0020	-0.9910	-0.0009	0.0017
Clothing	-0.0092	0.0030	-0.0110	-0.0046	-0.0027	-0.9729	-0.0153
Education	0.1986	0.0490	0.1046	0.0885	0.0246	0.1803	-1.0738
SAR Total Effect							
Habitation	-0.9206	-0.0253	-0.0078	0.0013	-0.0219	-0.0104	-0.0037
Food	0.0436	-0.9319	0.0408	0.0185	0.0086	0.0325	0.0344
Transportation	-0.0593	-0.0008	-0.9038	-0.0529	-0.0073	-0.0623	-0.0277
Personal Expenses	-0.0249	-0.0486	-0.0433	-0.9339	0.0048	-0.0206	-0.0096
Health	-0.0786	-0.0263	0.0079	0.0234	-0.8948	-0.0109	0.0198
Clothing	-0.0937	0.0299	-0.1117	-0.0476	-0.0270	-0.7248	-0.1549
Education	-0.2352	-0.0576	-0.1236	-0.1048	-0.0292	-0.2131	-0.9120

Table A.19: Compensated and Expenditure Elasticities - Broad Categories POF 2011-2013

Elasticity of	**With respect to price of**							**Expenditure**
	Habitation	Food	Transp.	Personal Exp.	Health	Clothing	Education	**Elasticity**
Traditional model								
Habitation	-0.6139	0.2380	0.1048	0.1303	0.0586	0.0566	0.0255	0.9904
Food	0.2838	-0.7340	0.1251	0.1174	0.0705	0.0819	0.0554	0.7698
Transportation	0.2925	0.2929	-0.7803	0.0929	0.0817	0.0136	0.0066	1.1054
Personal Expenses	0.3153	0.2382	0.0805	-0.7987	0.0896	0.0524	0.0228	1.0726
Health	0.2313	0.2333	0.1155	0.1462	-0.8272	0.0560	0.0450	0.9697
Clothing	0.2654	0.3224	0.0229	0.1017	0.0665	-0.6711	-0.1078	1.1069
Education	0.2730	0.4970	0.0255	0.1009	0.1220	-0.2460	-0.7723	2.2830
SAR Direct Effect								
Habitation	-0.6148	0.2384	0.1047	0.1302	0.0589	0.0570	0.0257	0.9893
Food	0.2840	-0.7328	0.1249	0.1178	0.0697	0.0819	0.0544	0.7735
Transportation	0.2930	0.2927	-0.7822	0.0940	0.0817	0.0148	0.0061	1.1094
Personal Expenses	0.3146	0.2382	0.0809	-0.7992	0.0900	0.0529	0.0226	1.0705
Health	0.2318	0.2308	0.1160	0.1471	-0.8269	0.0547	0.0465	0.9631
Clothing	0.2680	0.3224	0.0256	0.1027	0.0649	-0.6768	-0.1068	1.1172
Education	0.2750	0.4879	0.0255	0.0999	0.1257	-0.2423	-0.7720	2.2473
SAR Indirect Effect								
Habitation	-0.6786	0.2623	0.1123	0.1304	0.0781	0.0663	0.0291	0.9991
Food	0.3127	-0.7352	0.1141	0.1293	0.0790	0.0685	0.0317	0.9801
Transportation	0.3145	0.2657	-0.8826	0.1289	0.0800	0.0650	0.0285	1.0045
Personal Expenses	0.3153	0.2625	0.1105	-0.8640	0.0807	0.0661	0.0289	1.0056
Health	0.3077	0.2613	0.1133	0.1319	-0.9113	0.0661	0.0311	0.9965
Clothing	0.3102	0.2709	0.1035	0.1274	0.0783	-0.9048	0.0146	1.0128
Education	0.3337	0.1624	0.1531	0.1443	0.0589	0.2091	-1.0612	0.4284
SAR Total Effect								
Habitation	-0.6088	0.2361	0.1040	0.1302	0.0570	0.0561	0.0254	0.9884
Food	0.2813	-0.7326	0.1260	0.1167	0.0688	0.0831	0.0566	0.7536
Transportation	0.2921	0.2939	-0.7779	0.0924	0.0817	0.0126	0.0051	1.1140
Personal Expenses	0.3146	0.2361	0.0784	-0.7936	0.0908	0.0517	0.0221	1.0761
Health	0.2241	0.2275	0.1164	0.1486	-0.8181	0.0536	0.0481	0.9596
Clothing	0.2628	0.3288	0.0160	0.0998	0.0632	-0.6488	-0.1216	1.1300
Education	0.2934	0.3857	0.0658	0.1138	0.1047	-0.1004	-0.8626	1.6758

Table A.20: Compensated Elasticities - Food Categories POF 2008/2010

Elasticity of	**With respect to price of**								
	Cereals	Flour P.	Veg.	Sugar	Fruits	Meat & Fish	Poultry	Dairy P.	Oil & Fats
Traditional model									
Cereals	-0.713	0.146	0.238	-0.163	0.063	0.235	0.113	0.168	-0.088
Flour Products	0.071	-0.755	0.147	0.148	0.086	0.124	0.070	0.112	-0.005
Vegetables	0.171	0.219	-0.976	0.044	0.130	0.149	0.022	0.176	0.065
Sugar and Sweets	-0.110	0.205	0.041	-0.781	0.049	0.491	0.041	0.103	-0.039
Fruits	0.048	0.136	0.138	0.055	-0.882	0.186	0.093	0.146	0.080
Meat and Fish	0.075	0.081	0.066	0.231	0.077	-0.709	0.072	0.042	0.065
Poultry and Eggs	0.116	0.149	0.031	0.063	0.124	0.234	-0.838	0.010	0.110
Dairy products	0.114	0.157	0.166	0.104	0.130	0.091	0.007	-0.749	-0.019
Oil and Fats	-0.240	-0.027	0.248	-0.160	0.287	0.564	0.293	-0.077	-0.889
SAR Direct Effect									
Cereals	-0.750	0.119	0.244	-0.193	0.079	0.268	0.120	0.143	-0.030
Flour Products	0.060	-0.762	0.147	0.155	0.108	0.105	0.075	0.118	-0.006
Vegetables	0.175	0.217	-0.967	0.049	0.132	0.177	0.037	0.158	0.023
Sugar and Sweets	-0.131	0.214	0.044	-0.797	0.050	0.493	0.045	0.097	-0.016
Fruits	0.059	0.169	0.143	0.055	-0.879	0.183	0.095	0.148	0.028
Meat and Fish	0.085	0.067	0.080	0.231	0.075	-0.706	0.074	0.044	0.050
Poultry and Eggs	0.120	0.155	0.059	0.070	0.130	0.236	-0.850	0.014	0.067
Dairy products	0.099	0.165	0.148	0.095	0.134	0.098	0.009	-0.776	0.028
Oil and Fats	-0.086	-0.036	0.083	-0.060	0.104	0.442	0.176	0.112	-0.734
SAR Indirect Effect									
Cereals	-0.908	0.152	0.118	0.083	0.097	0.242	0.078	0.114	0.022
Flour Products	0.075	-0.839	0.108	0.115	0.100	0.230	0.074	0.112	0.026
Vegetables	0.084	0.161	-0.901	0.107	0.102	0.234	0.071	0.115	0.027
Sugar and Sweets	0.059	0.160	0.100	-0.880	0.095	0.259	0.072	0.110	0.024
Fruits	0.075	0.157	0.107	0.109	-0.900	0.236	0.075	0.114	0.028
Meat and Fish	0.076	0.149	0.103	0.121	0.097	-0.757	0.074	0.106	0.029
Poultry and Eggs	0.078	0.156	0.103	0.110	0.101	0.239	-0.923	0.107	0.030
Dairy products	0.077	0.157	0.108	0.111	0.102	0.229	0.069	-0.880	0.028
Oil and Fats	0.164	0.260	0.117	0.207	0.097	0.128	0.019	0.111	-1.102
SAR Total Effect									
Cereals	-0.734	0.116	0.257	-0.223	0.077	0.270	0.125	0.147	-0.035
Flour Products	0.059	-0.756	0.150	0.158	0.109	0.097	0.075	0.118	-0.008
Vegetables	0.184	0.222	-0.973	0.044	0.135	0.171	0.034	0.162	0.022
Sugar and Sweets	-0.148	0.219	0.039	-0.790	0.046	0.513	0.043	0.096	-0.019
Fruits	0.058	0.169	0.145	0.052	-0.878	0.179	0.096	0.150	0.028
Meat and Fish	0.085	0.061	0.078	0.240	0.073	-0.701	0.073	0.039	0.052
Poultry and Eggs	0.122	0.155	0.057	0.067	0.132	0.236	-0.847	0.009	0.068
Dairy products	0.101	0.166	0.151	0.094	0.137	0.087	0.004	-0.768	0.028
Oil and Fats	0.002	0.069	0.095	0.034	0.102	0.331	0.121	0.111	-0.864

Table A.21: Uncompensated and Income Elasticities - Food Categories POF 2008/2010

Elasticity of	**With respect to price of**									**Income**
	Cereals	Flour P.	Veg.	Sugar	Fruits	Meat & Fish	Poultry	Dairy P.	Oil & Fats	**Elasticity**
Traditional model										
Cereals	-0.764	0.041	0.167	-0.239	-0.004	0.074	0.064	0.092	-0.106	0.676
Flour Products	0.020	-0.859	0.077	0.073	0.020	-0.036	0.021	0.038	-0.023	0.670
Vegetables	0.093	0.058	-1.084	-0.072	0.028	-0.096	-0.054	0.061	0.037	1.029
Sugar and Sweets	-0.182	0.057	-0.059	-0.888	-0.046	0.263	-0.029	-0.003	-0.066	0.952
Fruits	-0.010	0.016	0.057	-0.031	-0.959	0.002	0.036	0.060	0.059	0.770
Meat and Fish	-0.016	-0.104	-0.059	0.097	-0.041	-0.994	-0.016	-0.090	0.032	1.190
Poultry and Eggs	0.046	0.003	-0.067	-0.042	0.032	0.011	-0.907	-0.093	0.084	0.933
Dairy products	0.041	0.007	0.065	-0.004	0.034	-0.139	-0.064	-0.856	-0.046	0.962
Oil and Fats	-0.493	-0.548	-0.103	-0.535	-0.045	-0.235	0.046	-0.450	-0.982	3.345
SAR Direct Effect										
Cereals	-0.801	0.014	0.173	-0.269	0.012	0.106	0.070	0.068	-0.048	0.676
Flour Products	0.009	-0.866	0.077	0.080	0.042	-0.055	0.025	0.043	-0.024	0.670
Vegetables	0.097	0.056	-1.075	-0.066	0.030	-0.069	-0.039	0.043	-0.006	1.029
Sugar and Sweets	-0.203	0.066	-0.056	-0.904	-0.044	0.266	-0.025	-0.009	-0.042	0.952
Fruits	0.001	0.049	0.062	-0.031	-0.956	-0.001	0.038	0.062	0.007	0.770
Meat and Fish	-0.006	-0.118	-0.046	0.098	-0.043	-0.990	-0.014	-0.088	0.017	1.190
Poultry and Eggs	0.049	0.010	-0.039	-0.035	0.038	0.013	-0.919	-0.090	0.041	0.933
Dairy products	0.026	0.015	0.047	-0.013	0.039	-0.132	-0.062	-0.883	0.001	0.962
Oil and Fats	-0.339	-0.557	-0.269	-0.436	-0.227	-0.358	-0.071	-0.261	-0.827	3.345
SAR Indirect Effect										
Cereals	-0.982	-0.001	0.015	-0.027	0.000	0.007	0.006	0.005	-0.005	0.982
Flour Products	0.000	-0.992	0.005	0.005	0.003	-0.004	0.002	0.003	-0.002	0.981
Vegetables	0.008	0.004	-1.007	-0.006	0.002	-0.007	-0.004	0.003	-0.001	1.008
Sugar and Sweets	-0.016	0.005	-0.005	-0.993	-0.004	0.020	-0.002	-0.001	-0.003	0.999
Fruits	0.000	0.002	0.003	-0.002	-0.998	-0.001	0.002	0.003	0.000	0.991
Meat and Fish	-0.001	-0.009	-0.004	0.007	-0.003	-1.000	-0.001	-0.007	0.001	1.017
Poultry and Eggs	0.002	-0.001	-0.003	-0.003	0.001	-0.001	-0.997	-0.005	0.002	1.004
Dairy products	0.002	0.001	0.003	-0.001	0.002	-0.011	-0.005	-0.992	0.000	1.001
Oil and Fats	0.095	0.119	0.022	0.105	0.006	-0.090	-0.048	0.009	-1.127	0.910
SAR Total Effect										
Cereals	-0.794	-0.009	0.173	-0.312	-0.002	0.080	0.066	0.058	-0.057	0.798
Flour Products	0.007	-0.863	0.078	0.080	0.040	-0.068	0.024	0.041	-0.027	0.688
Vegetables	0.100	0.051	-1.089	-0.080	0.026	-0.091	-0.047	0.039	-0.008	1.098
Sugar and Sweets	-0.222	0.065	-0.065	-0.900	-0.051	0.278	-0.030	-0.014	-0.046	0.986
Fruits	-0.006	0.039	0.057	-0.042	-0.961	-0.021	0.034	0.056	0.005	0.840
Meat and Fish	-0.009	-0.133	-0.053	0.101	-0.050	-0.998	-0.018	-0.099	0.017	1.244
Poultry and Eggs	0.040	-0.014	-0.057	-0.054	0.024	-0.024	-0.927	-0.112	0.038	1.085
Dairy products	0.024	0.007	0.044	-0.020	0.036	-0.156	-0.071	-0.881	0.000	1.017
Oil and Fats	-0.079	-0.099	-0.018	-0.086	-0.005	0.074	0.042	-0.009	-0.894	1.074

Table A.22: Compensated Elasticities - Food Categories POF 2011/2013

Elasticity of	**With respect to price of**								
	Cereals	Flour P.	Veg.	Sugar	Fruits	Meat & Fish	Poultry	Dairy P.	Oil & Fats
Traditional model									
Cereals	-0.875	0.119	0.261	-0.081	0.144	0.297	0.127	0.112	-0.104
Flour Products	0.055	-0.725	0.080	0.041	0.158	0.283	0.088	-0.002	0.023
Vegetables	0.136	0.089	-1.053	0.188	-0.094	0.325	0.089	0.244	0.076
Sugar and Sweets	-0.053	0.057	0.236	-0.790	0.111	0.253	0.089	0.062	0.035
Fruits	0.084	0.198	-0.105	0.099	-0.728	0.212	0.036	0.101	0.103
Meat and Fish	0.084	0.171	0.175	0.109	0.102	-0.730	0.026	0.067	-0.002
Poultry and Eggs	0.115	0.169	0.154	0.123	0.056	0.083	-0.834	0.061	0.072
Dairy products	0.076	-0.004	0.319	0.064	0.117	0.161	0.046	-0.758	-0.022
Oil and Fats	-0.228	0.107	0.323	0.118	0.391	-0.016	0.177	-0.073	-0.798
SAR Direct Effect									
Cereals	-0.985	0.118	0.263	-0.089	0.197	0.287	0.154	0.100	-0.045
Flour Products	0.056	-0.734	0.080	0.044	0.160	0.267	0.093	0.006	0.027
Vegetables	0.137	0.089	-1.051	0.197	-0.088	0.321	0.092	0.245	0.057
Sugar and Sweets	-0.058	0.063	0.247	-0.789	0.131	0.251	0.101	0.050	0.004
Fruits	0.117	0.204	-0.099	0.115	-0.733	0.219	0.041	0.117	0.019
Meat and Fish	0.081	0.161	0.172	0.107	0.106	-0.741	0.025	0.063	0.027
Poultry and Eggs	0.138	0.180	0.161	0.138	0.065	0.077	-0.862	0.058	0.044
Dairy products	0.064	0.006	0.321	0.054	0.138	0.156	0.042	-0.786	0.005
Oil and Fats	-0.099	0.125	0.243	0.011	0.074	0.206	0.108	0.019	-0.687
SAR Indirect Effect									
Cereals	-0.937	0.142	0.140	0.086	0.122	0.243	0.081	0.099	0.024
Flour Products	0.066	-0.844	0.124	0.097	0.119	0.242	0.076	0.090	0.030
Vegetables	0.075	0.138	-0.892	0.113	0.092	0.248	0.076	0.116	0.033
Sugar and Sweets	0.060	0.139	0.136	-0.891	0.116	0.240	0.076	0.096	0.029
Fruits	0.073	0.151	0.102	0.104	-0.867	0.237	0.071	0.101	0.029
Meat and Fish	0.069	0.146	0.133	0.103	0.114	-0.759	0.069	0.095	0.030
Poultry and Eggs	0.071	0.146	0.131	0.104	0.113	0.231	-0.922	0.097	0.031
Dairy products	0.067	0.129	0.150	0.097	0.117	0.230	0.071	-0.889	0.028
Oil and Fats	0.179	0.157	0.052	0.164	0.143	0.261	0.052	0.152	-1.160
SAR Total Effect									
Cereals	-0.989	0.116	0.274	-0.105	0.204	0.291	0.161	0.100	-0.051
Flour Products	0.055	-0.722	0.075	0.039	0.164	0.270	0.095	-0.003	0.027
Vegetables	0.144	0.083	-1.071	0.208	-0.111	0.330	0.094	0.262	0.060
Sugar and Sweets	-0.065	0.058	0.254	-0.783	0.132	0.252	0.102	0.047	0.003
Fruits	0.123	0.211	-0.125	0.117	-0.715	0.217	0.037	0.119	0.018
Meat and Fish	0.083	0.163	0.176	0.107	0.105	-0.739	0.020	0.059	0.027
Poultry and Eggs	0.141	0.182	0.163	0.140	0.063	0.069	-0.859	0.056	0.045
Dairy products	0.064	-0.008	0.341	0.048	0.140	0.147	0.038	-0.773	0.003
Oil and Fats	0.013	0.138	0.166	0.073	0.102	0.228	0.085	0.072	-0.877

Table A.23: Uncompensated and Income Elasticities - Food Categories POF 2011/2013

Elasticity of	**With respect to price of**									**Income**
	Cereals	Flour P.	Veg.	Sugar	Fruits	Meat & Fish	Poultry	Dairy P.	Oil & Fats	**Elasticity**
Traditional model										
Cereals	-0.918	0.028	0.179	-0.146	0.071	0.146	0.080	0.049	-0.123	0.634
Flour Products	0.012	-0.817	-0.003	-0.025	0.084	0.130	0.040	-0.066	0.003	0.643
Vegetables	0.067	-0.058	-1.185	0.083	-0.211	0.080	0.013	0.143	0.045	1.023
Sugar and Sweets	-0.117	-0.079	0.114	-0.887	0.002	0.027	0.018	-0.032	0.006	0.947
Fruits	0.030	0.083	-0.208	0.017	-0.821	0.020	-0.023	0.021	0.079	0.801
Meat and Fish	0.004	-0.001	0.022	-0.013	-0.035	-1.015	-0.063	-0.051	-0.038	1.190
Poultry and Eggs	0.052	0.035	0.034	0.027	-0.051	-0.140	-0.903	-0.031	0.044	0.933
Dairy products	0.012	-0.141	0.196	-0.034	0.007	-0.067	-0.025	-0.852	-0.051	0.957
Oil and Fats	-0.439	-0.345	-0.082	-0.204	0.030	-0.766	-0.056	-0.383	-0.894	3.138
SAR Direct Effect										
Cereals	-1.041	-0.002	0.155	-0.174	0.101	0.087	0.092	0.017	-0.070	0.836
Flour Products	0.011	-0.831	-0.007	-0.024	0.083	0.107	0.043	-0.060	0.007	0.672
Vegetables	0.068	-0.057	-1.182	0.093	-0.205	0.078	0.016	0.145	0.026	1.016
Sugar and Sweets	-0.124	-0.078	0.120	-0.890	0.019	0.016	0.027	-0.047	-0.026	0.982
Fruits	0.054	0.069	-0.220	0.019	-0.841	-0.006	-0.029	0.024	-0.009	0.940
Meat and Fish	0.000	-0.013	0.016	-0.017	-0.033	-1.029	-0.065	-0.056	-0.010	1.207
Poultry and Eggs	0.068	0.030	0.027	0.031	-0.055	-0.172	-0.940	-0.045	0.013	1.043
Dairy products	-0.009	-0.150	0.180	-0.058	0.013	-0.104	-0.039	-0.893	-0.028	1.087
Oil and Fats	-0.174	-0.036	0.099	-0.103	-0.054	-0.061	0.025	-0.091	-0.721	1.116
SAR Indirect Effect										
Cereals	-1.004	0.000	0.013	-0.015	0.009	0.008	0.008	0.001	-0.006	0.986
Flour Products	0.001	-0.984	-0.001	-0.002	0.008	0.010	0.004	-0.006	0.001	0.968
Vegetables	0.008	-0.007	-1.021	0.011	-0.023	0.009	0.002	0.017	0.003	1.002
Sugar and Sweets	-0.007	-0.005	0.007	-0.994	0.001	0.001	0.002	-0.003	-0.001	0.999
Fruits	0.006	0.008	-0.026	0.002	-0.981	-0.001	-0.003	0.003	-0.001	0.993
Meat and Fish	0.000	-0.001	0.002	-0.002	-0.003	-1.003	-0.007	-0.006	-0.001	1.021
Poultry and Eggs	0.003	0.001	0.001	0.002	-0.003	-0.009	-0.997	-0.002	0.001	1.002
Dairy products	-0.001	-0.016	0.019	-0.006	0.001	-0.011	-0.004	-0.989	-0.003	1.009
Oil and Fats	0.117	0.024	-0.067	0.069	0.037	0.041	-0.017	0.061	-1.188	0.922
SAR Total Effect										
Cereals	-1.045	-0.003	0.168	-0.189	0.109	0.095	0.100	0.019	-0.076	0.822
Flour Products	0.012	-0.815	-0.007	-0.027	0.091	0.117	0.047	-0.066	0.007	0.641
Vegetables	0.076	-0.063	-1.202	0.104	-0.228	0.087	0.018	0.161	0.029	1.018
Sugar and Sweets	-0.131	-0.083	0.127	-0.884	0.020	0.017	0.029	-0.050	-0.027	0.981
Fruits	0.060	0.077	-0.246	0.021	-0.823	-0.006	-0.032	0.026	-0.010	0.933
Meat and Fish	0.000	-0.014	0.018	-0.018	-0.036	-1.032	-0.072	-0.062	-0.011	1.228
Poultry and Eggs	0.071	0.031	0.028	0.033	-0.057	-0.181	-0.937	-0.047	0.013	1.045
Dairy products	-0.010	-0.166	0.200	-0.064	0.014	-0.115	-0.043	-0.882	-0.031	1.097
Oil and Fats	-0.057	-0.012	0.032	-0.034	-0.017	-0.019	0.008	-0.030	-0.909	1.038

Table A.24: SAR AIDS Estimation Robust W - Broad Categories POF 2008/2010

	Habitation		**Food**		**Transportation**		**Personal Expenses**		**Health**		**Clothing**		**Education**	
Variable	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value
Constant	**0.552**	0.000	**0.479**	0.000	**0.118**	0.004	**0.122**	0.001	0.057	0.098	-0.001	0.968	**-0.326**	0.000
Log Price Hab	**0.022**	0.000	-0.005	0.059	**-0.007**	0.012	-0.003	0.146	**-0.006**	0.001	-0.001	0.566	-0.001	0.539
Log Price Food	-0.005	0.059	0.003	0.299	0.001	0.806	-0.003	0.087	-0.003	0.050	**0.003**	0.047	**0.004**	0.025
Log Price Transp	**-0.007**	0.012	0.001	0.806	**0.015**	0.000	-0.001	0.757	0.000	0.762	-0.003	0.071	**-0.004**	0.025
Log Price Personal	-0.003	0.146	-0.003	0.087	-0.001	0.757	**0.011**	0.000	0.000	0.865	-0.002	0.187	-0.002	0.180
Log Price Health	**-0.006**	0.001	-0.003	0.050	0.000	0.762	0.000	0.865	**0.010**	0.000	-0.001	0.323	0.001	0.626
Log Price Cloth	-0.001	0.566	**0.003**	0.047	-0.003	0.071	-0.002	0.187	-0.001	0.323	**0.007**	0.007	**-0.003**	0.022
Log Price Educ	-0.001	0.539	**0.004**	0.025	**-0.004**	0.025	-0.002	0.180	0.001	0.626	**-0.003**	0.022	**0.006**	0.002
Log Real Expend	**-0.034**	0.000	**-0.036**	0.000	**0.014**	0.009	-0.004	0.265	-0.006	0.126	**0.013**	0.000	**0.054**	0.000
HH Age	0.001	0.150	0.000	0.565	**-0.001**	0.000	0.000	0.398	**0.002**	0.000	**0.000**	0.045	0.000	0.137
HH Comp. Elem	-0.012	0.657	**-0.039**	0.024	0.003	0.891	0.013	0.365	0.028	0.087	0.016	0.120	-0.009	0.523
HH Comp. Junior	0.012	0.672	**-0.050**	0.008	-0.004	0.838	0.015	0.350	0.032	0.066	0.006	0.608	-0.011	0.487
HH Comp. High	-0.009	0.750	**-0.053**	0.006	0.001	0.981	0.031	0.054	0.026	0.134	0.012	0.262	-0.009	0.567
HH Incomp. College	-0.017	0.618	**-0.071**	0.003	0.006	0.800	0.015	0.450	0.032	0.127	0.010	0.446	0.025	0.182
HH Comp. College	0.021	0.482	**-0.082**	0.000	-0.008	0.705	0.027	0.116	**0.043**	0.024	-0.004	0.705	0.003	0.863
HH Female	0.015	0.187	-0.009	0.200	**-0.021**	0.009	-0.001	0.842	0.009	0.203	0.001	0.784	0.007	0.250
H Size	-0.008	0.119	**0.007**	0.036	**0.011**	0.002	0.002	0.474	**-0.011**	0.001	-0.001	0.654	-0.001	0.778
H Total Child	-0.013	0.279	**0.019**	0.017	-0.011	0.166	-0.008	0.229	0.013	0.081	-0.002	0.742	0.002	0.724
H Total Youngster	0.001	0.923	**0.014**	0.009	**-0.019**	0.002	-0.006	0.191	0.003	0.587	0.003	0.307	0.005	0.253
H Total Adults	-0.009	0.398	0.004	0.563	0.007	0.294	0.008	0.166	**-0.021**	0.002	0.002	0.586	0.009	0.114
H Total Eldery	-0.010	0.325	0.009	0.176	-0.004	0.535	-0.011	0.053	**0.032**	0.000	-0.007	0.075	-0.008	0.164
Mills	-0.022	0.169	**-0.067**	0.000	**-0.017**	0.002	**-0.014**	0.018	**-0.033**	0.000	**-0.040**	0.000	**0.193**	0.000
λ_{slm}	0.033	0.385	**0.133**	0.002	0.005	0.900	0.043	0.383	0.047	0.238	-0.047	0.366	-0.214	0.141
Demographics	Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Mills	Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Observations	1119		1119		1119		1119		1119		1119		1119	
Log Likelihood	-6840.94		-6840.94		-6840.94		-6840.94		-6840.94		-6840.94		-6840.94	

Coefficients in bold are significant with p < 0.05.

Table A.25: SAR AIDS Estimation Robust W - Broad Categories POF 2011/2013

	Habitation		**Food**		**Transportation**		**Personal Expenses**		**Health**		**Clothing**		**Education**	
Variable	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value
Constant	**0.353**	0.000	**0.643**	0.000	**0.070**	0.010	**0.078**	0.002	0.024	0.311	**0.084**	0.001	**-0.252**	0.000
Log Price Hab	**0.022**	0.000	**-0.008**	0.000	-0.003	0.100	0.000	0.966	**-0.007**	0.000	**-0.003**	0.025	-0.001	0.309
Log Price Food	**-0.008**	0.000	0.000	0.823	**0.003**	0.024	**-0.003**	0.012	**-0.003**	0.008	**0.004**	0.004	**0.007**	0.000
Log Price Transp	-0.003	0.100	**0.003**	0.024	**0.012**	0.000	**-0.004**	0.004	0.000	0.799	**-0.006**	0.001	**-0.003**	0.032
Log Price Personal	0.000	0.966	**-0.003**	0.012	**-0.004**	0.004	**0.009**	0.000	0.001	0.119	-0.002	0.151	-0.001	0.449
Log Price Health	**-0.007**	0.000	**-0.003**	0.008	0.000	0.799	0.001	0.119	**0.008**	0.000	-0.001	0.276	0.001	0.066
Log Price Cloth	**-0.003**	0.025	**0.004**	0.004	**-0.006**	0.001	-0.002	0.151	-0.001	0.276	**0.017**	0.000	**-0.009**	0.000
Log Price Educ	-0.001	0.309	**0.007**	0.000	**-0.003**	0.032	-0.001	0.449	0.001	0.066	**-0.009**	0.000	**0.006**	0.000
Log Real Expend	-0.003	0.564	**-0.061**	0.000	**0.012**	0.003	**0.009**	0.007	-0.002	0.493	**0.008**	0.020	**0.037**	0.000
HH Age	0.000	0.476	0.000	0.421	0.000	0.178	**-0.001**	0.002	**0.001**	0.000	**-0.001**	0.000	0.000	0.077
HH Comp. Elem	0.019	0.208	-0.011	0.326	-0.007	0.487	0.006	0.461	0.018	0.059	-0.007	0.427	**-0.019**	0.031
HH Comp. Junior	0.020	0.220	**-0.032**	0.013	0.003	0.794	0.006	0.536	0.016	0.124	0.004	0.635	-0.016	0.061
HH Comp. High	0.005	0.759	**-0.035**	0.006	0.016	0.124	0.001	0.920	**0.024**	0.024	-0.006	0.476	-0.004	0.606
HH Incomp. College	0.023	0.256	**-0.067**	0.000	-0.002	0.853	-0.009	0.431	**0.029**	0.031	-0.013	0.251	**0.040**	0.001
HH Comp. College	0.007	0.692	**-0.042**	0.003	0.002	0.893	0.014	0.180	**0.039**	0.002	**-0.029**	0.006	0.011	0.221
HH Female	0.009	0.195	-0.003	0.586	**-0.019**	0.000	0.005	0.291	0.007	0.121	0.004	0.320	-0.003	0.458
H Size	**-0.021**	0.000	**0.014**	0.000	**0.009**	0.000	0.004	0.079	**-0.007**	0.002	-0.002	0.298	**0.004**	0.029
H Total Child	**0.026**	0.003	-0.001	0.905	**-0.020**	0.001	**-0.012**	0.019	0.008	0.141	0.000	0.952	-0.002	0.579
H Total Youngster	**0.013**	0.023	0.004	0.326	**-0.013**	0.001	**-0.010**	0.005	0.004	0.269	0.003	0.352	-0.001	0.777
H Total Adults	**-0.014**	0.038	-0.002	0.618	0.006	0.191	0.007	0.067	**-0.015**	0.002	0.007	0.059	**0.011**	0.003
H Total Eldery	0.002	0.716	**0.011**	0.036	**-0.015**	0.002	-0.001	0.732	**0.025**	0.000	0.000	0.929	**-0.022**	0.000
Mills	-0.031	0.135	**0.645**	0.001	**-0.029**	0.000	**-0.033**	0.007	**-0.037**	0.000	**-0.040**	0.000	**-0.476**	0.011
λ_{slm}	0.032	0.231	0.012	0.629	0.004	0.906	0.050	0.160	0.044	0.127	0.045	0.188	-0.187	0.094
Demographics	Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Mills	Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Observations	1985		1985		1985		1985		1985		1985		1985	
Log Likelihood	-13214.93		-13214.93		-13214.93		-13214.93		-13214.93		-13214.93		-13214.93	

Coefficients in bold are significant with $p < 0.05$.

Table A.26: SAR AIDS Estimation Robust W - Food Categories POF 2008/2010

	Cereals		**Flour Products**		**Vegetables**		**Sugar and Sweets**		**Fruits**		**Meat and Fish**		**Poultry and Eggs**		**Dairy products**		**Oil and Fats**	
Variable	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value
Constant	**0.188**	0.000	**0.304**	0.000	0.021	0.342	**0.098**	0.001	0.052	0.064	0.070	0.087	**0.084**	0.000	**0.173**	0.000	0.011	0.638
Log Price Cereals	0.013	0.101	-0.003	0.641	**0.012**	0.028	**-0.025**	0.000	-0.001	0.760	0.003	0.743	0.004	0.278	0.002	0.667	**-0.006**	0.046
Log Price Flour	-0.003	0.641	0.013	0.219	0.007	0.251	0.006	0.308	0.000	0.969	-0.019	0.060	0.000	0.996	0.001	0.868	**-0.005**	0.036
Log Price Vegetables	**0.012**	0.028	0.007	0.251	-0.007	0.321	-0.007	0.115	0.006	0.182	-0.010	0.195	-0.003	0.353	0.003	0.506	-0.001	0.834
Log Price Sugar	**-0.025**	0.000	0.006	0.308	-0.007	0.115	0.011	0.094	-0.006	0.139	**0.030**	0.000	-0.004	0.268	-0.001	0.896	**-0.004**	0.022
Log Price Fruits	-0.001	0.760	0.000	0.969	0.006	0.182	-0.006	0.139	0.004	0.513	-0.008	0.273	0.002	0.468	0.003	0.493	0.000	0.948
Log Price Meat & Fish	0.003	0.743	-0.019	0.060	-0.010	0.195	**0.030**	0.000	-0.008	0.273	0.014	0.393	-0.001	0.892	-0.016	0.071	0.006	0.122
Log Price Poultry	0.004	0.278	0.000	0.996	-0.003	0.353	-0.004	0.268	0.002	0.468	-0.001	0.892	0.006	0.115	-0.008	0.063	0.003	0.100
Log Price Dairy	0.002	0.667	0.001	0.868	0.003	0.506	-0.001	0.896	0.003	0.493	-0.016	0.071	-0.008	0.063	0.014	0.114	0.000	0.904
Log Price Fat & Oils	**-0.006**	0.046	**-0.005**	0.036	-0.001	0.834	**-0.004**	0.022	0.000	0.948	0.006	0.122	0.003	0.100	0.000	0.904	**0.007**	0.005
Log Real Expenditure	**-0.009**	0.023	**-0.050**	0.000	**0.021**	0.000	-0.006	0.158	0.001	0.852	**0.039**	0.000	**0.008**	0.014	-0.009	0.066	**0.005**	0.002
HH Age	**-0.001**	0.002	0.001	0.096	0.000	0.993	0.000	0.274	**0.001**	0.001	0.000	0.718	0.000	0.763	-0.001	0.160	0.000	0.862
HH Educ	**-0.007**	0.000	**0.005**	0.016	0.002	0.184	0.003	0.104	**0.008**	0.000	**-0.008**	0.001	**-0.005**	0.000	0.003	0.058	-0.001	0.109
HH Female	-0.002	0.713	-0.004	0.563	**0.016**	0.004	0.005	0.448	-0.006	0.376	**-0.024**	0.017	0.004	0.404	0.012	0.092	-0.001	0.575
H Size	0.003	0.136	**0.016**	0.000	**-0.008**	0.003	-0.003	0.221	**-0.010**	0.002	0.008	0.071	**-0.004**	0.040	-0.002	0.425	0.000	0.814
H Total Child	-0.006	0.243	0.000	0.977	-0.004	0.426	**0.013**	0.047	0.007	0.333	**-0.023**	0.024	0.001	0.913	**0.016**	0.041	-0.002	0.218
H Total Youngster	0.003	0.405	0.004	0.424	**-0.009**	0.014	0.007	0.110	-0.007	0.166	-0.008	0.238	0.002	0.472	0.007	0.146	0.000	0.990
H Total Adults	0.009	0.059	0.011	0.140	-0.008	0.114	0.010	0.086	-0.007	0.237	-0.012	0.159	-0.007	0.077	0.005	0.457	0.000	0.826
H Total Eldery	0.000	0.973	**0.017**	0.019	**0.010**	0.044	-0.008	0.166	0.004	0.497	**-0.023**	0.010	-0.001	0.849	-0.002	0.716	0.003	0.075
Mills	-0.002	0.250	-0.005	0.074	-0.002	0.217	0.004	0.070	-0.003	0.100	**0.007**	0.002	**-0.009**	0.000	-0.001	0.512	**0.012**	0.006
λ_{slm}	0.033	0.203	0.029	0.242	0.033	0.251	0.007	0.788	0.035	0.201	0.017	0.490	-0.017	0.585	-0.014	0.592	-0.123	0.470
Demographics	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Mills	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Observations	1078		1078		1078		1078		1078		1078		1078		1078		1078	
Log Likelihood	-11079.61		-11079.61		-11079.61		-11079.61		-11079.61		-11079.61		-11079.61		-11079.61		-11079.61	

Coefficients in bold are significant with $p < 0.05$.

Table A.27: SAR AIDS Estimation Robust W - Food Categories POF 2011/2013

	Cereals		**Flour Products**		**Vegetables**		**Sugar and Sweets**		**Fruits**		**Meat and Fish**		**Poultry and Eggs**		**Dairy products**		**Oil and Fats**	
Variable	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value	Coeff	p-value
Constant	**0.183**	0.000	**0.363**	0.000	**-0.042**	0.023	**0.148**	0.000	-0.029	0.174	**0.142**	0.000	**0.112**	0.000	**0.075**	0.001	**0.049**	0.009
Log Price Cereals	-0.003	0.508	-0.002	0.672	**0.011**	0.001	**-0.013**	0.000	0.006	0.183	0.001	0.806	**0.006**	0.040	-0.001	0.770	**-0.005**	0.017
Log Price Flour	-0.002	0.672	**0.019**	0.008	**-0.009**	0.013	**-0.009**	0.037	0.006	0.245	0.006	0.399	0.003	0.423	**-0.013**	0.005	-0.001	0.667
Log Price Vegetables	**0.011**	0.001	**-0.009**	0.013	**-0.022**	0.000	**0.013**	0.000	**-0.027**	0.000	0.009	0.079	0.003	0.234	**0.018**	0.000	**0.005**	0.001
Log Price Sugar	**-0.013**	0.000	**-0.009**	0.037	**0.013**	0.000	**0.011**	0.025	0.003	0.411	0.000	0.978	0.003	0.337	-0.005	0.141	-0.003	0.064
Log Price Fruits	0.006	0.183	0.006	0.245	**-0.027**	0.000	0.003	0.411	0.015	0.053	-0.001	0.929	-0.004	0.257	0.003	0.524	-0.001	0.748
Log Price Meat & Fish	0.001	0.806	0.006	0.399	0.009	0.079	0.000	0.978	-0.001	0.929	0.006	0.608	**-0.012**	0.017	-0.008	0.166	-0.001	0.687
Log Price Poultry	**0.006**	0.040	0.003	0.423	0.003	0.234	0.003	0.337	-0.004	0.257	**-0.012**	0.017	0.005	0.152	-0.004	0.215	0.001	0.588
Log Price Dairy	-0.001	0.770	**-0.013**	0.005	**0.018**	0.000	-0.005	0.141	0.003	0.524	-0.008	0.166	-0.004	0.215	**0.013**	0.019	-0.003	0.081
Log Price Fat & Oils	**-0.005**	0.017	-0.001	0.667	**0.005**	0.001	-0.003	0.064	-0.001	0.748	-0.001	0.687	0.001	0.588	-0.003	0.081	**0.008**	0.001
Log Real Expenditure	**-0.007**	0.007	**-0.051**	0.000	**0.022**	0.000	**-0.009**	0.010	**0.011**	0.003	**0.029**	0.000	0.002	0.278	-0.002	0.508	**0.004**	0.003
HH Age	**-0.001**	0.000	0.000	0.514	0.000	0.067	0.000	0.621	**0.001**	0.000	-0.001	0.063	**0.000**	0.007	0.000	0.109	0.000	0.188
HH Educ	**-0.007**	0.000	0.001	0.665	0.000	0.741	0.002	0.092	**0.007**	0.000	**-0.006**	0.002	**-0.002**	0.005	**0.007**	0.000	**-0.001**	0.030
HH Female	-0.002	0.635	-0.003	0.541	**0.021**	0.000	-0.004	0.320	0.002	0.685	**-0.024**	0.001	0.004	0.175	0.006	0.216	0.000	0.873
H Size	0.000	0.798	**0.010**	0.000	**-0.006**	0.005	0.004	0.051	**-0.009**	0.001	0.000	0.880	-0.002	0.257	0.002	0.264	-0.001	0.170
H Total Child	0.007	0.083	-0.005	0.332	-0.005	0.234	0.005	0.278	-0.004	0.474	-0.015	0.053	-0.003	0.337	**0.019**	0.001	0.001	0.498
H Total Youngster	-0.001	0.747	0.007	0.075	-0.001	0.778	-0.001	0.794	0.001	0.795	-0.002	0.676	0.001	0.563	-0.005	0.207	0.000	0.958
H Total Adults	0.002	0.593	**0.011**	0.021	**-0.013**	0.002	-0.001	0.768	**-0.015**	0.002	**0.014**	0.026	0.000	0.880	0.003	0.457	0.000	0.951
H Total Eldery	0.000	0.951	**0.014**	0.004	0.005	0.166	**-0.013**	0.003	0.002	0.561	-0.004	0.501	0.002	0.444	-0.007	0.089	0.000	0.916
Mills	**-0.004**	0.006	**0.005**	0.009	**-0.005**	0.011	0.002	0.195	0.000	0.884	**0.009**	0.000	**-0.010**	0.000	**-0.003**	0.044	0.005	0.100
lambda_slm	0.008	0.708	**0.040**	0.046	0.026	0.236	0.025	0.227	0.038	0.074	0.023	0.212	0.009	0.699	**0.049**	0.020	-0.218	0.093
Demographics	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Mills	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes	
Observations	1965		1965		1965		1965		1965		1965		1965		1965		1965	
Log Likelihood	-21188.71		-21188.71		-21188.71		-21188.71		-21188.71		-21188.71		-21188.71		-21188.71		-21188.71	

Coefficients in bold are significant with $p < 0.05$.