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ESTIMATING EXPENDITURE WEIGHTS WITH LIMITED INFORMATION

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1. Introduction

The construction of indexes to measure the purchasing power parity (PPP) among countries or regions requires the knowledge of the respective weighting structures. Such structures are used in Summers and Heston (1991), in their construction of PPP indicators for several countries, within the International Comparisons Project (ICP) of the United Nations and the World Bank; Kokoski et al (1999), for cities in the US; Aten (1999) and Azzoni et al (2001), for cities in Brazil; Ravallion and Walle (1991), for cities in China; and Prasada (1995), for cities in India. In the majority of cases, household expenditure surveys (HES) are used to identify the weighting structures. However, these surveys are lengthy and very expensive to implement, what makes HES a very scarce good. The ICP effort aims at comparing PPP for all countries in the world, and for this sort of endeavor, some alternative procedure should be utilized.

The objective of this paper is to present a method for the estimation of weighting structures for the construction of urban cost of living levels, when information is limited. In order to do that, we refer to the Almost Ideal Demand System (AID) proposed by Deaton and Muelbauer (1980), in which they developed a system to identify demand patterns. Instead, we will use their system to identify consumption patterns for a representative consumer, based on available price and weight data.

Initially, we discuss some aspects involved in the estimation of weighting structures for the construction of urban cost of living indexes, which is the subject of section 2. In section 3 we present the database used in the study of Brazilian cities. Section 4 applies the methodology presented in section 2 to the data base to estimate weighting structures, which are in turn used in section 5 to calculate cost of living indexes for those cities. In section 5 we compare the results and present our conclusions.

2. Methodology

In their demand study for the UK, Deaton and Muellbauer (1980) propose a demand functional form (AID) that was later extended by Blundel, Pashardes and Weber (1993), who presented a quadratic extension of that model (QUAID). In their calculation of the demand structure, both studies admit that preferences are time-related. In this paper we adapt the QUAID model to a spatial perspective. The authors of that model estimated demand functions for the UK for different years; in this study we intend to do a similar exercise on Brazil, but for different urban areas in the same period of time.

Let **q** represent the basket containing the 12 products directly considered in our model, and let **z** indicate both the basket of the other products consumed by individuals and regional characteristics. We thus have two sets of goods and, although the relative consumption of one group depends on the other, preferences between the two groups are assumed to be weakly separated. Since the demand function is aggregation-consistent, it is possible to estimate its components individually.

The model hypothesizes that families first decide, exogenously to the model, on how much to spend on basket **q** and how much is left to spend on **z**. Only after that decision is made families will allocate their expenditure among the goods in basket **q**. Preferences for family *h* are such that, in each time period *t,* families decide on how much to consume from basket **q**, conditional to the products of basket **z**.

Let q^h_{il} indicate the quantity of good *i* consumed by family h, in city *l*; let m^h_l indicate the expenditure of family *h* with basket **q** in city *l*. Expenditure with good *i*, for a given $\mathbf{z}_l^h$, can be written as

$$p_{il}q_{il}^h = f_i(\mathbf{p}_l, m_l^h; \mathbf{z}_l^h) \qquad (1)$$

Where f_i describes preferences in each city, and $\mathbf{p}_l$ is the vector of prices of goods in the city. Under weak separability of preferences, and knowing m^h_l, it is possible to establish the value of f_i without knowing the prices and expenditures with other products in the other cities.

Family preferences are first described ignoring the existence of different characteristics among regions. Thus, assuming that families are utility maximizers, and working with an indirect (Marshalian) utility function, the share of product *i* in the family *h* expenditure with basket **q** in city *l* is given by

$$w_{ik}^h = \alpha_i + b_0^i(\boldsymbol{p}_k) + \sum_j^J b_i^l(\boldsymbol{p}_k) g_j(x_k^h) \qquad (2)$$

With x^h_k being the total real expenditure of family *h* in city *k*. The coefficients $b^i_0(\boldsymbol{p}_k)$, $b^i_1(\boldsymbol{p}_k)$, ..., $b^i_J(\boldsymbol{p}_k)$ are homogeneous functions of degree zero in prices, and $g_j(x^h_k)$ are polynomials of total real expenditures.

Gorman (1981) shows that, for a preference structure such as (1), the integrability condition required by Demand Theory is that the *n x J* matrix of the coefficients $\alpha_i + b^i_0, b^i_1, \ldots, b^i_J$. ($k=1, 2 \ldots n$) must have a rank no greater than 3[1]. In that case, expression (2) may be written as

$$w_{ik} = \alpha_i + b_0^i(\boldsymbol{p}_k) + b_1^i(\boldsymbol{p}_k)\ln x + b_2^i(\boldsymbol{p}_k)(\ln x)^2 \qquad (3)$$

where household subscripts have been omitted for simplicity. Thus, the coefficient for ln*x* and $(\ln x)^2$ are restricted to one price-independent term, that is, $b^i_1(\boldsymbol{p}_k) = \beta_i$ and $b^i_2(\boldsymbol{p}_k) = \eta_I$. The system's integrability, especially the symmetry of the Slutsky's matrix, requires that $\eta_i = \beta_i \varepsilon$, that is, the ratio of the coefficients for income and income squared must be the same

[1] This condition is illustrated in Blundel, Pashardes and Weber (1993) for a situation in which J = 2 and the g_j´s are simple logarithmic polynomials terms.

for all commodities. In this case, the rank of the coefficients matrix is reduced to 2, and (4) can be written as

$$w_{ik} = \alpha_i + b_0^i(p_t) + \beta_{ik}\left[\ln x_k + \varepsilon\left(\ln x_k\right)^2\right] \quad (3')$$

Here we follow Deaton and Muellbauer (1980), imposing an additional restriction to the model, that is, $\varepsilon = 0$. It is thus assumed that only the logarithm of income influences demand, living aside the income squared term. With these modifications, the model becomes

$$w_{ik}^h = \alpha_{ik}^h + \sum_j \gamma_{ji} \ln p_{jk} + \beta_{ik}^h \ln x_k^h \quad (4)$$

The control for regional characteristics is done through the coefficients $\alpha^h{}_{ik}$[2]. Supposing that the intercept is a function of the characteristics of the city, we get

$$\alpha^h{}_{ik} = \alpha_0 + \Sigma_k \alpha_{in} z^h{}_{kr} \quad (5)$$

Where $z^h{}_{rk}$ corresponds to characteristic r, supposed to be common to all citizens in city k. A consistent aggregation relationship may be written as

$$w_{ik} = \alpha_0 + \sum_j \lambda_{ij} \ln \boldsymbol{p_{jk}} + \beta_i \ \ln X_k + \beta_i \sum \mu_{hk} \ln(x_k^h / X_k) + \sum_r \alpha_{ir} \sum \mu_{hk} z_{rk}^h \quad (6)$$

where $\ln X_k = \Sigma_h x^h{}_k / H_k$ is the average total real expenditure, and H_k is the number of households in region k and $\mu^h{}_k = (m^h{}_k / M_k)$ is each household's relative weight, in terms of expenditure. Multiplying $w^h{}_{ik}$ by $\mu^h{}_k$, one gets the share of aggregate expenditure on good i out of total aggregate expenditure M_k. From (6), the following equation could be estimated:

$$w_{ik} = \alpha_0 + \sum_j \lambda_{ij} \ln \boldsymbol{p_{jk}} + \beta_i \ \eta_{0k} \ln X_k + \sum_r \alpha_{ir} \theta_{rk} \sum \mu_{hk} z_{rk}^h \quad (7)$$

Comparison with equation (6) shows that

$$\theta_{rk} = \sum_h \mu_k^h z_{rk}^h / \sum_h z_{rk}^h \quad (8a)$$

$$\eta_{0k} = \sum_h \mu_k^h \ln x_k^h / \ln X_k \quad (8b)$$

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[2] The same procedure is adopted by Blundel, Pashardes and Weber (1993), in which they allow for the parameters to vary according to family characteristics.

Where θ_{rk} and η_{0k} are the aggregation factors. Since the numerator in (8b) is close to its denominator, η_{0k} tends to be close to unity for every city, and can thus be assumed constant. It is also assumed that θ_{rk} are functions of deterministic variables only, so that the parameters of the aggregate model are stable, and γ_{ij} may be consistently estimated.

Equation (7) gives the participation of good *i* in the aggregate expenditure of all families in city *k*. Under the model's assumptions, this result confirms that rational consumption decisions of a representative family, with AID demand, generate an aggregate weighting structure. Adding a random term, we come to expression (9).

$$w_{ik} = \alpha_0 + \alpha_k \ln z_k + \sum_j \lambda_{ij} \ln \boldsymbol{p}_{\boldsymbol{jk}} + \beta_k \ln X_k + e_{ik} \qquad (9)$$

3. The database

In order to test the above methodology, we have calculated weights for a limited list of basic food items ("cesta básica" – basic basket) for 16 state capital cities in Brazil. Prices were collected by DIEESE (www.dieese.org.br) in May 2000 for 12 items: meat, milk, bens, rice, wheat flower, tomato, bread, coffee, banana, sugar, oil and butter. For 11 of those 16 cities, IBGE (www.ibge.gov.br) provides weights based on the 1995/96 household expenditure survey, for households earning between 2 and 3 minimum wages. Tables A1 and A2 in the appendix provide information on the prices for products in each city in 1999 and the respective weights. Table A3 provides information on income and population for the same cities. Considering that in this study we use a limited list of products, the weights were distributed proportionally, so that the sum of weights is 1, that is, expenditures with food products correspond to 100% of total expenditure. Data on income for the cities were collected from IPEA (www.nemesis.org.br); population data come from IBGE's census.

4. Calculating the weighting structure

4.1. Estimated Coefficients

If income is no independent from the prices, the model in equation (9) is not linear. This problem is a serious one when we deal with time series, as discussed in Blundell (1998). In our case, we are dealing with spatial cross-sections, in which it is not reasonable to believe that prices in one city can influence income in the other cities. Thus, the model becomes linear and we can estimate equation (9) with OLS.

As a first step, the coefficients of equation (9) were estimate for the cities for which weights are available; these coefficients were then used to calculated weights for the other 5 cities, for which weights are not available. One city pertaining to the first group was set aside, to check for the robustness of the proposed procedure.

Equation (9) was estimated separately for each good, with Ordinary Least Squares, with heteroskedasticity being corrected with the White matrix. In the equation for good *i*, in addition to its price and income, all other prices should be included, in order to take into account complementarity and substitution effects among goods. However, given the limited degrees of freedom available, only two selected prices were included in each equation, what is equivalent to setting the other compensated cross-price elasticities equal to zero. The population of the cities is included to capture regional characteristics that might influence price levels. Results are presented in table 1.

Some coefficients do not pass the t test. This is in part related to the limited number of observations, that increases the regression standard deviations, and reduces the efficiency of the test. Thus, the criterion to include a product in the regression was based in the t test, in the adjusted R2 and in the joint significance F test. The estimated price and income coefficients are not standard price and income elasticities. A positive (negative) price coefficient indicates that consumer expenditures with that product in a city increases (decreases) as its price rises in that city. A positive coefficient for income indicates that as income rises, the share of expenditure with that product also rises, in the proportion indicated by the coefficient value. Since the model supposes that expenditure exhausts income, or that expenditure equals income, the estimated income coefficients are super income elasticities, in that they overestimate the value of that elasticity. Thus, products should not be classified as superior or inferior based on the estimated income coefficients.

The estimated income coefficients are generally significant and with the expected signs: beans, rice, wheat flower, tomato, bread, banana, sugar and oil show negative signs; meat, milk, and coffee, present positive signs. Population appears with positive sign in four cases only: tomato, banana, coffee and rice, indicating that the larger (smaller) the city, the larger (smaller) the participation of these items in the consumption basket of the average family in the income class considered. Own price coefficients are positive and significant at 5%. It is important to note that positive signs should not be taken as positive price-elasticities; they just indicate that the participation of that product in expenditure is higher in cities in which prices are higher.

Results are in general quite encouraging. Despite the low efficiency revealed by the t tests, price coefficients are, in general, significant at 5% and present the expected sign. Besides, the adjusted R2 values are quite high and, together with the F tests, indicate a good fit for the model.

4.2. Estimated weighting structures

We proceed with the following steps: 1) equation (9) is estimated, generating the values for the coefficients $\hat{\alpha}, \hat{\beta}$ *and* $\hat{\gamma}$; 2) these coefficient values are applied to equation (9), together with the logarithms of prices, population and income values for each city; 3) thus calculating the weights for each product in each city. Table 2 presents the estimated weighting structures for each city, including the 10 cities present in the sample; weights are also presented for Goiânia, a city not included in the sample but for which IBGE calculated weights. Thus, we can compare the estimated weights with the ones provided by a household expenditure surveys.

In order to check for robustness, we compare observed and estimated weights for the 10 cities included in the sample. Results are displayed in Table 3 and in Figure 1. The last column in Table 3 refers to Goiânia, the control city. In general, the differences are very small, with the great majority of cases situated below 8%, although in some spotted cases it went over 10%. For Goiânia, the biggest difference is in wheat flower, with a 24.6% difference, followed by coffee, with 13.9%, and oil, with 10.9%; the other differences were very small.

5. Resulting comparative basket costs

We now use the weights presented in the previous section to construct a comparative cost index for the basket of goods for the 16 cities. We use the Country Product Dummy (CPD) method, a hedonic model usually employed for the comparison of prices among different countries. The subjacent hypothesis in the CPD model is that the city-characteristic regression lines have identical slopes, such that the intercept captures all variations in prices. Thus, taking out the intercept of the model, the city dummy coefficients become deviations around the mean, corresponding to the multilateral price index among the cities[3]. The estimated model is

$$\ln p_{ik} = \sum_{k=2}^{K} b_k X_k + \sum_{i=1}^{I} \gamma_i Y_i + e_{ik} \qquad (10)$$

Where: $\ln p_{ik}$ = is the nepperian logarithm of the price of good i in city k

X_k (k = 2...K) = *dummy* variable: X=1 if price of good i was collect in city k; X=0 otherwise. (for the city used as a comparison basis, k=1).

Y_i (i = 1...I) = *dummy* variable: Y=1 for good i; Y=0 otherwise

e_{ik} = is a random variable, with zero mean and heterosketastic variance

The coefficient for X_k, (b_k), for one specific city corresponds to the nepperian logarithm of the relative price of that city in comparison to all other cities. Under the model hypotheses, the exponentials of $\hat{b}_k$ are consistent estimators of the relative price levels, that is, they are multilateral price indexes.

We have estimated three different regressions, taking Goiânia as a base city. The first version ignores expenditure weights at all, to show the importance of considering proper expenditure weights. The other two are estimated using Weighted Least Squares, the weights being the product shares in household expenditure described in the previous section. One of these weighted versions considers the observed weights for 11 cities (as provided by IBGE) and the estimated weights for the other 5 cities; the other version uses the estimated weights for all 16 cities. Results are presented in Table 4 and in Figure 2.

The first thing to point out is the evident discrepancy between the weighted and unweighted results, indicating the importance of using expenditure weights in any exercise of this type. The other important aspect is the small differences in the calculated indexes, as

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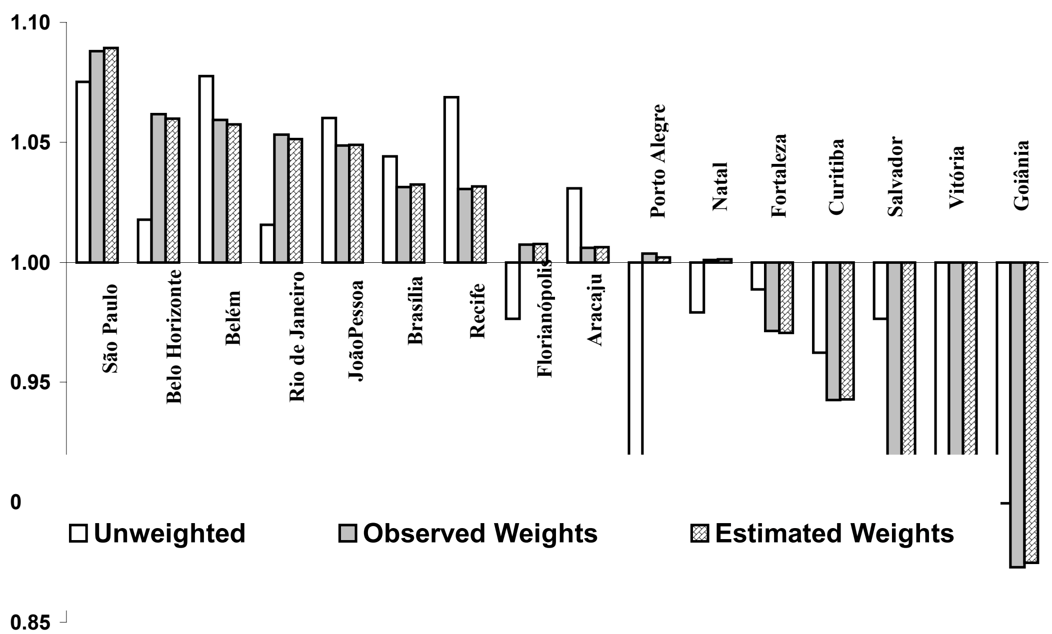
observed comparing the second and third columns of Figure 2. This is an important point, for the second column uses the observed weights for the cities for which they are available, and the weights estimated in section 4.2 for the other 5 cities, and the third column uses the estimated weights for all 16 cities. The fact that differences are minor is a good indicator of the quality of results we get when using the proposed methodology.

Figure 2 - Resulting cost of basket indexes



6. Conclusions

In this paper a methodology was tested to estimate weighting structures for the construction of urban cost of living indexes in cases in which household expenditure surveys are not available. Our results indicate that the methodology proposed provides good estimates of the real weights and that the resulting price indexes are quite consistent.

The high cost of household expenditure surveys restricts the construction of cost of living and inflation indexes to a limited number of cities in a country, usually the largest metropolitan areas. That limits the regional comparative analysis of monetary figures such as wages, income, etc. The methodology proposed here allows for the construction of that sort of index with lower costs, for only local prices are needed.

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Table 1 – Estimated Coefficients

	Meat	Milk	Beans	Rice	Wheat Flower	Tomato	Bread	Coffee	Banana	Sugar	Oil	Butter
Meat	0,352** (0,036)											
Milk		0,037** (0,012)						-0,058** (0,013)				0,0126 (0,008)
Beans			0,04** (0,005)									
Rice			0,0095 (0,008)	0,038** (0,029)		0,055** (0,015)						
Wheat Flower	-0,205** (0,032)	-0,017 (0,01)			0,0202** (0,007)					-0,0048 (0,003)	-0,006** (0,0007)	
Tomato						0,153** (0,014)	-0,086* (0,037)					
Bread							0,144** (0,007)				-0,0041** (0,0004)	-0,016 (0,008)
Coffee				0,028** (0,008)	0,049** (0,01)	0,200** (0,02)		-0,028* (0,012)		0,013** (0,004)		
Banana									0,081** (0,003)			
Sugar								0,037** (0,012)	0,0332* (0,01)	0,018** (0,0025)		
Oil					0,014 (0,008)						0,0129** (0,0015)	
Butter							-0,025* (0,01)					0,062** (0,003)
Income	0,024 (0,015)	0,0018 (0,003)	-0,0023 (0,016)	-0,0082** (0,0005)	-0,0168** (0,003)	-0,076** (0,003)	-0,018** (0,005)	0,0105* (0,004)	-0,012** (0,004)	-0,003** (0,001)	-0,0012** (0,0003)	-0,004 (0,003)
Population	0,0035 (0,006)	0,0017 (0,0012)	-0,00087 (0,0009)	-0,0013** (0,0004)	-0,002 (0,001)	-0,0096** (0,0018)	0,004 (0,004)	0,0042** (0,001)	-0,004** (0,001)	-0,0003 (0,0003)	-0,0002 (0,00013)	-0,0009 (0,0012)
Constant	-0,414** (0,048)	0,032* (0,014)	0,063** (0,0125)	0,0109 (0,014)	-0,016 (0,033)	-0,0118* (0,043)	0,102 (0,057)	0,0114 (0,03)	0,171** (0,01)	0,0117 (0,011)	0,019** (0,0021)	-0,0293* (0,0115)
R2	0,9743	0,6959	0,9294	0,9882	0,9855	0,9963	0,969	0,9806	0,9808	0,9344	0,9936	0,9811
Prob > F	0,0000	0,024	0,0007	0,0000	0,0004	0,0000	0,0001	0,0001	0,0000	0,0036	0,0001	0,0002
Amostra	10	10	10	10	10	10	10	10	10	10	10	10

Regressions are heteroskedasticity-robust; highlighted values reject H_0 at 5%; bold characters indicate rejection at 10%

Table 2: Estimated weighting structures

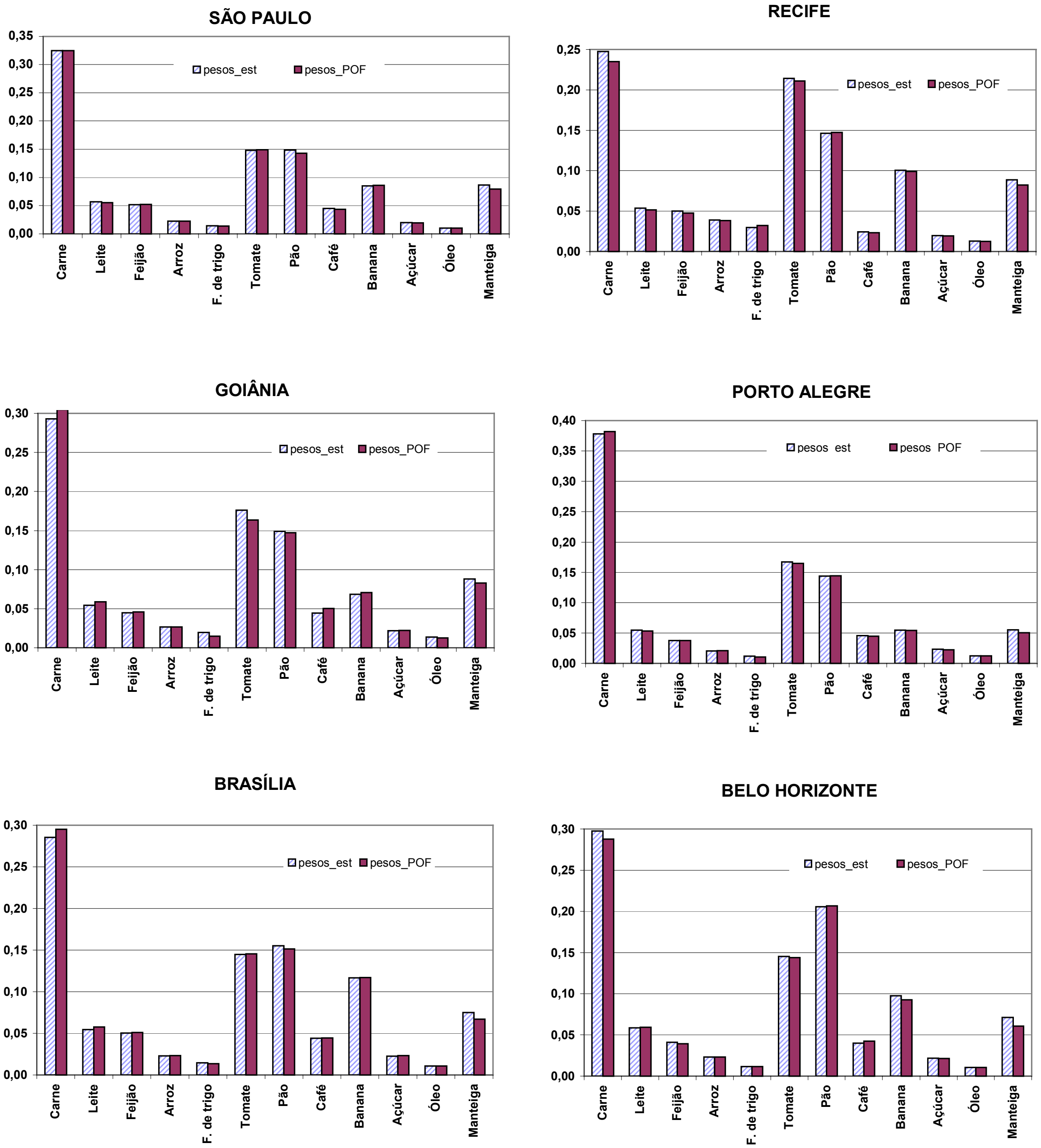
	Meat	Milk	Beans	Rice	Wheat Flower	Tomato	Bread	Coffee	Banana	Sugar	Oil	Butter
Brasília	0,286	0,055	0,05	0,023	0,014	0,145	0,155	0,044	0,1166	0,023	0,011	0,075
Goiânia	0,263	0,049	0,04	0,024	0,018	0,1579	0,134	0,04	0,0611	0,02	0,012	0,079
Belo Horizonte	0,298	0,059	0,041	0,023	0,012	0,1453	0,206	0,04	0,0973	0,022	0,011	0,071
Rio de Janeiro	0,293	0,06	0,039	0,026	0,011	0,1781	0,175	0,042	0,0816	0,021	0,01	0,064
São Paulo	0,325	0,057	0,052	0,023	0,014	0,1482	0,148	0,045	0,0851	0,02	0,01	0,087
Vitória	0,301	0,043	0,048	0,016	-0,007	0,0703	0,145	0,061	0,0561	0,015	0,011	0,0598
Curitiba	0,344	0,055	0,051	0,029	0,01	0,1485	0,126	0,046	0,0855	0,021	0,016	0,066
Florianópolis	0,342	0,046	0,052	0,028	0,013	0,1232	0,159	0,047	0,0435	0,021	0,012	0,072
Porto Alegre	0,378	0,055	0,037	0,021	0,012	0,1675	0,144	0,046	0,0548	0,024	0,012	0,055
Aracaju	0,285	0,054	0,048	0,035	0,019	0,1568	0,115	0,031	0,1302	0,02	0,015	0,078
Belém	0,198	0,058	0,046	0,034	0,032	0,2253	0,16	0,027	0,1357	0,026	0,013	0,049
Fortaleza	0,236	0,054	0,047	0,035	0,034	0,2369	0,16	0,023	0,0726	0,021	0,014	0,069
João Pessoa	0,255	0,056	0,049	0,037	0,03	0,2393	0,13	0,026	0,1186	0,025	0,014	0,067
Natal	0,27	0,053	0,044	0,033	0,024	0,2152	0,1	0,023	0,0662	0,017	0,014	0,065
Recife	0,248	0,053	0,05	0,039	0,0295	0,2143	0,146	0,024	0,1006	0,02	0,013	0,089
Salvador	0,247	0,054	0,038	0,041	0,032	0,2197	0,131	0,029	0,0779	0,023	0,013	0,078

Table 3 – Comparing estimated to known weights (*)

	São Paulo	Recife	Porto Alegre	Brasília	Belo Horizonte	Rio de Janeiro	Belém	Fortaleza	Salvador	Curitiba	Goiânia
Meat	0,001	-0,050	0,010	0,034	-0,033	0,004	0,028	0,029	-0,017	-0,004	0,039
Milk	-0,024	-0,035	-0,026	0,057	0,010	0,008	-0,012	0,014	0,015	-0,010	0,086
Beans	0,005	-0,048	0,007	0,019	-0,033	-0,037	-0,027	0,013	0,067	0,031	0,025
Rice	-0,005	-0,010	0,028	0,013	0,001	-0,023	-0,050	0,006	0,031	0,012	-0,006
Wheat Flower	-0,040	0,087	-0,086	-0,066	-0,006	0,085	-0,032	-0,043	0,022	0,086	-0,246
Tomato	0,006	-0,015	-0,017	0,004	-0,009	-0,004	0,015	0,005	-0,005	0,019	-0,072
Bread	-0,037	0,008	0,004	-0,024	0,005	0,036	-0,023	-0,020	0,048	0,003	-0,012
Coffee	-0,035	-0,047	-0,008	0,004	0,067	0,018	-0,043	0,002	0,056	-0,022	0,139
Banana	0,011	-0,017	-0,010	0,003	-0,049	-0,020	0,011	-0,035	0,093	0,013	0,037
Sugar	-0,014	-0,016	-0,032	0,038	-0,015	0,004	-0,006	0,002	0,017	0,020	0,016
Oil	-0,004	-0,009	0,011	-0,024	-0,003	0,012	0,015	-0,007	0,014	-0,009	-0,109
Butter	-0,082	-0,070	-0,084	-0,110	-0,145	-0,100	-0,110	-0,085	0,006	-0,068	-0,061

(*) Displayed values are [(estimated weight/known weight) – 1].

Figure 1: Comparing estimated and known weights



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