Interarea price levels: an experimental methodology

Differences in relative price levels for areas of the United States can be estimated with a modified Country-Product-Dummy (CPD) method often used in international comparisons of the purchasing power of currencies; CPI observations and CE weights are used to estimate experimental price level differentials for 2003 and 2004

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Although the Consumer Price Index (CPI) survey is not designed as an interarea survey, it is possible to use its price observations and sampling weights to obtain estimates of area price levels for various categories of consumer expenditure. Combining these estimates across the expenditure categories produces an experimental index of the price level differences for the areas. This was first done some 15 years ago by Mary Kokoski, Patrick Cardiff, Brent Moulton, and Kim Zieschang using 1988–89 prices, and more recently by Bettina Aten using 2003 prices.[1] This article shows a shortcut approach for calculating the 2003 interarea prices and repeats the exercise for 2004. It also describes the methodology, presents the detailed results for 2003, and provides a comparison with the 2004 results.

General methodology and data

The headline CPI (the CPI-U) measures the average price change for urban consumers, who comprise approximately 87 percent of the total U.S. population. The CPI collects prices in selected urban areas throughout the country from about 23,000 retail and service establishments. In addition, data on rents are collected for about 50,000 renter-occupied housing units.[2] Each price observation has a reference date and represents a good or service that is uniquely identified by a set of characteristics, including the geographic area. Not all areas have the same goods and services priced; rather, items are selected within categories to represent those sold in each area. Each observation also has a weight. The weight is an estimate of the amount of consumer expenditure the observation represents. In other contexts this is called the representativity[3] of the price in the framework of the probability sample from which it is drawn.

Because there are multiple quotes for most observations, there are in total more than 1 million price quotes per year. Nonrent items are priced monthly or bimonthly; for rents, there are two quotes per year for each dwelling, taken 6 months apart. (See table 1.) Due to the multiple pricings, there are approximately 245,000 unique annual observations, each identified by outlet, quote code, and version. The price of these unique observations is the geometric average of all of its prices collected over the year.

The CPI is organized in a four-tier system of increasing detail: major group, expenditure class, item stratum, and entry level item (ELI). Many ELI's make use of a fifth tier called a cluster. These observations are organized into eight groups of goods and services: housing, transportation, food and beverages, education, recreation, medical, apparel, and other. Table 1 also shows the number of item strata in each group. An example of an item stratum within the housing group is major appliances. However, the actual price observations are on

Table 1. Distribution of price observations by major expenditure group, 2003

	Major expenditure group	Observations (in thousands)		Weight (percent)	Item strata levels	Number of regressions	
		Original	Unique			Long	Shortcut
	Total	1,079	245	100	211	373	72
1	Housing (including rents)	236	83	42	36	102	16
2	Transportation	118	24	17	21	25	8
3	Food and beverages	381	57	15	62	130	5
4	Education	54	9	6	17	20	8
5	Recreation	77	20	6	26	29	14
6	Medical	84	14	6	14	9	4
7	Apparel	86	30	4	20	34	10
8	Other	43	8	4	15	24	7

specific major appliances such as refrigerators, washers, dryers, and so forth, called ELIS. An item stratum corresponds to the lowest level of detail for which expenditure weights are available in all 38 geographic areas and is therefore the target level of the estimation process described in the next paragraph. The two columns in table 1 labeled "Number of regressions" are explained below.

Step one: estimating price parities (item stratum "prices" in each area). The first step of the estimation process consists of obtaining price levels, also known as price parities, for each item stratum in each geographic location, such as flour in Boston or women's shoes in Chicago. Price parities refer to the predicted dollar value of an item stratum *with particular characteristics*, while price levels are generally expressed relative to one area, or the average of all areas.[4] For example, suppose the estimated price parity for an ounce of white flour in a 1 pound bag sold in a supermarket in Philadelphia is $0.01, and in Honolulu, $0.02. If the average price across all areas is $0.015, the price level for flour in Philadelphia will be 0.67 and for Honolulu, 1.33.

The price parities are obtained from a hedonic regression that has the log of the observed prices as the dependent variable, and the geographic areas, outlet types, and product characteristics as independent variables. The coefficients are estimated using a weighted least squares regression where the weights are the quote weights for each price observation.[5] This is shown in equation (1) which is run separately for each stratum.

$$\ln P_{ijn} = \sum_{i=1}^{M} \alpha_i A_i + \sum_{j=1}^{J} \sum_{n=1}^{N} \beta_{jn} Z_{jn} + \varepsilon_{ijn} \qquad (1)$$

where:

(A_i, Z_{jn}) are two sets of dummy variables with i=1,…,M (geographic areas);
j=1,…J (classifications); and
n=1,…, N (characteristic values).
Because the equation is overidentified,

$\beta_{jn} = 0$ (for one arbitrarily chosen n=1,…N within each j).

The antilogarithm of each (α_i) is area i's price parity,[6] (the average price of the base item) and the antilog of each β_{jn} is the factor by which the price of the item differs from its base value. Each estimated regression results in a set of 38 price parities, the 38 antilog (α_i)'s.

For example, a regression analysis using equation (1) can be run on item stratum FX01: alcoholic beverages away from home. The four classification variables for this item stratum are cluster, outlet type, serving time, and serving size. The cluster variable consists of three values or products—beer, ale, and malt products; wine products; and distilled alcohol products—thus N_1=3. Within outlet types there are 16 different types, hence N_2=16. Serving time has two values: "happy hours" or "non-happy hours" (N_3=2), and lastly, serving size was coded into three values: bottle, multiple serving, and single serving (N_4=3). Because the equation is overidentified, one value from each characteristic is arbitrarily chosen to be the base and set to 0, leaving a total of 20 β_{jn}'s to be estimated.

One might expect interaction between some of these characteristics, such as outlet type and serving time, or cluster and serving size. The general procedure followed here is to keep the model specification simple because of the sheer number of characteristics in the CPI. In instances when the number of observations for an item stratum was sufficiently large, such as for airline travel, more complex specifications were tested.

Under the "long" method reported by Aten,[7] a total of 373 regressions (See table 1.) at the item stratum level or below were estimated for 2003; this number, obviously, exceeds the number of item strata (211). The four strata for medical insurance prices were excluded from this article. Many item strata are subdivided into multiple ELI's or clusters, and the regressions were run at the most detailed level possible, hence, the larger number of regressions. In addition, there are 25 item strata labeled “other” that have weights but no price observations. These are assigned a price level equal to the weighted geometric average of the price levels obtained from the regressions within the same expenditure class. The long study therefore aggregated 398 categories (373 + 25) for each area.

However, for the 38 metropolitan levels, data on expenditures from the Consumer Expenditure Survey (CE) are available only at the item stratum level, so if more detailed ELI or cluster price levels were obtained, they were averaged to the item stratum level for the nonfood strata. For the food expenditure category, the more detailed prices and uses were kept and expenditures from the region level, which are available, were allocated to the area level.[8]

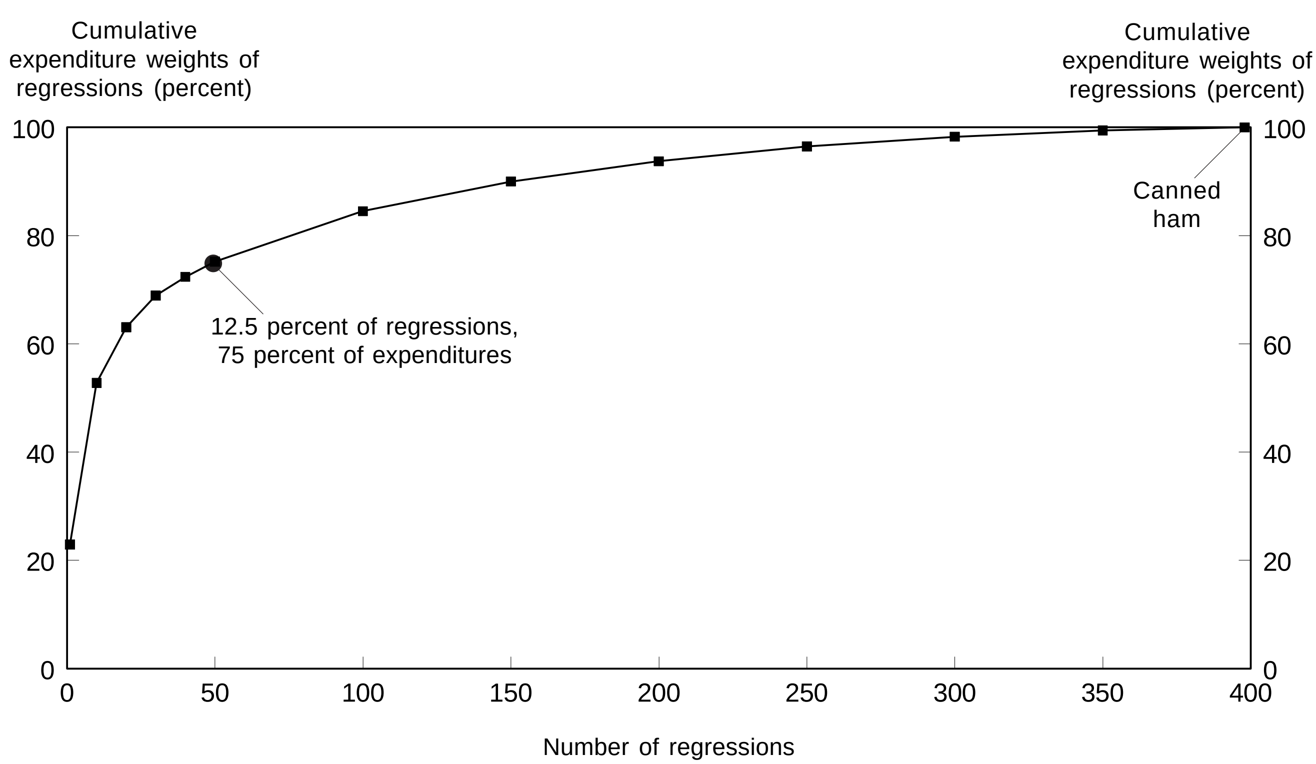
In the previous BLS study by Kokoski, Cardiff, and Moulton, the regressions included all the characteristics for all items—a kitchen sink approach that may have led to overparameterization in some models.[9] In contrast, this study attempts to evaluate each individual regression, and to include the characteristics recommended by the CPI in their documentation, in the hope of discarding irrelevant variables and producing more efficient estimates of the area coefficients.[10] This slower, one-at-a-time regression approach may limit the operational feasibility of implementing annual estimates, and a shortcut approach that reduced the number of estimated regressions (last column in table 1) is discussed below.

Shortcut estimates. If the 398 item categories of the “long” method are ranked by their weights, the top 50 account for nearly three-quarters of the total expenditure weight and the top 100 for 85 percent of the total weight. The contribution of any 1 item stratum whose weight was below the top 100 was less than 0.13 percent, with the smallest weight (0.004 percent) going to canned ham, a cluster in the food group. (See chart 1.)

Comparisons were made between the overall price levels obtained using the full set of 373 regressions and an abbreviated set of the top 50 regressions (ranked by their expenditure weights). Differences were small, in the range of 5 percentage points, with a maximum of 2.9 percentage points and a minimum of –2.1 percentage points for any given area. Thus, reducing the number of detailed hedonic regressions by a factor of eight does not appear to significantly affect the overall results.[11] Further, a slight variation of this shortcut was tested that produced even tighter results, and this is the version described here.

Instead of doing all possible regressions (at ELI or cluster level) and then ranking them, the top 50 were chosen based on their 2001–02 weight from the CE. Regression analyses

Chart 1. Expenditure distribution by number of regressions, 2003



were run on these 50 item strata, which represent 77 percent of total expenditure weights across all areas. One advantage of choosing item strata first, rather than regressions first, is that the item strata remain the same over a 2-year period, and are generally stable in the short run, so it is not necessary to redo all regressions every year in order to rank the top 50.

For the remaining item strata, price levels were obtained from a single weighted regression with only areas and ELI's (and clusters, when available) as independent variables. For example, item stratum FB01, bread, has only one ELI and two clusters: white bread and bread other than white. Thus, although there are different varieties, brands, and packaging of breads within each type, and they are sold in a wide range of outlets, only a dummy variable for cluster is entered as a classification variable in the regression. This is a weighted version of the basic Country Product Dummy (CPD) approach and is shown in equation (2).[12] It is a simpler variation of equation (1), and is also estimated for each item stratum, but the difference is that instead of entering outlet type, brand, and other classification variables, only the ELI or cluster type is used.

$$1nP_{ij} = \sum_{i=1}^{M} \alpha_i A_i + \sum_{j=1}^{J} \beta_j Z_j + \varepsilon_{ij} \quad \text{(for each item stratum } k\text{)} \qquad (2)$$

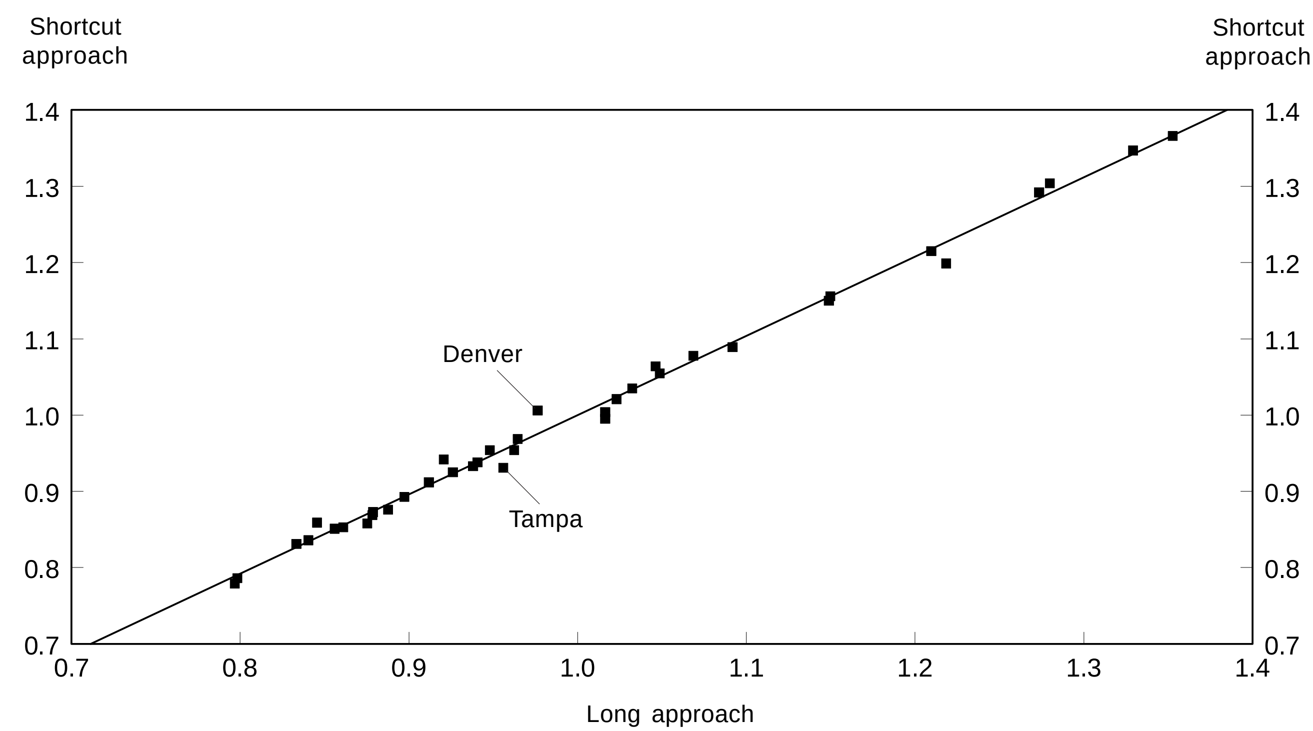
where:

$(A_i, Z_j$ are two sets of dummy variables with
$i = 1,...,M$ (geographic areas) and
$j = 1,...,J$ (ELI/clusters).
Because the equation is overidentified,
$\beta_j = 0$ (for any one arbitrarily chosen j).

Differences between the original estimates and this shortcut approach's estimates remained small, 2.5 and –3.0 percentage points between the price levels. The results are discussed in more detail later in the article.

Step two: estimating aggregate price levels. The second step—for both long and shortcut approaches—consists of aggregating the item stratum price parities for each metropolitan area into an overall price level that extends across all expenditure headings. The aggregation chosen here is known as a variation of the CPD approach similar to equation (2). It consists of a weighted least squares regression and is shown in equation (3).[13] The expenditure weights are the annual dollar expenditures from the 2001–02 CE, in percentage, or share-weight form.[14]

Chart 2. Long versus shortcut approach to price levels, 2003



$$1nP_{ik}\{=(\alpha_i)_k\} = \sum_{i=1}^{M} \lambda_i A_i + \sum_{k=1}^{K} \delta_k X_k + \varepsilon_{i,k} \quad (3)$$

where:

(A_i, X_k) are two sets of dummy variables with i=1,…,M (geographic areas) and k=1,…K (item strata).
Because the equation is overidentified,
$\delta_k = 0$ (for one arbitrarily chosen k).

The dependent variable ($ln\ P_{ik}$) is now the predicted price level (α_i) estimated for each item stratum k from equation (1) or equation (2) in the previous step, and the independent variables are the areas and item strata themselves. The interpretation of the coefficients is similar to that of the first step: the price parity of area i is the antilogarithm of λ_i. The overall price level of area i is the ratio of this antilog relative to the U.S. average of the antilogs of the λ_i's.

Detailed results: 2003

Price level differences range from a drop of 0.03 relative to the U.S. average in Tampa to an increase of 0.03 for Denver when using the shortcut approach. (See table 2.) In general, areas with low price levels were slightly lower using the shortcut and areas with high price levels were slightly higher so that the range increased.

Table 2. Area price levels, 2003: long versus shortcut approach

Area name	Long	Short	Difference: long – short	Long rank	Short rank	Difference: long rank–short rank
Philadelphia	1.02	1.00	0.02	15	16	–1
Boston	1.15	1.16	–.01	7	7	0
Pittsburgh	.83	.83	.00	36	36	0
New York City	1.27	1.29	–.02	4	4	0
New York suburbs	1.28	1.30	–.02	3	3	0
New Jersey suburbs	1.15	1.15	.00	8	8	0
Chicago	1.03	1.04	–.01	13	13	0
Detroit	.94	.94	.00	22	22	0
St. Louis	.85	.86	–.01	34	31	3
Cleveland	.88	.87	.01	30	30	0
Minneapolis	1.02	1.00	.02	16	17	–1
Milwaukee	.90	.89	.01	27	27	0
Cincinnati	.88	.86	.02	31	32	–1
Kansas City	.86	.85	.01	32	33	–1
District of Columbia	1.07	1.08	–.01	10	10	0
Baltimore	.96	.95	.01	19	20	–1
Dallas	.96	.97	–.01	18	18	0
Houston	.92	.94	–.02	25	21	4
Atlanta	.94	.93	.01	23	23	0
Miami	1.02	1.02	.00	14	14	0
Tampa	.96	.93	.03	20	24	–4
Los Angeles	1.21	1.22	–.01	6	5	1
Greater Los Angeles	1.09	1.09	.00	9	9	0
San Francisco	1.35	1.37	–.02	1	1	0
Seattle	1.05	1.06	–.01	11	12	–1
San Diego	1.22	1.20	.02	5	6	–1
Portland	.95	.95	.00	21	19	2
Honolulu	1.33	1.35	–.02	2	2	0
Anchorage	1.05	1.06	–.01	12	11	1
Phoenix	.93	.93	.00	24	25	–1
Denver	.98	1.01	–.03	17	15	2
Midwest C[1]	.80	.79	.01	37	37	0
South C[1]	.80	.78	.02	38	38	0
West C[1]	.89	.88	.01	28	28	0
Northeast B[1]	.91	.91	.00	26	26	0
Midwest B[1]	.84	.84	.00	35	35	0
South B[1]	.86	.85	.01	33	34	–1
West B[1]	.88	.87	.01	29	29	0
Statistical distributions						
Maximum	1.35	1.37	…	…	…	…
Minimum	.80	.78	…	…	…	…
Range	.56	.59	…	…	…	…
Coefficient of variation (percent)	15.2	15.8	…	…	…	…
Mean	1.00	1.00	…	…	…	…

[1] See appendix exhibit A–2 for description of area.

Areas are listed in roughly regional order: Northeast, Midwest, South, and West. The names of the areas have been abbreviated to their main city, but often comprise a number of counties and surrounding areas. For example, the District of Columbia includes 6 counties in Maryland, 11 counties and 6 cities in Virginia, and 2 counties in West Virginia. There are 31 such cities, plus 7 regional area groupings: C areas in the Midwest, South, and West and B areas in the Midwest, South, West, and Northeast. The C areas are a sample of urban, nonmetropolitan areas, while the B areas consist of medium-size and small metropolitan areas. There currently is no C-size area sample for the Northeast. (See appendix for a complete list of the areas.)

Chart 2 compares the long and shortcut results for 2003. The shortcut values that are below the line of equality, such as the one for Tampa, indicate that the price level estimate from the shortcut method is below the estimate from the long method, while those above the line of equality, such as Denver, correspond to higher shortcut estimates of price level. The pattern reflects the higher range and greater variation of the shortcut approach.

Major expenditure groups. Table 3 provides more detail on the pattern of the price levels, in decreasing expenditure weight order of the eight major expenditure groups of the CPI: housing, including rents; transport; food and beverages; education; recreation; medical; apparel; and other expenditures. These subaggregate price levels are also obtained using equation (2), but the weights are normalized to each expenditure group, rather than to the total sum of expenditures.

Rents and owners' equivalent rents. Housing is the largest expenditure group, with 42 percent of total expenditures. Within housing, the distribution is as follows: owners' equivalent rents at 23 percent, followed by household furnishings at 13 percent, and rents at 6 percent of total expenditures. The owners' equivalent rents and rents are observations culled from the same housing database and require elaboration. Because rents and owners' equivalent rents account for nearly 30 percent of overall consumer expenditures, the regression models for these two categories will have the largest single impact on the overall price levels.[15] The importance of housing, specifically rents and owners' equivalent rents, suggests that these regressions require more sophisticated prediction criteria and more detailed analysis of the source data.[16]

The housing observations total nearly 80,000 renter units for the year 2003. They include observations on the same unit priced twice, on a 6-month cycle: January and July,

Chart 3. Area price levels by adjusted gross income per household, 2003 and 2004

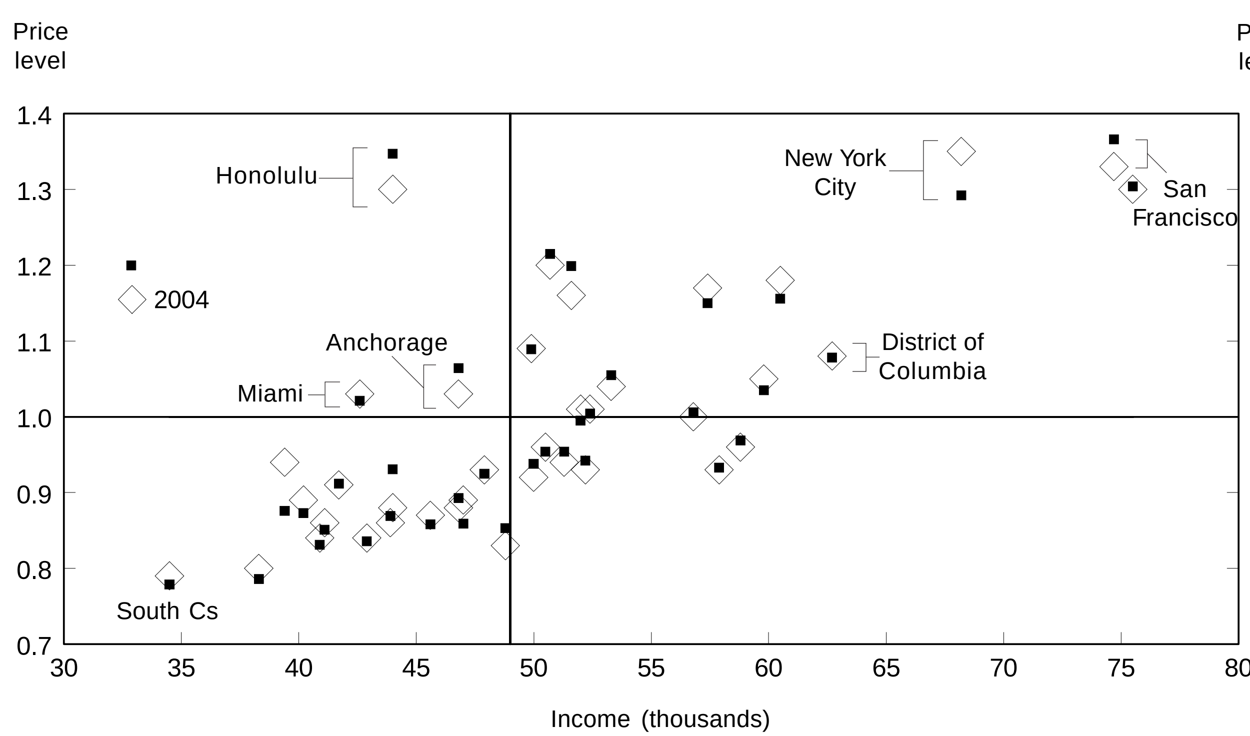


Table 3. Area price levels for major expenditure groups by descending weight in the Consumer Expenditure Survey, 2003

Area name	Major expenditure groups (percent weight in Consumer Expenditure Survey)							
	Housing (42)	Transport (17)	Food and beverages (15)	Education (6)	Recreation (6)	Medical (6)	Apparel (4)	Other (4)
Philadelphia	1.01	1.01	1.03	0.97	1.05	1.21	0.85	0.98
Boston	1.32	.95	.96	1.40	1.09	.76	1.08	1.05
Pittsburgh	.73	.95	.88	.97	.85	.80	.90	.83
New York City	1.44	1.05	1.29	1.32	.97	1.20	.99	1.02
New York suburbs	1.38	1.10	1.23	1.44	1.16	1.30	.97	1.17
New Jersey suburbs	1.29	1.05	1.05	.91	1.12	1.06	.96	1.20
Chicago	1.01	1.00	1.11	.98	1.22	.98	1.04	1.01
Detroit	.85	1.00	1.02	.92	1.07	.91	1.04	1.06
St. Louis	.75	.92	.91	.97	.85	1.02	1.03	.73
Cleveland	.82	.93	.93	.80	.97	.90	.95	.95
Minneapolis	.93	1.06	1.06	1.16	.89	2.10	.98	1.13
Milwaukee	.82	.95	.92	1.00	1.06	.71	1.11	1.09
Cincinnati	.77	.99	.85	.98	1.04	1.02	.98	.77
Kansas City	.78	.91	.93	.94	.94	.77	.95	1.04
District of Columbia	1.07	1.04	1.08	1.07	1.00	1.18	1.10	.96
Baltimore	.92	.94	1.02	1.10	1.15	.77	1.03	.99
Dallas	.91	1.04	.93	1.14	.96	.91	1.06	1.05
Houston	.89	.96	.90	.85	1.07	.86	.99	.92
Atlanta	.92	.96	.90	1.11	.94	.86	1.03	.92
Miami	1.01	1.00	.97	1.08	1.03	1.07	1.17	1.17
Tampa	.93	1.04	.94	.82	1.15	.82	1.07	.96
Los Angeles	1.47	1.10	1.07	.79	.84	1.05	1.11	1.11
Greater Los Angeles	1.25	1.05	.95	.82	.93	.93	1.07	.95
San Francisco	1.70	1.09	1.11	.96	1.14	1.15	.93	1.25
Seattle	1.00	1.07	1.02	1.03	.96	1.47	1.31	1.12
San Diego	1.47	1.05	1.05	.94	1.02	1.07	1.09	1.05
Portland	.90	1.04	.97	1.00	.94	.88	.93	1.07
Honolulu	1.55	1.19	1.26	1.10	1.20	1.10	.97	1.10
Anchorage	1.04	.95	1.27	.87	.96	1.11	1.12	1.10
Phoenix	.84	1.01	.98	.86	.95	1.23	.94	.97
Denver	.96	1.04	.97	.85	1.15	.76	.98	1.16
Midwest C[1]	.65	.91	.91	1.07	.88	.75	.87	.81
South C[1]	.66	.92	.88	.85	.82	.91	.85	.85
West C[1]	.75	.96	1.01	1.20	.94	.93	.90	.88
Northeast B[1]	.88	.91	.91	1.19	.97	.77	.86	.97
Midwest B[1]	.75	.90	.88	.87	.94	.93	.94	.88
South B[1]	.75	.95	.92	.95	.91	.94	.93	.86
West B[1]	.83	1.00	.92	.75	.88	.85	.90	.84
Statistical distributions								
Maximum	1.70	1.19	1.29	1.44	1.22	2.10	1.31	1.25
Minimum	.65	.90	.85	.75	.82	.71	.85	.73
Range	1.05	.29	.44	.68	.39	1.39	.46	.53
Coefficient of variation (percent)	27	7	11	16	11	26	10	13
Mean	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

[1] See appendix exhibit A–2 for description of area.

February and August, and so forth. Most observations have two item weights, one for the rent index and one for the owners' equivalent rent index. (Some renter units are only for owners' equivalent rent.) The implicit rents of owner-occupied housing units are not directly observable; current CPI practice is to impute them.[17] After taking the geometric mean of the observations for each uniquely identified housing unit, the observations are reduced to a total of 27,222 for rents and 30,289 for owners' equivalent rents. Three percent are new construction units.

In addition to the collection cycle and rental/owners' equivalent classification, numerous housing characteristics are available for most observations, including the type of structure (single, multi-unit, detached, mobile), the number of rooms and bathrooms, the utilities that are included, the availability and type of parking, air conditioning, rent control status, length of occupancy, and approximate age of the unit. The quote weights associated with the rent/owner equivalent rent observations were adjusted to reflect sampling proportional to expenditures, rather than proportional to the population. This makes them consistent with the weights used in the regressions for all the remaining items in the CPI.

Table 4 gives the results for rent and owners' equivalent rent. Census variables were not used in these regressions for this article.[18] However, rent regressions that BLS conducts to correct for housing depreciation (sometimes called "age bias") do use Census variables. There are two main types of Census variables: demographic and neighborhood characteristics, both at the zip code level. The former includes race, education, age, and proportion of people under poverty, while the latter includes the proportion of renters, the proportion of large buildings, and the infrastructure available—lack of plumbing, for example. Although many of these are correlated with the price level of rents, they are also highly correlated with income levels.[19] When these proxies for income are omitted from the rent regressions, the predicted price levels for rents are higher in high-income areas such as San Francisco, New York, and Boston, and lower in the smaller, less-densely populated regions such as the South C metropolitan areas. This article views income-associated differences in rent levels as part of the interarea price level differences.

Should race and income be included in a hedonic regression of rents? No, because price level differences associated with them are valid differences and their effect should not be removed from the estimates of area price levels. One could argue for the inclusion of some but not all Census variables, such as the proportion of renters versus owners, or for a more sophisticated modeling approach. One such approach might disentangle the income, race, and education variables more effectively, or take into account the zip code level spatial autocorrelation that they introduce. However, for this article, only observed differences in the actual sampled housing units were included.

Comparison of 2003 versus 2004 results

Price levels, 2004. The shortcut approach was applied to 2004 prices using the same methodology as described in the previous section. Detailed hedonic regressions for the same top 50 item strata as in 2003 were estimated; the shortcut CPD for the remaining items and for the aggregation procedure was repeated using 2004 prices and weights. The hedonic regression for 2004 had about the same number of observations as 2003. The 2004 price levels are shown in table 5, in descending income order, with 2003 shortcut price levels repeated from table 2 for comparison. The income column is the annual adjusted gross income from the Internal Revenue Service (IRS), in thousands of dollars.[20]

Chart 4. Benchmark versus extrapolated price levels, 2004

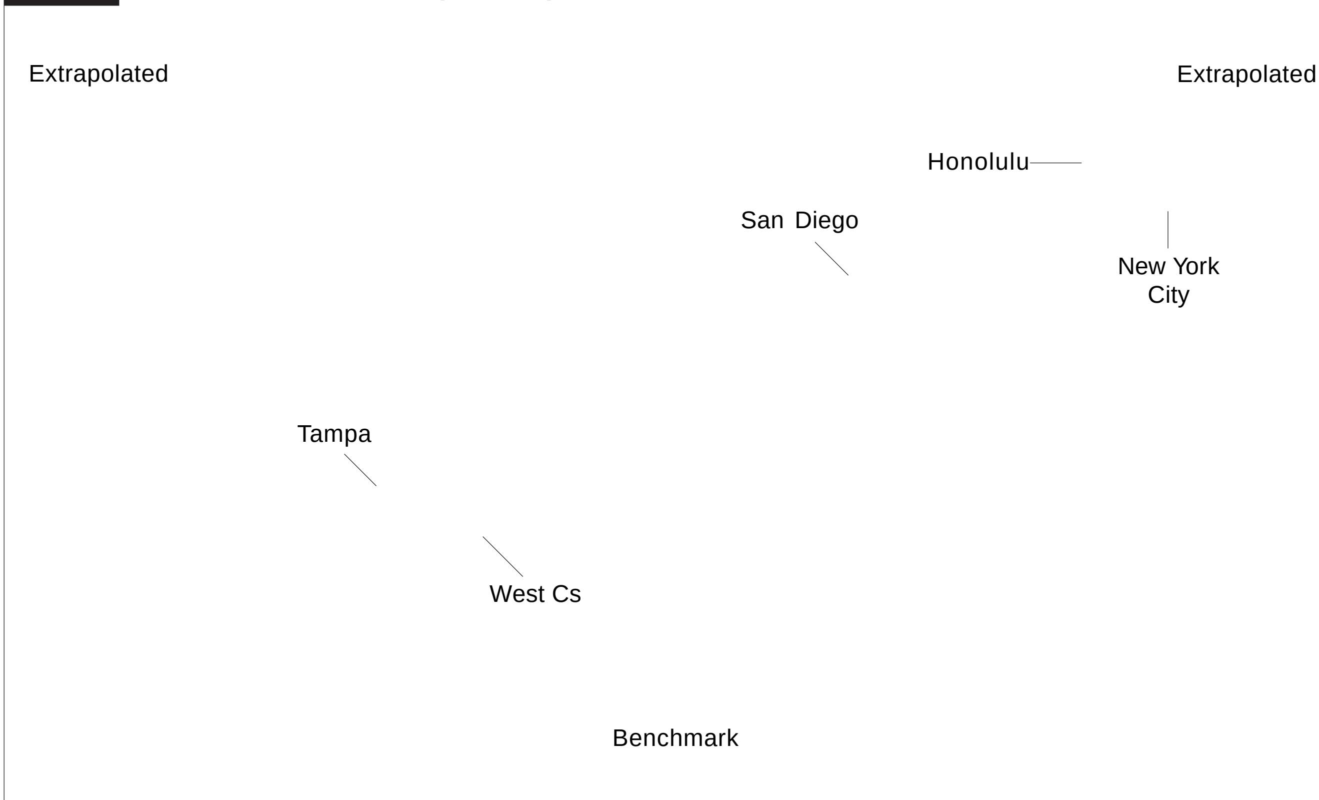


Table 4. Area price levels, 2003: rents and owner equivalent rents				
Area name	Owner-equivalent	Owner-equivalent rank	Rent	Rent rank
Philadelphia	0.93	16	1.05	12
Boston	1.45	7	1.44	4
Pittsburgh	.61	36	.68	36
New York City	1.57	5	1.43	5
New York suburbs	1.60	4	1.42	6
New Jersey suburbs	1.35	8	1.31	9
Chicago	1.02	12	1.05	13
Detroit	.80	24	.80	27
St. Louis	.68	33	.74	32
Cleveland	.72	31	.74	30
Minneapolis	.91	19	.87	22
Milwaukee	.77	28	.76	29
Cincinnati	.72	30	.78	28
Kansas City	.73	29	.73	33
District of Columbia	1.09	10	1.18	10
Baltimore	.92	18	.95	18
Dallas	.89	21	.89	20
Houston	.85	23	.86	24
Atlanta	.89	22	.94	19
Miami	.97	14	1.06	11
Tampa	.90	20	.95	17
Los Angeles	1.67	3	1.39	7
Greater Los Angeles	1.30	9	1.33	8
San Francisco	1.92	1	1.82	1
Seattle	1.06	11	.98	16
San Diego	1.54	6	1.49	3
Portland	.94	15	.89	21
Honolulu	1.74	2	1.54	2
Anchorage	.99	13	.99	15
Phoenix	.78	27	.85	25
Denver	.92	17	1.02	14
Midwest C[1]	.57	37	.61	37
South C[1]	.56	38	.60	38
West C[1]	.72	32	.74	31
Northeast B[1]	.79	26	.82	26
Midwest B[1]	.67	34	.72	35
South B[1]	.67	35	.72	34
West B[1]	.79	25	.87	23
Statistical distributions				
Maximum	1.919	…	1.816	…
Minimum	.560	…	.599	…
Range	1.359	…	1.217	…
Coefficient of variation (percent)	35.7	…	29.9	…
Mean	1.00	…	1.00	…

[1] See appendix exhibit A-2 for description of area.

Chart 3 reflects a relationship that has been found at the international level, namely that price levels rise with income levels. The lines in the middle of the graph indicate the mean levels—$49,000 per return for the adjusted gross income in 2001, and 1.00 for the price level. Areas in the top right quadrant of the chart are areas of higher than average price levels, and higher than average income levels, such as San Francisco and the New York areas. Honolulu, Anchorage, and Miami are the only three areas in the top left quadrant, indicating areas with high price levels but low incomes relative to the mean.

Benchmark versus extrapolation. The preceding section highlighted the overall price levels using the original (long) and shortcut approaches for 2003, followed by the 2004 shortcut results. Each of these use actual prices for the year in question, and are termed "benchmark" estimates in what follows. If we take the 2003 results and extrapolate them using the CPI price-change between 2003 and 2004 for each item stratum,will these be similar to the 2004 benchmark results?

There are two main ways in which this can be done. The first involves simply multiplying the aggregate 2003 results by the overall CPI price change for each area, then re-normalizing the price levels to the U.S. average. This is termed "aggregate extrapolation." (See table 6 and chart 4.) The second method is the disaggregate version, multiplying each

Table 5. Shortcut area price levels, 2003 and 2004

Income rank	Area name	Shortcut 2003	Shortcut 2004	Income (thousands)
1	New York suburbs	1.30	1.30	75.5
2	San Francisco	1.37	1.33	74.7
3	New York City	1.29	1.35	68.2
4	District of Columbia	1.08	1.08	62.7
5	Boston	1.16	1.18	60.5
6	Chicago	1.04	1.05	59.8
7	Dallas	.97	.96	58.8
8	Atlanta	.93	.93	57.9
9	New Jersey suburbs	1.15	1.17	57.4
10	Denver	1.01	1.00	56.8
11	Seattle	1.06	1.04	53.3
12	Philadelphia	1.00	1.01	52.4
13	Houston	.94	.93	52.2
14	Minneapolis	1.00	1.01	52.0
15	San Diego	1.20	1.16	51.6
16	Baltimore	.95	.94	51.3
17	Los Angeles	1.22	1.20	50.7
18	Portland	.95	.96	50.5
19	Detroit	.94	.92	50.0
20	Greater Los Angeles	1.09	1.09	49.9
21	Kansas City	.85	.83	48.8
22	Phoenix	.93	.93	47.9
23	St. Louis	.86	.89	47.0
24	Anchorage	1.06	1.03	46.8
25	Milwaukee	.89	.88	46.8
26	Cincinnati	.86	.87	45.6
27	Honolulu	1.35	1.30	44.0
28	Tampa	.93	.88	44.0
29	Cleveland	.87	.86	43.9
30	Midwest B[1]	.84	.84	42.9
31	Miami	1.02	1.03	42.6
32	Northeast B[1]	.91	.91	41.7
33	South B[1]	.85	.86	41.1
34	Pittsburgh	.83	.84	40.9
35	West B[1]	.87	.89	40.2
36	West C[1]	.88	.94	39.4
37	Midwest C[1]	.79	.80	38.3
38	South C[1]	.78	.79	34.5
	Statistical distributions			
	Maximum	1.37	1.35	75.5
	Minimum	.78	.79	34.5
	Range	.59	.56	41.0
	Coefficient of variation (percent)	15.7	15.3	18.7
	Mean	1.00	1.00	50.6

[1] See appendix exhibit A–2 for description of area.

of the 2003 item stratum price levels from the first stage equation using the CPI for that stratum as a deflator for each item stratum and area, then reaggregating them using equation (2), termed "detailed extrapolations." The detailed extrapolation results are not included, as they were nearly identical to the aggregate extrapolations, differing only at the third decimal place in 34 out of 38 areas, and by only 0.01 in Pittsburgh, New York (City and suburbs), and the Milwaukee areas.

The benchmark estimates do differ from the extrapolated price levels, with Tampa, San Diego, and Honolulu showing higher extrapolated levels than their benchmarks, and New York City and the West C region showing lower extrapolated price levels than the 2004 long approach. This may raise consistency and reconciliation issues common in time-space comparisons, such as those faced by the Organisation for Economic Co-operation and Development (OECD) in their purchasing power parity comparisons.[21] Note that it would be highly unusual for there to be no differences, implying that all item strata prices in all areas changed at the same rate, assuming that both quote weights and expenditures weights remained unchanged.

Conclusions

This article follows groundbreaking work done at BLS based on 1989 prices. Changes from that work include a more tailored approach to each hedonic regression, the use of normalized quote weights, the use of weights at a more

Table 6. Area price levels, 2004: benchmark versus extrapolated

Area name	2004 benchmark	2004 aggregate extrapolation
Philadelphia	1.01	1.02
Boston	1.18	1.16
Pittsburgh	.84	.84
New York City	1.35	1.30
New York suburbs	1.30	1.31
New Jersey suburbs	1.17	1.16
Chicago	1.05	1.03
Detroit	.92	.93
St. Louis	.89	.87
Cleveland	.86	.87
Minneapolis	1.01	1.00
Milwaukee	.88	.88
Cincinnati	.87	.85
Kansas City	.83	.85
District of Columbia	1.08	1.08
Baltimore	.94	.95
Dallas	.96	.96
Houston	.93	.95
Atlanta	.93	.92
Miami	1.03	1.02
Tampa	.88	.93
Los Angeles	1.20	1.22
Greater Los Angeles	1.09	1.10
San Francisco	1.33	1.35
Seattle	1.04	1.04
San Diego	1.16	1.21
Portland	.96	.95
Honolulu	1.30	1.36
Anchorage	1.03	1.06
Phoenix	.93	.92
Denver	1.00	.98
Midwest C[1]	.80	.78
South C[1]	.79	.78
West C[1]	.94	.87
Northeast B[1]	.91	.92
Midwest B[1]	.84	.84
South B[1]	.86	.85
West B[1]	.89	.87
Statistical distributions		
Maximum	1.350	1.357
Minimum	.787	.779
Range	.563	.578
Coefficient of variation (percent)	15.3	15.9
Mean	1.00	1.00

[1] See appendix exhibit A–2 for description of area.

detailed level, and the choice of multilateral aggregation method. In the previous work, an overall price level was not calculated, partly because of the method of aggregation that was employed.

An attempt was made to keep the process of specifying regressions consistent and transparent for the entire CPI, but there were differences in the treatment of certain categories. For example, more time was spent on the expenditure groups with larger weights, such as housing, transportation, and food. Care was also taken to look at numerous alternative specifications in some of the more complex items, such as new cars and trucks, personal computers, airline travel, and particularly rents and owners' equivalent rents, but no formal hypothesis tests were done to determine the degree of improvement of one model over another.

In principle, one could obtain the aggregate area price levels using just one large regression if it included all price quotes and all the characteristics for each item stratum, ELI, or cluster. Some decision would be needed on how to reconcile the two sets of available weights—the sampling quote weights and the consumer expenditure weights, and how to determine which item characteristics were more important than others. In practice, however, the structure of the CPI makes it very difficult to attempt such a one-step process. The advantage of taking two steps is that it provides flexibility in determining each regression, and the process is similar to current methods for estimating time-to-time price indexes, which also makes individual item level hedonic adjustments, and then aggregates them across expenditure groups.

The two-step process is also consistent with the methodology being developed in the International Comparison Program (ICP), whereby participating countries provide average price parities for a set of overlapping items across broad regions of the world in the first step of a benchmark comparison. The price parities are then aggregated to the major expenditure levels of Gross Domestic Product (GDP) using a weighted CPD method similar to the one described here.

There are two main directions for analysis that seem to follow directly from this work—the first emerges from the estimates of the first-stage regressions, where the range of item level price parities across areas can be large. Preliminary work on estimating the variances of these area price levels for 1 year has been done using a Monte Carlo approach, but it would be useful to know if these variations persist over time and remain similar across items.[22]

Secondly, how might these estimates be expanded to other geographic aggregations, such as the State or more microareas? For smaller geographic areas, one might use fewer item stratum regressions in the first-stage models and modify both the quote weights and expenditure weights to obtain more than 38 metropolitan area price levels. For State-level estimates, one suggestion is to supplement the interarea variation from the CPI with housing and energy price information that is also available for rural areas, and then aggregate the urban with the nonurban prices to predict State or regional price levels. □

Notes

[1] See Mary Kokoski, Patrick Cardiff, and Brent Moulton, "Interarea Price Indices for Consumer Goods and Services: An Hedonic Approach Using CPI Data," working paper No. 256, available from the Office of Prices and Living Conditions, July 1994 and Mary Kokoski, Brent

Moulton and Kim Zieschang, "Interarea Price Comparisons for Heterogeneous Goods and Several Levels of Commodity Aggregation," in Alan Heston and Robert Lipsey, eds., International and Interarea Comparisons of Income, Output and Prices, (University of Chicago Press, 1999), pp. 123–66; see also Bettina Aten, "Report on Interarea Price Levels, 2003," working paper No. 2005–11 (Bureau of Economic Analysis, May 2005).

[2] See the BLS Web site for detailed information at http://www.bls.gov/cpi/cpiovrvw.htm#item1and http://www.bls.gov/cpi/cpifact6.htm.

[3] The term representativity is used in the International Comparison Program to denote the relative importance of items that are priced, usually at a level where expenditure weights are not available. See the World Bank ICP Web site at http://web.worldbank.org.

[4] Using price parities or price levels makes no difference to the aggregate results, but the explained variances can be inflated because of the differences in scale—say between flour with a mean predicted price of less than $1 and catered events in the hundreds of dollars.

[5] Quote weights adjust the individual price observations for the probability sampling procedure of the CPI and are normalized by area and item stratum. The weighted least squares estimates minimize the weighted residual sum of squares of equation (1). For an extensive discussion of the effects of weights on the Country Product Dummy, see Case 2, ICP Handbook, Chapter 10 on the Internet at **http://siteresources.worldbank.org/ICPINT/Resources/Ch10.doc**.

For analogous work on estimating purchasing power parities (PPP's) across countries, see S. Heravi, Alan Heston, and Mick Silver, "Using Scanner Data to Estimate Country Parities: An Exploratory Study," *The Review of Income and Wealth*, Volume 49, Issue 1, March 2003, pp. 1–22; Dietmar Moch and Jack Triplett, "PPPs for PCs: Hedonic Comparison of Computer Prices in France and Germany," 27th General Conference of the International Association for Income and Wealth, Sweden, 2002; and Jack Triplett, "Handbook on Hedonic Indexes and Quality Adjustments in Price Indexes: Special Application to Information Technology Products," SIT working paper 2004/9, Organisation for Economic Co-operation and Development, 2004.

[6] A correction for mean bias is applied to the coefficients. This is equal to adding half the standard error of the estimate to the coefficient before taking its antilog. See Arthur S. Goldberger, *Introductory Econometrics*, Harvard University Press, 1998.

[7] See Aten, "Report on Interarea Price Levels, 2003."

[8] For a more detailed description, see Aten, "Report on Interarea Price Levels, 2003."

[9] See Kokoski and others, "Interarea Price Indices."

[10] Documentation for each ELI and cluster combination can be obtained from the BLS CPI division.

[11] The sensitivity of the results to changes in the model specification is discussed in detail in Aten, "Report on Interarea Price Levels, 2003." The greatest sensitivity, as might be expected, is in the treatment of the rent and owner equivalent rent equations, which, on average, account for about 30 percent of total expenditures.

[12] The term was first used in this context by Robert Summers, "International Price Comparisons based upon Incomplete Data," The Review of Income and Wealth, Volume 19, Issue 1, March 1973. The area dummy variables in the hedonic regressions in the first step can also be considered multilateral price indexes based on the CPD approach, but generally, the term CPD is used when only the area and the product itself are the explanatory variables. Recent literature on the CPD includes Sergey Sergeev, "The Use of Weights within the CPD and EKS Methods at the basic heading level," Statistics Austria, mimeograph, 2004; Mick Silver, "Missing Data and the Hedonic Country-Product-Dummy (CPD) Variable Method," mimeograph, Cardiff University, UK, 2004; W.E. Diewert, "Weighted Country Product Dummy Variable Regressions and Index Number Formulae," Department of Economics, Discussion paper 02–15 (University of British Columbia, Vancouver, BC, Canada, 2002); D.S. Prasada Rao, "On the equivalence of Weighted Country Product Dummy Method and the Rao System for Multilateral Price Comparisons" (School of Economics, University of Queensland, Brisbane, Australia, 2002); and E. Selvanathan and D. S. Prasada Rao, Index Numbers: a Stochastic Approach (Ann Arbor, the University of Michigan Press, 1994).

[13] Angus Deaton with Jed Friedman, Vivi Alatas, "Purchasing Power Parity Exchange Rates from household survey data: India and Indonesia" (Research Program in Development Studies, Princeton University, 2004), pp. 5–10, has a clear discussion of the properties of the weighted CPD price levels derived from equation (2) in the context of multilateral index number theory.

[14] Actual rather than share weights are used in some multilateral aggregation procedures, such as the Geary-Khamis system used in the Penn World Tables 6.1. See Alan Heston, Robert Summers, and Bettina Aten, Penn World Table Version 6.1 (Center for International Comparisons at the University of Pennsylvania (CICUP), October 2002).

[15] An analysis of this sensitivity is given in Aten, "Report on Interarea Price Levels, 2003."

[16] For an example, see Brent Moulton, "Interarea Indexes of the Cost of Shelter Using Hedonic Quality Adjustment Techniques," Journal of Econometrics 68(1), 1995, pp. 181–204.

[17] The imputation procedure is beyond the scope of this paper. See, for example, BLS Handbook of Methods, Bulletin 2414 (Bureau of Labor Statistics, 1992), and Walter Lane and John Sommers, "Improved Measures of Shelter Costs," American Statistical Association Proceedings of the Business and Economic Statistics Section, 1984.

[18] Census variables are used in the first report. See Aten, "Report on Interarea Price Levels, 2003."

[19] A principal components analysis (Aten, "Report on Interarea Price Levels, 2003.") revealed that about a third of the standard variance among the Census variables was because of the first principal component that contrasts race (percent white, percent white occupancy) with income levels (percent under poverty, percent renters and percent ownership of 2+ cars).

[20] The income variable is the adjusted gross income per IRS tax return for 2001, kindly provided by Ann Dunbar of the Bureau of Economic Analysis.

[21] For an example, see Seppo Varjonen, "Consistency between GDP based on PPPs and National Accounts Time Series," OECD, Paris, France, October 2001.

[22] See Bettina Aten and Alan Heston, "Putting Confidence Levels on Price Level Estimates, a Proposal for Discussion," Workshop at the University of California at Davis, Institute of Governmental Affairs, Davis, CA, May 31–June 1, 2005.

Exhibit A–1. List of geographical areas

Rank	Region	Area	Name	Areas included
1	Northeast	A102	Philadelphia	Atlantic, Burlington, Cape May, Camden, Cumberland, Gloucester, Salem, NJ; New Castle, DE; Cecil, MD; Bucks, Chester, Delaware, Montgomery, Philadelphia, PA
2		A103	Boston	Windham[1], CT; Bristol[1], Essex, Hampden[1], Middlesex, Norfolk, Plymouth, Suffolk, Worcester[1], MA; York[1], ME; Hillsborough[1], Merrimack[1], Rockingham[1], Strafford[1], NH
3		A104	Pittsburgh	Alleghany, Beaver, Butler, Fayette, Washington, Westmoreland, PA
4		A109	New York City	Bronx, Kings, New York, Queens, Richmond, NY
5		A110	New York suburbs	Dutchess, Nassau, Orange, Putnam, Rockland, Suffolk, Westchester, NY; Fairfield[1], Litchfield[1], Middlesex[1], New Haven[1], CT
6		A111	New Jersey suburbs	Bergen, Essex, Hudson, Hunterdon, Mercer, Middlesex, Monmouth, Morris, Ocean, Passaic, Somerset, Sussex, Union, Warren, NJ; Pike, PA
7	Midwest	A207	Chicago	Cook, Dekalb, Dupage, Grundy, Kane, Kankakee, Kendall, Lake Mchenry, suburbs Will, IL; Lake, Porter, IN; Kenosha, WI
8		A208	Detroit	Genessee, Lapeer, Lenawee, Livingston, Macomb, Monroe, Oakland, St. Clair, Washtenaw, Wayne, MI
9		A209	St. Louis	Clinton, Jersey, Madison, Monroe, St. Clair, IL; Crawford[1], Franklin, Jefferson, Lincoln, St. Charles, St. Louis, Warren, St. Louis City, MO
10		A210	Cleveland	Ashtabula, Cuyahoga, Geauga, Lake Lorain, Medina, Portage, Summit, OH
11		A211	Minneapolis	Anoka, Carver, Chisago, Dakota, Hennepin, Isanti, Ramsey, Scott, Sherbune, Washington, Wright, MN; Pierce, St. Croix, WI
12		A212	Milwaukee	Milwaukee, Ozaukee, Racine, Washington, Waukesha, WI
13		A213	Cincinnati	Dearborn, Ohio, IN; Boone, Campbell, Gallatin, Grant, Kenton, Pendleton, KY; Brown, Butler, Clermont, Hamilton, Warren, OH
14		A214	Kansas City	Johnson, Leavenworth, Miami, Wyandotte, KS; Cass, Clay, Clinton, Jackson, Lafayette, Platte, Ray, MO
15	South	A312	Washington	Calvert, Charles, Frederick, Montgomery, Prince George's, Washington, MD; Arlington, Clarke, Culpeper, Fairfax, Fauquier, King George, Loudoun, Prince William, Spotsylvania, Stafford, Warren, Alexandria City, Fairfax City, Falls Church City, Fredericksburg City, Manassas City, Manassas Park City, VA; Berkeley, Jefferson, WV.
16		A313	Baltimore	Anne Arundel, Baltimore, Carroll, Harford, Howard, Queen Anne's, Baltimore City, MD
17		A316	Dallas	Collin, Dallas, Denton, Ellis, Henderson, Hood, Hunt, Johnson, Kaufman, Parker, Rockwall, Tarrant, TX
18		A318	Houston	Brazoria, Chambers, Fort Bend, Galveston, Harris, Liberty, Montgomery, Waller, TX
19		A319	Atlanta	Barrow, Bartow, Carroll, Cherokee, Clayton, Cobb, Coweta, Dekalb, Douglas, Fayette, Forsyth, Fulton, Gwinnett, Henry, Newton, Paulding, Pickens, Rockdale, Spalding, Walton, GA
20		A320	Miami	Broward, Dade, FL
21		A321	Tampa	Hernando, Hillsborough, Pasco, Pinellas, FL
22	West	A419	Los Angeles	Los Angeles County, CA
23		A420	Greater LA	Orange, Riverside, San Bernardino, Ventura, CA
24		A422	San Francisco	Alameda, Contra Costa, Marin, Napa, Santa Clara, Santa Cruz, San Francisco, San Mateo, Solano, Sonoma, CA
25		A423	Seattle	Island, King, Kitsap, Pierce, Snohomish, Thurston, WA
26		A424	San Diego	San Diego, CA
27		A425	Portland	Clackamas, Columbia, Marion, Multnomah, Polk, Washington, Yamhill, OR; Clark, WA
28		A426	Honolulu	Honolulu, HI

See footnote at end of table.

Exhibit A–1. Continued—List of geographical areas

Rank	Region	Area	Name	Areas included
29		A427	Anchorage	Anchorage, AK
30		A429	Phoenix	Maricopa, Pinal, AZ
31		A433	Denver	Adams, Arapohoe, Boulder, Denver, Douglas, Jefferson, Weld, CO
32	Midwest	D200	Midwest C	Urban nonmetro – see details in exhibit A–2
33	South	D300	South C	Urban nonmetro
34	West	D400	West C	Urban nonmetro
35	Northeast	X100	Northeast B	Medium, small
36	Midwest	X200	Midwest B	Medium, small
37	South	X300	South B	Medium, small
38	West	X400	West B	Medium, small

[1] Only partially included.

Exhibit A–2. List of aggregated areas (D200–X400)

Rank	Aggregation	Area	Name	Description
1	Midwest C	D200	C212 Faribault	Urban parts of Rice, MN
			C216 Chanute	Urban parts of Allen, Neosho, KS
			C218 Brookings	Urban parts of Brookings, Lake, Moody, SD
			C222 Mt. Vernon	Urban parts of Jefferson, IL
2	South C	D300	C328 Arcadia	Urban parts of De Soto, Hardee, FL
			C332 Morristown	Urban parts of Hamblen, Jefferson, TN
			C334 Picayune	Urban parts of Pearl River, MS
			C344 Statesboro	Urban parts of Burke, Bulloch, Jenkins, Screven, GA
3	West C	D400	C450 Bend	Urban parts of Deschutes, OR
			C456 Pullman	Pullman, WA
4	Northeast B	X100	B102 Reading	Berks, PA
			B104 Syracuse	Cayuga, Madison, Onondaga, Owego, NY
			B106 Buffalo	Erie, Niagara, NY
			B108 Hartford	Hartford[1], Litchfield[1], Middlesex[1], New London[1], Tolland[1], Windham[1], CT
			B110 Burlington	Chittenden[1], Franklin[1], Grand Isle[1], VT
			B112 Sharon	Mercer, PA
			B114 Johnstown	Cambria, Somerset, PA
5	Midwest B	X200	B218 Wausau	Marathon, WI
			B220 Dayton	Clark, Greene, Miami, Montgomery, OH
			B222 Evansville	Posey, Vanderburgh, Warrick, IN; Henderson, KY
			B224 Columbus	Delaware, Fairfield, Franklin, Licking, Madison, Pickaway, OG
			B226 Saginaw	Bay, Midland, Saginaw, MI
			B228 Elkhart	Elkhart, IN
			B230 Decatur	Macon, IL
			B232 Youngstown	Columbiana, Mahoning, Trumbull, OH
			B234 Madison	Dane, WI
			B236 Lincoln	Lancaster, NE
6	South B	X300	B338 Chattanooga	Catoosa, Dade, Walker, GA; Hamilton, TN
			B340 Florence	Florence, SC
			B342 Albany	Dougherty, Lee, GA

See footnote at end of table.

Exhibit A–2. List of aggregated areas (D200–X400)

Rank	Aggregation	Area	Name	Description
			B344 Norfolk	Currituck, NC; Gloucester, Isle of Wight, James City, Mathews, York, Chesapeake City, Hampton City, Newport News City, Norfolk City, Poquoson City, Portsmouth City, Suffolk City, Virginia Beach City, Williamsburg City, VA
			B346 Pine Bluff	Jefferson, AR
			B348 Raleigh	Chatham, Durham, Franklin, Johnstown, Orange, Wake, NC
			B350 Richmond	Charles City, Chesterfield, Dinwiddie, Goochland, Hanover, Henrico, New Kent, Powhatan, Prince George, Colonial Heights City, Hopewell City, Petersburg City, Richmond City, VA
			B352 Beaumont	Hardin, Jefferson, Orange, TX
			B354 Brownsville	Cameron, TX
			B356 Florence	Colbert, Lauderdale, AL
			B358 Greenville	Anderson, Cherokee, Greenville, Pickens, Spartanburg, SC
			B360 Fort Myers	Lee, FL
			B362 Birmingham	Blount, Jefferson, St. Clair, Shelby, AL
			B364 Melbourne	Brevard, FL
			B366 Lafayette	Acadia, Lafayette, St. Landry, St. Martin, LA
			B368 Ocala	Marion, FL
			B370 Gainesville	Alachua, FL
			B372 Amarillo	Potter, Randall, TX
			B374 San Antonio	Bexar, Comal, Guadalupe, Wilson, TX
			B376 Oklahoma City	Canadian, Cleveland, Logan, Mcclain, Oklahoma, Pottawattamie, OK
			B378 Baton Rouge	East Baton Rouge, Livingston, West Baton Rouge, LA
			B380 Midland	Ector, Midland, TX
7	West B	X400	B482 Chico	Chico, CA
			B484 Provo	Utah, UT
			B486 Modesto	Stanislaus, CA
			B488 Boise City	Ada, Canyon, ID
			B490 Las Vegas	Mohave, AZ; Clark, Nye, NV
			B492 Yuma	Yuma, AZ

[1] Only partially included.