



Australian School of Business

Working Paper

Never Stand Still

Australian School of Business

Australian School of Business Research Paper No. 2010 ECON 25

Accounting for Unrepresentative Products and Urban-Rural Price Differences in
International Comparisons of Real Income: An Application to the Asia-Pacific Region

Robert J. Hill
Iqbal Syed

This paper can be downloaded without charge from
The Social Science Research Network Electronic Paper Collection:
<http://ssrn.com/abstract=1728428>

Accounting for Unrepresentative Products and Urban-Rural Price Differences in International Comparisons of Real Income: An Application to the Asia-Pacific Region

Robert J. Hill^{a*} and Iqbal A. Syed^b

^aDepartment of Economics, University of Graz, Universitätsstrasse 15/F4, 8010 Graz, Austria: robert.hill@uni-graz.at

^bSchool of Economics, University of New South Wales, Sydney 2052, Australia: i.syed@unsw.edu.au

August 17, 2012

Abstract:

The International Comparisons Program (ICP) run by the World Bank compares the purchasing power of currencies and real income across countries. Using a unique data set consisting of over 600,000 ICP price quotes drawn from nine countries in the Asia-Pacific region, we consider a number of ways of improving the basic heading price indexes that form the building blocks of ICP. In particular, we show how the results can be adjusted to take account of unrepresentative products, urban-rural price differences and differing outlet-type mixes across countries. We also consider the plausibility of the most striking result that emerged from ICP 2005 – that China came out 40 percent smaller than previously thought. Our results suggest that part of this discrepancy can be attributed to excessive sampling in China of unrepresentative products in urban locations.

Keywords: International Comparisons Program; Country-Product-Dummy Method; Price Index; Rural-Urban Price Differences; Representative and Unrepresentative Products; Shopping Outlet; China

JEL Classification Codes: C43; E01; E31; O47; O53

*Corresponding author.

We thank the World Bank for funding this project and for providing the data, and Angus Deaton, Erwin Diewert, Yuri Dikhanov, and Prasada Rao for their comments. The views expressed here are those of the authors and do not necessarily represent those of the World Bank.

1 Introduction

The International Comparisons Program (ICP) dates back to the 1960s. Its objective is to compare the purchasing power of currencies and real income across countries. ICP benchmarks, of which the most recent is for 2005, play a pivotal role in the construction of the Penn World Table.

ICP 2005 had a much larger budget than earlier rounds. This allowed far more data to be gathered for more countries (146 participated in ICP 2005).¹ Perhaps the most surprising result that emerged from ICP 2005 was that China and India came out 39.5 and 38.5 percent smaller, respectively, than previously thought (see Maddison 2008, Chen and Ravallion 2010, Deaton and Heston 2010, and Feenstra, Ma, Neary and Rao 2010).² We return to this issue after some preliminary discussion of the mechanics of ICP 2005 and of the main innovations introduced in this paper.

The ICP 2005 aggregate results at the level of GDP are obtained from 155 basic heading price indexes and corresponding expenditure levels.³ The basic heading price indexes, which are typically calculated using the Country-Product-Dummy (CPD) regression method (see Summers 1973), together with their corresponding expenditure shares provide the building blocks from which the overall comparison is constructed. If these building blocks are biased or otherwise flawed, then everything that builds on them will be likewise tainted. Most errors are likely to arise in the process of calculating these basic heading price indexes and expenditure shares. It is here at this disaggregated level that the most pressing research problems can be found.⁴

An important distinction in an ICP context is between products that are representative and those that are unrepresentative in a country. The representative products are

¹Earlier rounds include 1970, 1973, 1975, 1980, 1985 and 1993. The number of participating countries increased gradually, from only 10 in 1970 to 117 in 1993.

²The World Bank's pre-ICP 2005 estimates for 2005 can be found in its World Development Indicators 2007 report (CD version). The printed version provides per capita gross national income (in Table 1.1) rather than per capita GDP. The corresponding per capita GDP data, converted into US dollars using pre-ICP 2005 purchasing power parities (PPPs), can be obtained by dividing total PPP GDP (see <http://www.pdwb.de/archiv/weltbank/gdpppp05.pdf>) by total population (see http://siteresources.worldbank.org/DATASTATISTICS/Resources/table2_1.pdf). Corresponding post ICP-2005 results can be found in the World Development Indicators (WDI) 2008 report supplement (in Table S.3). The numbers in WDI (2008), however, differ slightly from the official ICP 2005 results (see <http://siteresources.worldbank.org/ICPINT/Resources/summary-tables.pdf>). Therefore we compare WDI (2007) directly with the the official ICP 2005 results.

³A basic heading is the lowest level of aggregation at which expenditure data are available. A basic heading consists of a group of similar products defined within a general product classification. Food and non-alcoholic beverages account for 29 headings, alcoholic beverages, tobacco and narcotics for 5 headings, clothing and footwear for 5 headings, etc. (see Blades 2007a).

⁴Above basic heading level standard multilateral price index formulas such as GEKS or Geary-Khamis can be used. This higher level of aggregation has tended to attract much more attention in the literature (see for example Diewert 1999, Hill 2000 and Neary 2004).

those that are widely available in that country and account for a significant proportion of total expenditure within a basic heading (see World Bank 2008, p. 143). Unrepresentative products, therefore, are those products that are not widely available in an economy, and do not constitute a significant proportion of total expenditure within a basic heading. Other things equal, representative products tend to be cheaper than unrepresentative products. Likewise, a product typically sells at a lower price in rural locations than in urban locations. It follows that countries that sample disproportionately unrepresentative products from urban locations – as may have been the case for China (see Deaton and Heston 2010) in ICP 2005 – will end up with price levels that are overestimated and per capita incomes that are underestimated.

The main objective of this study is to consider some extensions of the basic CPD model used in ICP that can be used to account for unrepresentative products and urban-rural price differences. We do this using a unique data set consisting of 605,998 price quotes drawn from 92 basic headings (covering most of household consumption) for nine countries in the Asia-Pacific region in 2005.

A further focus is the ICP's current approach of averaging the individual price quotes on each product in each country prior to using the CPD. A disadvantage of averaging the price quotes is that it dramatically reduces the sample size, thus sacrificing degrees of freedom and reducing the efficiency of the price indexes derived from the CPD model. We estimate the CPD model on both the individual prices and country-product average prices and find that there are quite big differences in the resulting price indexes.

The fact that we have the individual price quotes for countries in the Asia-Pacific region with some corresponding urban-rural, representative-unrepresentative, and outlet-type identifiers allows us to consider a number of possible ways of improving and extending the existing CPD methodology. The basic issue here is that a price index should compare like with like. Hence one should not compare directly the price of a product purchased in a rural area in country A where it is representative with the price of the same product bought in an urban area in country B where it is unrepresentative.

Representative dummies can be included in either the average or the individual price version of CPD, since it is assumed that representativity is defined at the product level in each country and not at the level of the individual price quotes. Urban and outlet-type dummies, by contrast, can only be included when a CPD-type model is estimated on the individual price quotes, since the price quotes for each product in a country are drawn from both urban and rural areas, and from different outlet-types. Including representative, urban and outlet-type dummies in a CPD-type regression has the potential to correct the biases discussed by Deaton and Heston.

The CPD model in ICP 2005 is estimated using ordinary least squares (OLS). We also consider some extensions on OLS that could improve the efficiency of our estimated basic heading price indexes. First, we estimate the CPD model on the country-product average

prices using weighted least squares (WLS) with the weights provided by the standard errors on the country-product average prices. Second, we correct for heteroscedasticity using feasible generalized least squares (FGLS). Third we check whether simultaneous estimation of the CPD-type models over a group of basic headings in a seemingly unrelated regression (SUR).

Returning to the issue of discrepancies between the pre and post ICP 2005 results, Table 1 provides estimates of per capita GDP in 2005 in US dollars, converted using pre and post ICP 2005 purchasing power parities, for 17 countries in the Asia-Pacific region. Per capita GDP is revised downwards for 11 of these countries as a result of ICP 2005, while for the remaining 6 it rises. Per capita GDP falls on average (calculated as a geometric mean) by 17.4 percent. The downward revisions for China and India, therefore, are clearly bigger than average for the Asia-Pacific region.

Insert Table 1 Here

ICP 2005 has the advantage that it is a much more detailed comparison than the previous rounds and that China and India both participated.⁵ It is tempting therefore to conclude that the problems lie with the pre-ICP 2005 results.

However, China's participation in ICP 2005 was on a limited scale and the price quotes were obtained from only 11 cities and their surrounding areas (see Blades 2007b). We show using our estimated representative-unrepresentative and urban-rural price differentials that part of this discrepancy can be explained by an excessive focus in the Chinese ICP 2005 data on unrepresentative products and urban outlets.

The remainder of this paper consists of five sections and an appendix. Section 2 explains the basic CPD model and some ways of extending it. The data set is described in section 3. The estimated basic heading price indexes derived from various versions of the CPD model are discussed in section 4. Urban-rural and representative-unrepresentative price differentials are calculated in section 5. Section 6 concludes the paper. Finally the appendix discusses some issues related to the estimation of the CPD model.

2 The Country-Product-Dummy Method and its Extensions

Most regions in ICP 2005, including the Asia-Pacific region, used the country-product-dummy (CPD) method to calculate the within-region basic-heading price indexes for each

⁵The methodologies used to derive the pre-ICP 2005 results for China and India in 2005 are both somewhat tenuous. The result for China is obtained by extrapolation from a bilateral comparison between China and the US in 1986 (see Rouen and Kai 1995), while the result for India, who was not an active participant in the previous round, is obtained from a mixture of updating and regression extrapolation from the previous ICP round (see Deaton and Heston 2010).

country.⁶ The CPD model estimates the following regression equation separately for each basic heading:⁷

$$\ln p_{km} = \sum_{\mu=2}^M \alpha_{\mu} x_{\mu} + \sum_{j=1}^K \beta_j y_j + \varepsilon_{km}, \quad (1)$$

where p_{km} denotes the (geometric) average of the price quotes for product m in country k , x_{μ} denotes a product dummy variable that equals 1 if $m = \mu$, and zero otherwise, while y_j denotes a country dummy variable that equals 1 if $k = j$ and zero otherwise, and ε_{km} denotes a random error term. The α_m and β_k parameters are typically estimated by ordinary least squares (OLS). Exponentiating the estimated β_k parameter, we obtain the price index p_k for this particular basic heading for country k , as follows:⁸

$$\hat{p}_k = \exp(\hat{\beta}_k).$$

In an ICP context, product m will only typically be available in a subset of the countries in the comparison. It is sufficient that m is priced in at least two countries for it to be included.

An extension of the CPD method, the country-product-representative-dummy (CPRD) method was proposed by Cuthbert and Cuthbert (1988). It simply adds an additional dummy variable z to the model as follows:

$$\ln p_{km} = \sum_{\mu=2}^M \alpha_{\mu} x_{\mu} + \sum_{j=1}^K \beta_j y_j + \gamma z + \varepsilon_{km},$$

where z equals 1 if product m is representative in country k and zero otherwise.

At its meeting in September 2004, the ICP 2005 Technical Advisory Group

“recommended that regions should use the CPRD method to estimate basic heading PPPs. Of course, the method can only be implemented satisfactorily if the countries within a region are able to identify representative products correctly.” (Hill 2007)

Hence all participating countries were asked to identify which of the products they priced were representative. Eurostat and the OECD have already been doing this for many years. Unfortunately,

⁶One advantage of the CPD method is that its stochastic specification allows the use of a range of econometric tools and techniques that are not normally used in the computation of price indexes (see Rao 2004). By contrast, for example, Eurostat and the OECD use the nonstochastic EKS-S method to construct their basic heading price indexes (see Hill and Hill 2009).

⁷It is common when estimating the CPD model to normalize the prices of one of the products and one of the countries to one. In this formulation, an additional constant term should be inserted in the equation. Here instead we omit the constant term but do not include a country normalization. Hence the summation over countries in (1) runs from $j = 1$ to K . The price of one product is still normalized to one, which is why the summation over products runs from $\mu = 2$ to M .

⁸ $\exp(\hat{\beta}_k)$ is in fact a biased estimator of $\exp(\beta_k)$. We find, however, that use of Kennedy’s (1981) bias correction has virtually no impact on the results. Hence we ignore this correction here.

“Economies in the Asia-Pacific, Africa, Western Asia, and South America regions that either had not participated in an international comparison for an extended period or had never participated had difficulty applying the representativity concept, therefore, it was not used in their intraregional comparisons.” (World Bank 2008, p. 185)

It turns out this statement is not quite correct since South America did in fact use CPRD (see Diewert 2008a). It is true though that the Asia-Pacific region used CPD. This means that some of the estimated basic heading price indexes in the Asia-Pacific region could be affected by the types of bias discussed by Deaton and Heston.

In ICP, p_{km} is an average of the price quotes on product m obtained in country k . An alternative approach would be to include all the individual price quotes for product m directly in the CPD or CPRD regression. We would then have multiple observations on the price of product m in country k . The CPRD method can be further extended, when the individual price quotes are used, to include urban and outlet type dummies [i.e., the country-product-representative-urban-outlet-dummy (CPRUOD) method] as follows:

$$\ln p_{km} = \sum_{\mu=2}^M \alpha_{\mu} x_{\mu} + \sum_{j=1}^K \beta_j y_j + \gamma z + \delta w + \sum_{i=2}^I \theta_i u_i + \varepsilon_{km}, \quad (2)$$

where now we also include a dummy w that equals 1 if product m is from an urban area in country k and zero otherwise, while $i = 1, \dots, I$ indexes a series of outlet types (e.g., supermarket, department store, open market, etc.). u_i is a dummy variable that equals 1 only if product m in country k was bought in an outlet of type i .

We assess the feasibility of using the CPRUOD model and its country-product-urban-dummy (CPUD) and country-product-representative-urban-dummy (CPRUD) variants in an ICP context.

3 The Data Set

Our data set consists of 605,998 price quotes for 2005 from the following nine countries in the Asia-Pacific region: Bhutan, Fiji, Hong Kong, Indonesia, Macao, Malaysia, the Philippines, Sri Lanka and Vietnam.⁹ In total there are 142 basic headings in ICP 2005 for the Asia-Pacific region (some other regions used 13 additional headings). Our price quotes are drawn from 92 of these headings, all of which belong in the Final Consumption

⁹Strictly speaking we should refer to economies rather than countries, given that two of our sample (Hong Kong and Macao) are not countries. Nevertheless, for convenience we will henceforth use the term ‘countries’.

Expenditure by Households category.¹⁰ Our list of basic headings is shown in Table 2.¹¹

Insert Table 2 Here

For our purposes the data set while large has some problems. Three countries (Fiji, Hong Kong and Malaysia) identified all products as representative, while Vietnam failed to identify products as either representative or unrepresentative. More generally, it seems likely that representativity was not identified in a consistent way across countries. The fact that three of the nine countries identified all products as representative is symptomatic of this lack of consistency. It is important that countries are provided with more guidance on this issue in future rounds of ICP.

Similarly, only six countries (Fiji, Indonesia, Malaysia, the Philippines, Sri Lanka, and Vietnam) supplied urban/rural identifiers. All the price quotes from Fiji are urban. Our biggest problems, however, related to the outlet-type data. As many as 41 different outlet types are identified in our data. However, it is impossible to match outlets across countries at this level of detail. We settled on sorting the outlet types into six groups. These are as follows: (i) Department stores; (ii) Supermarkets; (iii) Open markets/stalls; (iv) Specialized shops (traditional outlets); (v) Wholesale and discount stores; (vi) Other stores. Some summary information is provided in Table 3. Some more discussions on the quality of data are provided in section 5.2.¹²

Insert Table 3 Here

¹⁰In fact, we began with 95 basic headings. Our base country in all our comparisons is Hong Kong (Hong Kong is also the base in the official ICP 2005 comparisons for the Asia-Pacific region). Given that no data are available for Hong Kong for three headings, we decided therefore to exclude these from the comparison. This reduces the number of price quotes in our data set from 610,024 to 605,998.

¹¹Two of the most important and hard-to-measure headings in household consumption – namely consumption on rents of owner-occupiers and financial services indirectly measured (FISIM) – unfortunately are excluded. See for example Deaton (2005) for a discussion of these two headings and their potential impacts on international comparisons.

¹²A number of other outlet types were represented in the data (often sparsely and only for a small subset of countries). These included the following: Minimarkets, kiosks and neighborhood shops; Mobile shops and street vendors; Other kinds of trade (mailorder, internet, etc); Agencies; Bakery; Bank; Book store; Bowling centre; Cinema; Communication services; Communication shop; Computer shop; Courier services; Food court; Furniture shop; Gymnasium; Holiday agencies; Hotel; Insurance agencies; Motor vehicle outlet; Music store; Newspaper advertising; Nursery; Pet shop; Petrol kiosk; Photo kiosk; Saloon; Services outlet; Shoe repair outlet; Sundry shop; Swimming pool; Transportation services; Pharmacy/drugstore; Private doctor's clinic; Public/government doctor's clinic; Private hospital; Public/government hospital; Private dental clinic; Public/government dental clinic; Private laboratory; Public/government laboratory; Private optical clinic; Puublic/government optical clinic; Private outlet for therapeutic, appliances and equipment; Public/government clinic for physiotherapist; Private primary school; Private secondary school; Private college/university; Private tutor.

4 CPD-Type Regression Results

4.1 Country-product average prices versus individual price quotes in CPD-type regressions

The CPD and CPRD models can be estimated using either country-product average prices or the individual price quotes. There are two main advantages to using the individual price quotes. First, this dramatically increases the degrees of freedom when estimating the model. Second, it allows the inclusion of outlet or urban-rural dummies. One disadvantage is that, when the number of price quotes available differ very significantly across countries, using the individual price quotes could create distortions in the resulting price indexes. More particularly, the country which has many price quotes for a particular product may have more influence on the overall quality adjustment factor for that product (for a detailed proof, see Diewert 2004). Diewert further shows that the average price method is democratic in the sense that each country has roughly the same influence on the determination of the quality adjustment factor for a basic heading category.¹³

Focusing on the CPD model, the sensitivity of the resulting basic heading price indexes of country k to the choice between two methods x and y (e.g., CPD, CPRD, etc) can be measured using the following metric:

$$A_k(x, y) = \frac{1}{N(K-1)} \sum_{b \neq k}^K \sum_{n=1}^N \max(P_{bn, kn}^x / P_{bn, kn}^y, P_{bn, kn}^y / P_{bn, kn}^x), \quad (3)$$

where N is the number of basic headings and K the number of countries in the comparison. $P_{bn, kn}^x$ denotes the price index of country k for basic heading n , expressed relative to the corresponding price index of the base country b , obtained using method x . The comparison is made by using each of the other countries in turn as the base. In this sense it treats all countries symmetrically.

Setting method x as CPD using the individual price quotes and y as CPD using country-product average prices [denoted here by CPD(av)], we obtain the results shown in Table 4. The biggest change is observed for Bhutan for which $A_k(x, y) = 1.173$. This means that the basic heading price indexes for Bhutan change on average by 17.3 percent as a result of switching from using individual price quotes to country-product average prices as inputs into CPD. The smallest change is observed for Vietnam for which $A_k(x, y) = 1.106$, implying an average change of 10.6 percent. These differences are quite large. The choice between using individual price quotes and country-product average prices therefore can significantly affect the results.

Insert Table 4 Here

¹³One reason that might have influenced ICP to use the average price method is that it is more democratic (in the sense that it gives equal weight to the price data of all countries). Also some countries may be unable to provide individual prices quotes because of their national laws governing data confidentiality.

An alternative approach is to estimate CPD using weighted least squares (WLS) applied to the country-product average prices, with the weights provided by the inverses of the standard errors on the country-product average prices.¹⁴ The OLS and WLS versions of CPD applied to the country-product average prices, denoted here by CPD(av) and CPD(w-av) respectively, are also compared in Table 4. The use of WLS does not seem to have much impact on the price indexes. The average change in the basic heading price indexes ranges from 0.6 percent for Bhutan to 3.2 percent for Hong Kong.

Returning to the estimation of CPD on the individual price quotes, an important consideration is the number of price quotes from each country in our data set. These are shown in Table 3. Vietnam has 156,635 price quotes while Fiji has only 9,897. Such extreme mismatches could potentially cause problems for the individual price quote variant of CPD. To see why, it is useful to write out the CPD formula in matrix notation as follows:

$$\hat{y} = Z\hat{\alpha} + D\hat{\beta}, \quad (4)$$

where each element of y is the logarithm of one of the price quotes, Z is a matrix of product dummy variables, and D a matrix of country dummy variables.

The estimated CPD product shadow price vector $\hat{\alpha}$ and country price index vector $\hat{\beta}$ are derived as follows:

$$\hat{\alpha} = (Z^T Z)^{-1} Z^T (y - D\hat{\beta}), \quad (5)$$

$$\hat{\beta} = (D^T D)^{-1} D^T (y - Z\hat{\alpha}). \quad (6)$$

Since $D^T D$ in (6) is a diagonal matrix, the price index formula for a particular element $\hat{\beta}_k$ of $\hat{\beta}$ reduces to the following:

$$\hat{\beta}_k = \sum_{h=1}^{H_k} \left(\frac{\ln p_{kh}}{H_k} \right) - \sum_{m=1}^M \left[\hat{\alpha}_m \left(\frac{\sum_{h=1}^{H_k} z_{khm}}{H_k} \right) \right],$$

where $h = 1, \dots, H_k$ indexes all the price quotes in country k for that particular basic heading and $m = 1, \dots, M$ the list of products in the basic heading. Also, $\hat{\alpha}_m$ is the estimated shadow price of product m , and z_{khm} is a dummy variable that equals 1 only if price quote h in country k is for product m . Otherwise z_{khm} equals zero.

Taking exponents of both sides, we obtain the price of country k . Dividing this by a corresponding price index for country j we obtain the following formula:¹⁵

$$\frac{P_k}{P_j} = \frac{\left(\prod_{h=1}^{H_k} p_{kh} \right)^{1/H_k}}{\left(\prod_{h=1}^{H_j} p_{jh} \right)^{1/H_j}} \left/ \frac{\exp \left(\sum_{m=1}^M \hat{\alpha}_m \bar{z}_{km} \right)}{\exp \left(\sum_{m=1}^M \hat{\alpha}_m \bar{z}_{jm} \right)} \right., \quad (7)$$

¹⁴The standard error for the average price of product m in country k is calculated by dividing the standard deviation of the log prices of all the price quotes on product m in country k by the square root of the number of observations on product m in country k .

¹⁵The CPD model is closely related to the time-dummy hedonic model. The equivalent formula, in the context of the time-dummy hedonic model, can be found in Triplett (2004; p. 51), Diewert, Silver and Heravi (2009) and Hill (2012).

where

$$\bar{z}_{jm} = \sum_{h=1}^{H_j} z_{jhm}/H_j, \quad \bar{z}_{km} = \sum_{h=1}^{H_k} z_{khm}/H_k.$$

\bar{z}_{km} can be interpreted as the average product sampled in country k . Suppose for example that $\bar{z}_{km} = 0.2$. This means that 20 percent of the country k price quotes are for product m .

The term $(\prod_{h=1}^{H_k} p_{tk})^{1/H_k}/(\prod_{h=1}^{H_j} p_{jh})^{1/H_j}$ in the numerator of (7) compares the average price quote in the two countries without any adjustment for the different mix of products sampled in each country. The quality adjustment for the different product mix is provided by the term in the denominator of (7). This is a quantity index that compares the price of the average product in the two countries using the estimated product shadow prices as reference prices.

Countries with more price quotes have a greater influence on the resulting product shadow prices and hence also on the quality adjustment in the denominator of (7).¹⁶ This could lead to a Gerschenkron-type substitution bias (see for example Hill 2000), where the price indexes of these countries are systematically underestimated.

In our context it can be seen from Table 5 that the three countries with the most price quotes (Vietnam, the Philippines and Sri Lanka) also have relatively low price levels. A Gerschenkron-type substitution bias in this case therefore should cause the dispersion in price levels to be overestimated. To see whether this is the case, we compute the standard deviation of the logarithms of the price levels for each basic heading for both versions of CPD. The price levels are obtained by dividing each country k 's price index P_{kn} for basic heading n by its corresponding average 2005 market exchange rate MER_k , with Hong Kong in both cases normalized to 1).¹⁷

$$\sigma_n = \sqrt{\frac{\sum_{k=1}^K [\ln(P_{kn}/MER_k) - \overline{\ln(P_{kn}/MER_k)}]^2}{K-1}}, \quad (8)$$

where $\overline{\ln(P_{kn}/MER_k)}$ is the average log price level for basic heading n .

Insert Table 5 Here

As shown in Table 6, σ_n is higher for CPD applied to the individual price quotes for 50 headings while it is higher for CPD applied to the country-product average prices for the remaining 42 headings. Let X denote the number of basic headings for which CPD applied to the individual price quotes has the larger σ_n coefficient. Using the normal approximation to the binomial distribution, X is approximately normally distributed with mean $N/2 = 46$ and variance $N/4 = 23$. A value of $X = 50$, implies a standard normal test statistic $Z = (X - 46)/\sqrt{23} = 0.834$, which is not significant at the 5 percent level. Hence, while the result is mildly supportive of a Gerschenkron-type substitution bias,

¹⁶Diewert (2004) reached the same conclusion from a different direction.

¹⁷Taking logs before computing the standard deviation ensures that the results are invariant to the choice of base country.

we nevertheless cannot reject the null hypothesis that there is no systematic difference between the price level dispersion coefficients of the two versions of CPD.

Insert Table 6 Here

More generally, (7) suggests that even CPD applied to the country-product average prices will be affected by substitution bias. Now since all countries have equal weight it is less clear exactly how the bias manifests itself.

All things considered, in our opinion the increased degrees of freedom and flexibility obtained by running CPD on the individual price quotes may outweigh disadvantages arising from mismatches in the number of price quotes across countries. If necessary, such mismatches can be dealt with by duplicating the price quotes from countries with less data until the samples are more balanced. A better understanding of potential sources of bias in either version of the CPD methods can be obtained if the information on actual expenditure shares corresponding to the products are available. We recommend that ICP carries out further research in this area.

4.2 Plausibility of the estimated representative, urban and outlet-type dummy variable coefficients

For the remainder of this paper we focus exclusively on the CPD model estimated using the individual price quotes. The most general version of this model may be referred to as the country-product-representative-urban-outlet-dummy (CPRUOD) model. We assume that all prices in Vietnam are representative and that all prices in Bhutan, Hong Kong and Macao are urban. Even so, not all countries can be included in all 92 basic heading regressions. For example, Indonesia provided data only for 41 headings. Hence it is excluded from 51 of our basic heading regressions.

Some summary statistics from our estimated equations are shown in Table 7. Here we focus on the signs of the estimated representative, urban and outlet type coefficients. Taking the representative coefficients first, our prior expectation is that the sign of these coefficients should be negative. That is, other things equal, representative products should be cheaper than unrepresentative products. The results are only weakly supportive of this hypothesis. 42 coefficients are negative and 35 are positive. Of the statistically significant coefficients at the 5 percent level, 27 are negative and 21 positive. Our prior for the urban coefficients is that they should be positive since, other things equal, prices tend to be higher in urban areas than in rural areas. The situation in this case, however, is not so clear cut since there may be exceptions to this rule. For example, imported products may be more expensive in rural areas due to greater transport costs and less competition amongst retailers. The results broadly support our hypothesis, with 54 coefficients being positive (and 33 statistically significant) and only 26 being negative (with 11 statistically

significant).¹⁸

Insert Table 7 Here

The priors for outlet type are less obvious. Other things equal, it seems plausible that prices should be higher in ‘department stores’ than in ‘supermarkets’, and prices in ‘supermarkets’ should be higher than in ‘open markets’ and ‘wholesale discount stores’. Given the heterogeneity of the ‘specialized stores’ and ‘other store’ categories, it is difficult to form any priors on them. The base outlet type is ‘supermarkets’. The ‘department stores’ coefficient is positive for 28 headings (11 of which are significant) and negative for 27 coefficients (10 of which are significant). Hence there is no discernible pattern here. The results are more plausible for ‘open markets’ and ‘wholesale and discount stores’ (i.e., they are both cheaper than ‘supermarkets’) although still very noisy. For open markets, 47 coefficients are negative (of which 23 are significant), while 32 are positive (of which 12 are significant). For discount stores, 22 coefficients are negative (of which 12 are significant), while 12 are positive (of which 6 are significant).

We suspect that there may be serious inconsistencies with the way that outlet types are identified across countries, and that this may explain the erratic results. We would recommend that in the next round of ICP the range of outlet types be significantly reduced. The six we consider might constitute a useful starting point. Also, it is important that these six categories are interpreted in a consistent way across countries. For example, it seems from the current results that the term ‘department store’ may not mean the same thing in all nine countries in our data set.

For these reasons, we now exclude outlet-type dummies from our regression model. Our focus now is the country-product-representative-urban-dummy (CPRUD) model. The results are presented in Table 8. The sign of the representative coefficients here accords rather better with our prior expectations, with 48 negative coefficients (of which 43 are significant) and 29 positive coefficients (of which 20 are significant). This is in spite of the fact that Fiji, Hong Kong and Malaysia identified every single product as representative (a clear sign that this terminology was not interpreted in a consistent way across countries). The coefficient on the urban dummy is typically positive as expected, being 63 times positive (of which 45 are significant) and 21 times negative (of which 14 are significant). Also, shown in Table 8 are results for the CPRD method. The results for CPRD are similar to those obtained for the representative dummies in CPRUD.

Insert Table 8 Here

Given that Fiji, Hong Kong and Malaysia identified all products as representative, while Vietnam left this column blank, it is far from clear that the inclusion of representative dummies would have improved the results for the Asia-Pacific region in ICP 2005. In particular, the use of CPRD in this context would actually cause an upward bias in the

¹⁸The total number of headings covered changes depending on whether our focus is on representative, urban or outlet-type dummies since these identifiers are not available for all headings.

resulting price indexes for Fiji, Hong Kong and Malaysia (assuming that the classification of all products as representative in these countries was erroneous). Hence we are inclined to agree with the decision to use CPD in preference to CPRD for the Asia-Pacific region in ICP 2005.¹⁹

Our findings here suggest that estimation of a CPD-type model, inclusive of representative and urban dummies, directly from the individual price quotes is a viable alternative to the current ICP practice based on average prices. We have serious doubts though whether the inclusion of outlet types in the form available in ICP 2005 would improve the quality of the results.

It is evident from the above that while the data set is large and unique, it suffers from some serious drawbacks, some of which might have prevented us from reaching more definitive conclusions. It should be noted though that this data set was actually used in the computation of the results for the Asia-Pacific Region in ICP 2005. This demonstrates some of the challenge that ICP faces in arriving at its results. Our analysis of the data shows that much can be improved in price comparisons with regard to data collection, harmonization of important definitions and concepts across countries and sampling techniques. Attaining this objective will require continued effort from ICP and, perhaps more importantly, the participating countries.

4.3 Differences in estimated price indexes across methods

The average differences in the basic heading price indexes, as measured by the A_k metric defined in (3), of pairs of CPD-type methods are shown in Table 4. The pairs of methods considered in Table 4, in addition to those already discussed above, are as follows:

- (i) CPD-CPRD
- (ii) CPRD-CPRUD
- (iii) CPRUD-CPRUDhet,

where CPRUDhet denotes CPRUD corrected for heteroscedasticity using FGLS.

From Table 4 it can be seen that the choice between estimating CPD on the individual price quotes or average prices generally has a bigger impact on the resulting price indexes than the choice between different varieties of CPD all calculated using the individual price quotes.

One must be careful, however, comparing some of the A_k coefficients in Table 4 across countries for a few reasons. First, the coverage of basic headings differs significantly across countries (as shown in Table 3). Indonesia for example only provides data on 41 headings. Hence the low value of its $A_k(\text{CPD}, \text{CPRD})$ coefficient can be attributed largely to its complete omission of many of the more problematic headings. Second, often larger values of $A_k(x, y)$ may be attributable primarily to differences in the underlying data sets rather

¹⁹In recognition of these problems, ICP is asking participating countries to identify important (in terms of expenditure share) rather than representative products in the next round (i.e., ICP 2011).

than the methods themselves. For example, representative-unrepresentative indicators are available for only 22 percent of price quotes in Fiji. It follows that the CPRD results for Fiji are calculated on a much smaller data set than the corresponding CPD results. Third, for ten headings the CPRD and CPRUD models were not identified. For seven of these cases data were only available for Hong Kong and Macao, and all the price quotes were representative and urban. For these headings, we set the CPRD and CPRUD results equal to the CPD results. For two other headings (40-Water supply and 41-Electricity) all the price quotes were representative, although there were both urban and rural price quotes. In these cases it was possible to estimate the country-product-urban-dummy (CPUD) but not the CPRD or CPRUD model. For these headings we set CPRD equal to CPD and CPRUD equal to CPUD. Finally, for basic heading 75 (Repair of audio-visual, photographic and information processing equipment) all price quotes were representative for all countries except Macao, where all price quotes were unrepresentative. In this case again CPRD is set equal to CPD, and CPRUD is set equal to CPUD. These substitutions may cause the A_k coefficients to underestimate the underlying sensitivity of the results to the choice of method (although this effect is likely to be swamped by the effect of unmatched samples across methods discussed above).

There is a large difference in the A_k coefficient between the CPD and CPD(av) methods. The average difference across nine countries is 13.6 percent. The difference is quite small when the CPD(av) and CPD(w-av) are compared.

In a comparison between CPD and CPRD, the biggest changes are observed for Fiji, where the results on average change by 25.7 percent. As noted above, most of this change is probably attributable to the large differences in the data sets used to calculate the CPD and CPRD results, rather than inherent differences in the underlying methods.

For headings where a switch from CPD to CPRD causes a large fall in the number of usable price quotes, any gains from the additional information provided by the inclusion of representative dummies will probably be outweighed by the loss of information caused by the exclusion of price quotes for which representative-unrepresentative indicators are not available. An important implication of this insight is that even if CPRD was adopted in the next round of ICP, it would still be preferable to use CPD for headings where the representative-unrepresentative indicators are particularly sparse. The same principle applies for CPRUD and CPRUOD. These methods should not be applied uniformly to all headings. More generally, we can imagine a future scenario where CPRUOD is used for one group of headings, CPRUD for a second group, CPRD for a third group and finally CPD for a fourth group of particularly problematic headings.²⁰

²⁰It is possible to divide the basic headings in Table 2 into groups of similar headings, and then estimate the CPD-type model for pools of headings. Pooling has the potential to improve the efficiency of the estimated basic heading price indexes, a point that has been raised in an ICP context recently by Silver (2009). However, the result is at best mixed (see the Appendix for details).

4.4 Differences in price level dispersion across methods

We now turn to the issue of whether there are systematic differences between the price levels derived from the CPD, CPRD and CPRUD methods. We find that σ_n , as defined in (8), is higher for the CPRD method than for CPD for 47 headings and lower for 38 headings, as shown in Table 6.²¹ Again, using the normal approximation to the binomial distribution, this yields a standard normal test statistic $Z = (X - 42.5)/\sqrt{21.25} = -0.976$, which is not significant at the 5 percent level. Hence we cannot reject the null hypothesis that there is no systematic difference between the price level dispersion coefficients of the CPD and CPRD methods.

Nevertheless, given that Fiji, Hong Kong and Malaysia identified all products as representative (and we assumed that Vietnam's price quotes were all representative), it follows that the price levels of these countries should tend to be higher relative to the other countries under CPRD than under CPD. We do indeed observe this pattern in the data for most headings (although not for all since representative-unrepresentative indicators in some countries are only available for a subset of price quotes and hence the underlying universe of price quotes over which CPD and CPRD price indexes are calculated are not exactly matched). This pattern, however, does not have any systematic impact on overall price dispersion since while Fiji, Hong Kong and Malaysia are three of the four highest priced countries in our sample, Vietnam is the country with the lowest price level (see Table 5). The inclusion of Vietnam in this group acts to prevent a noticeable increase in price level dispersion.

By contrast, in a comparison of CPRD with CPRUD, the CPRD σ_n coefficient is higher for 55 headings, and smaller for only 29 headings. In this case $Z = 2.837$ which is significant at the 5 percent level. This finding can be explained by the fact that all the price quotes from the three countries with highest overall price levels (again see Table 5), namely Fiji, Hong Kong and Macao, are urban. The inclusion of urban dummies acts to lower slightly the relative price levels in these three countries, thus reducing overall price level dispersion.

4.5 Correcting for heteroscedasticity

We test for heteroscedasticity in the CPRD and CPRUD models using the Breusch-Pagan (BP) test (see Breusch and Pagan 1979). The BP tests for our basic headings clearly reject the assumption of homoscedasticity. Our primary concern here is with the efficiency of our point estimates from which price indexes are constructed rather than possible bias correction in the standard errors (such as using White's robust standard errors). If the

²¹As was noted above, for 7 headings, only Hong Kong and Macao supplied data and for these headings all products were representative and urban. Hence it follows that there is no difference between the CPD and CPRD models in these cases. Hence we are left with 85 usable headings.

variance of the OLS errors are functions of the explanatory variables, as indicated by the BP tests, then feasible generalized least squares (FGLS) should improve the efficiency of our price indexes (see the Appendix for details on how the FGLS model is implemented). We find that while the impact of the correction on the price indexes is generally quite small, it nevertheless seems to slightly reduce measured price level dispersion across countries (see Tables 4 and 6).

4.6 Correcting for Differences in the Price Quote and Urban-Rural Expenditure Mixes Across Countries in CPUD-Type Models

Hong Kong is 100 percent urban both in terms of its price quotes and population. CPUD-type methods tend to exert downward pressure on the observed price level for Hong Kong as a result of all its price quotes being identified as urban. Such an adjustment may not be justified since households in Hong Kong do not have the option of purchasing in rural areas (without travelling beyond its borders). At the heart of this is the following question.

Suppose countries j and k sell exactly the same products at exactly the same prices (converted at market exchange rates). However, country j is completely urban while country k is completely rural. Should these two countries have the same price level?

We assume that most users would say the answer is ‘yes’. According to the CPUD method, however, the answer is that the price level is higher in the completely rural country k .

The problem with CPUD is that it implicitly assumes that the expenditure mix across urban and rural areas is the same in all countries. Hence to prevent bias an adjustment is required. Let Exp_{Urb}^k and Exp^k denote urban and total expenditure, respectively, in country k . One possible way of adjusting CPUD basic heading price indexes is as follows:

$$\tilde{P}_n^k = \left[\left(\frac{\text{Exp}_{Urb}^k}{\text{Exp}^k} \right) (P_{Rur,Urb} - 1) + 1 \right] P_n^k, \quad (9)$$

where P_n^k denotes the original CPUD price index for basic heading n in country k , \tilde{P}_n^k is the adjusted index, and $P_{Rur,Urb}$ is the average CPUD rural-urban price differential derived from (11) below.²² From (9) we can see for a totally urban population such as Hong Kong that $\tilde{P}_n^k = P_{Rur,Urb} \times P_n^k > P_n^k$, while for a totally rural population $\tilde{P}_n^k = P_n^k$. That is, the price index of a totally urban country gets scaled up by the full rural-urban price differential while the price index of a completely rural country is left unchanged. This should ensure that the price levels of countries j and k in the example above are equal.

²²With this adjustment, it will in general no longer be the case that the price index of one country is normalized to one. If such a normalization is desired, this can be achieved by dividing through the price indexes of all countries by the price index of the base country.

More generally, the more urban is total expenditure, and the bigger the rural urban price differential, the bigger the upward adjustment in the price index and corresponding price level for predominantly urban countries in (9). Also, when all countries have the same urban-rural expenditure mix, then all the price indexes get scaled up by the same factor, which effectively means they do not change (since they are invariant to rescaling). That is, in this case the CPUD method gives the right answer.²³

Is a similar adjustment required for representativity for the CPRD or CPRUD methods? In our opinion the answer is not necessarily. The concept of representativity is somewhat vague and is likely to be interpreted in different ways by different countries unless they are given very precise guidelines. For it to be useful, it is critical that countries use the same definition. One possible definition is as follows: a representative product in country k is one of the top 50 percent of products bought there (weighted by expenditure) in that particular basic heading.²⁴ Our example, helps illustrate the key difference between representative and urban indicators. It is possible for 99 percent of expenditure in country k to be urban, but it is not possible for 99 percent of expenditure to be on representative products.²⁵

4.7 Results at the level of Household Consumption

We calculate aggregate price indexes at the level of Household Consumption using the Fisher formula with Hong Kong as the base. This approach was preferred to using the Gini-Eltetö-Köves-Szulc (GEKS) method (see Gini 1931, Eltetö and Köves 1964 and Szulc 1964) since the list of basic headings available differs from one country to the next. Hong Kong however has data on all 92 headings. Hence comparing each country only with Hong Kong maximizes the list of headings over which the Fisher price indexes are calculated.²⁶

Aggregate level Fisher price indexes for each of our methods are compared in Table 9. For example, the first column of results compares CPD and CPD(av) as follows: $P_{bk}^{CPD(av)}/P_{bk}^{CPD}$. Here P_{bk} denotes a Fisher price index between the base country b (i.e., Hong Kong) and country k , and P_{bk}^{CPD} is calculated using the CPD basic heading price indexes while $P_{bk}^{CPD(av)}$ is calculated using the CPD(av) basic heading price indexes. The expenditure shares used in the calculation of the Fisher price indexes are the same in both

²³Another option is to use weighted CPD where the weights reflect the urban-rural composition of the transactions for a product in a country.

²⁴Here we abstract from the possibility that a particular product may be representative in urban areas but not rural areas of the same country.

²⁵One potential source of confusion over the concept of representativity is that some basic headings themselves are inherently more representative than others in each country. For example, the headings ‘spirits’, ‘wines’ and ‘beers’, along with all the products within each of these headings, could be deemed unrepresentative in a predominantly Muslim country such as Indonesia. Representativity, in a CPD context, however is really a relative concept. Focusing on the ‘beer’ example above, Indonesia should identify those beers that are most representative, rather than simply classify them all as unrepresentative.

²⁶It follows that the results for each bilateral comparison only cover a subset of household consumption.

cases. The most noticeable result in Table 9 is that the CPD(av) price indexes are smaller – sometimes very significantly so – than their CPD counterparts for all countries except Vietnam. In other words, the quite large differences observed at the basic heading level in section 4.1 between the CPD and CPD(av) do not cancel each other out at the aggregate level.

Insert Table 9 Here

In the other comparisons, the differences in the Fisher price indexes are quite small. Therefore, even though there were some large differences at the basic heading level (for example, 21.9 percent difference for Fiji between the CPD and CPRD methods), these differences appear to have nearly disappeared when aggregated across the available basic headings.

5 Urban-Rural and Representative-Unrepresentative Price Differentials, and the China Discrepancy

5.1 Measuring price differences between urban and rural areas

Poverty counts in large countries such as India and China can be highly sensitive to measured price differences between urban and rural areas. CPD-type methods can be used to shed light on this issue.

Here we consider three approaches to calculating rural-urban price differentials. The first and simplest is to take the ratio of the geometric means of the rural and urban price quotes in a particular heading for a particular country k .

$$\frac{P_k^{Urb}}{P_k^{Rur}} = \frac{\left(\prod_{u=1}^U p_{ku}^{Urb}\right)^{1/U}}{\left(\prod_{r=1}^R p_{kr}^{Rur}\right)^{1/R}}, \quad (10)$$

where p_{kr}^{Rur} denotes rural price quote r and p_{ku}^{Urb} denotes urban price quote u . The resulting average rural-urban price differentials for all countries for which we have rural and urban identifiers (i.e., Indonesia, Malaysia, Philippines, Sri Lanka and Vietnam) are shown in Table 10. The overall average differential is 11 percent (i.e., urban prices are 11 percent higher than rural prices).

Insert Table 10 Here

One problem with this method is that it does not compare like with like. That is, the rural and urban price quotes are not matched to the same products. The country-product-urban-dummy (CPUD) method can be used to correct this problem. The CPUD regression model takes the following form:

$$\ln p_{km} = \kappa + \sum_{\mu=2}^M \alpha_{\mu} x_{\mu} + \sum_{j=2}^K \beta_j y_j + \delta w + \varepsilon_{km}, \quad (11)$$

where m indexes the products in the basic heading, α and β are respectively the coefficients on the product and country dummies, and δ is the coefficient on the urban dummies. Estimating the CPUD model for each basic heading, we obtain 92 $\hat{\delta}$ coefficients. The exponent of each of these coefficients $\exp(\hat{\delta})$ can be interpreted as a price index measuring the average price difference between urban and rural areas, with rural as the numeraire, for a heading.

For comparison purposes we also include $\exp(\hat{\delta})$ estimates derived from the CPRUD model:

$$\ln p_{km} = \sum_{\mu=2}^M \alpha_{\mu} x_{\mu} + \sum_{j=1}^K \beta_j y_j + \gamma z + \delta w + \varepsilon_{km}, \quad (12)$$

where now we also include a dummy z that equals 1 if product m is representative in country k and zero otherwise. The resulting price indexes are again shown in Table 10. The average rural-urban price differentials for CPUD and CPRUD are only 2.7 and 2.6 percent respectively.

One weakness of the CPUD and CPRUD methods is that they assume that the urban-rural price differential is the same for all countries. This is unlikely to be the case. For example, to the extent that price differentials are caused by transport costs, domestically produced food should be cheaper in rural areas where it is produced, while imported food should be cheaper in urban areas (e.g., ports). Hence countries that import more of their food may tend to have lower rural-urban price differentials than countries that produce most of their own food. In addition, concerns were raised in ICP 2005 that participating countries did not necessarily distinguish between rural and urban zones in a consistent manner (see Vogel 2010).

This problem can be addressed using a variant on the standard CPD method that treats the rural and urban areas in each country as two separate entities as follows:

$$\ln p_{km} = \kappa + \sum_{\mu=2}^M \alpha_{\mu} x_{\mu} + \sum_{j=2}^K \beta_j^{Rur} y_j^{Rur} + \sum_{j=2}^K \beta_j^{Urb} y_j^{Urb} + \varepsilon_{km}, \quad (13)$$

where y_j^{Rur} is a dummy that equals 1 only if that particular price quote is from a rural area in country j , while y_j^{Urb} equals 1 if the price quote is from an urban area in country j . The ratio $\exp(\hat{\beta}_j^{Urb}) / \exp(\hat{\beta}_j^{Rur})$ can be interpreted as a rural-urban price index for country j for that particular basic heading.²⁷ As shown in Table 10 the average differential now is 2.4 percent.²⁸

This finding suggests that the urban price quotes are drawn more from the expensive products within a basic heading while the rural price quotes are drawn more from the

²⁷We thank Angus Deaton for suggesting this method to us.

²⁸This is a weighted average and is obtained in two stages. In the first stage, an average is taken across basic headings with weights corresponding to the expenditure share of these basic headings. In the second stage, an average is taken across countries with weights corresponding to the relative share of GDP denominated in a common currency. The weights are for 2005 and are obtained from World Bank (2008).

cheaper (presumably lower quality) products. If so, it follows that a simple ratio of average price quotes, due to its failure to quality adjust, overstates the actual price differential between rural and urban areas. When we quality adjust, we find that urban prices are only about 2.5 percent higher than rural prices (taking a rough average of our three quality-adjusted estimates of 2.4, 2.6 and 2.7).²⁹

These low estimates of rural-urban price differentials are at odds with most of the existing literature for the Asia-Pacific region. For example, Ravallion and van de Walle (1991) find that the urban-rural price differential in Indonesia calculated over a basket consisting of food and housing is 10 percent, while Asra (1999) focusing on just food finds it is 13-16 percent. Deaton and Dupriez (2011) obtain a differential of 11.5 percent for food prices in India, while Dikhanov (2010a) focusing on food and clothing finds it is 3.2 percent. Ravallion and Chen (2007), focusing on food and non-food consumption, obtain a differential for China of 19 percent in 1980 rising to 41 percent in 2002. Almas and Johnsen (2010) using Engel curves obtain an even larger differential of 69 percent for China in 2002. Brandt and Holz (2006), and Gong and Meng (2008) compute spatial price differences across regions in China. While not explicitly discussing rural-urban price differentials, Brandt and Holz provide a table from which rural-urban price differentials can be calculated. From their Table 7 we obtain a price differential of 24 percent in 1990 rising to 31 percent or 40 percent in 2000 depending on the method used.

Part of the explanation for this low difference in the urban-rural prices might be that, due to cost considerations, the rural price quotes in ICP 2005 are not rural enough. In addition, the product lists in ICP 2005 were drawn up with urban consumers in mind (as is done in many cases in the consumer price index). It is therefore likely that quite a few products are representative in urban areas but unrepresentative in rural areas of the same country, while hardly any are representative in rural areas but not in urban areas. An analogy can be drawn here with Paasche and Laspeyres. An urban product list generates a Paasche-type index that underestimates the rural-urban price differential, while a rural product list generates a Laspeyres-type index that does the reverse. The Paasche analogy is applicable to ICP 2005.

Furthermore, Deaton and Dupriez (2011) show that even if rural price quotes are obtained, they may not reflect the actual prices faced by the rural consumers because a large portion of their consumption come from their own or neighbours' production. Dikhanov (2010a) did not impute prices for own-produced goods which, as pointed out by Deaton and Dupriez, may be the reason he found such low urban-rural price differentials. ICP does not collect information on home produced goods and, therefore, understates the urban-rural price differentials.

²⁹Our finding that quality adjustment reduces the urban-rural price differential by about 8 percentage points is consistent with a similar finding by Deaton and Dupriez (2011). Using unit value data obtained from India's household expenditure survey, they find that adjustment for income quality effects reduces the urban-rural price differential by 7.7 percentage points (from 19.2 to 11.5 percent).

This tendency of sampling a higher proportion of urban and unrepresentative products could cause the price levels in many Asia-Pacific countries to be over-estimated and, consequently, the GDP in US dollars underestimated. The CPRD method is unable to deal with this situation since it does not allow the representativity of a product to vary within a country. Hence even when CPRUD is used, differences between urban and rural prices may be partially masked by the failure to account for the fact that often urban representative prices are being compared with rural unrepresentative prices.

5.2 Measuring price differences between representative and unrepresentative products

A similar exercise can be undertaken to calculate representative-unrepresentative price differences. The results are again shown in Table 10.³⁰ The ratio of the geometric means of the representative and unrepresentative price quotes across all headings and countries is 3.4 percent. That is, contrary to what one might expect, we find that unrepresentative products are on average 3.4 percent cheaper than representative products. However, when the price quotes are quality adjusted using CPRD, CPRUD or CPD [with each country split into representative and unrepresentative parts rather than rural and urban parts as in equation (13)], this result is reversed.

This discrepancy can again be explained by the failure of the simple ratio of averages to quality adjust. When we quality adjust, we find as expected that unrepresentative products are more expensive by about 12 to 13 percent (i.e., $100 \times 1/0.88$ or $100 \times 1/0.89$ in Table 10).

Given that the concept of representativity is solely attributed to ICP (and Eurostat and the OECD), unlike urban-rural price differentials, it is not possible to compare our results with any other study. The fact that more than a third of the representativity coefficients in the CPRD model did not have the expected sign, however, indicates that representativity was not interpreted in a consistent way across countries in ICP 2005 (see also Dikhanov 2010b on this point).

5.3 Implications of our estimated urban-rural and representative-unrepresentative price differentials for China in ICP 2005

The average product prices for each country in ICP 2005 were, in most cases, calculated as a weighted average of the urban and rural price quotes, where the weights were supposed to reflect the relative urban and rural expenditure shares. This, however, is not true for

³⁰In our sample of nine countries only 6 percent of the price quotes with representative/unrepresentative identifiers are identified as unrepresentative (see Table 3). Ideally the percentages should have been much higher.

China since all its price quotes were urban. Furthermore, in the case of China, following Chen and Ravallion (2008), Deaton and Heston (2010) note that:

[T]he Chinese Bureau of Statistics chose the 11 cities because they were most likely to have outlets carrying the types of products and brands in the ICP specifications, and those prices are likely to be unrepresentatively high. (p. 21)

The problem of unrepresentativity of items is likely to be more acute in China than in other Asia-Pacific countries since China did not collect prices from any rural outlets. Furthermore, the 11 cities and the surrounding areas sampled in the Chinese data are located in provinces which are substantially richer than the average (see Chen and Ravallion 2008). This may be the reason that the downward revision of China's GDP in ICP 2005 was greater than the average of the Asia-Pacific region (the average fell by 17.4 percent, as compared with 39.5 percent for China).

The question is how much of the discrepancy in China's GDP can be explained by sample unrepresentativity (both in terms of the products priced and the location in which they are priced). According to Deaton and Heston (2010):

[W]e think that a conservative adjustment would be to treat the urban prices as collected in the 2005 ICP as 20 percent higher than national prices. Taking into account the distribution of consumption between urban and rural areas, this adjustment would raise estimates of Chinese GDP in 2005 by about 10 percent.

Assuming that half the Chinese price quotes are unrepresentative (we know all of them are urban) and like Deaton and Heston that half of all expenditure is in urban areas, then our empirical findings indicate that China's ICP prices will be $12.5/2 + 2.5/2 = 8.75$ percent too high (i.e., one-half of the representative-unrepresentative price differential plus one-half of the urban-rural price differential). Making this adjustment would raise China's GDP by 8.75 percent, which is quite close to Deaton and Heston's estimate. According to our calculations sample unrepresentativity therefore reduces China's GDP by $100(1 - 1/1.0875) = 8$ percent, and hence can account for about one-fifth of the total pre and post ICP discrepancy of 39.5 percent.

However, we think these figures are probably too low since China priced a much higher proportion of the products in each basic heading than did most other countries in the Asia-Pacific region. Some of these products may have been extremely unrepresentative for China, thus acting to push up its representative-unrepresentative price differential as compared with other Asia-Pacific region countries. Similarly, the selection of only high income cities may have acted to push up the rural-urban price differential in China relative to the rest of the Asia-Pacific region. Hence our estimate of one-fifth for sample unrepresentativity's share in the discrepancy for China should be treated as a lower bound.

Two other factors may also have contributed to the pre and post-ICP 2005 discrepancy. First, the pre-ICP 2005 comparison for China was of dubious quality (as was discussed in section 1). Second, one important difference between ICP 2005 and earlier ICP benchmarks was that some of the regions in ICP 2005 made productivity adjustments for government services. The way this productivity adjustment interacted with the method used to link the regions in ICP 2005 may have acted to reduce measured per capita income in the whole Asia-Pacific region (see Deaton and Heston 2010).

6 Conclusion

We have considered a number of problems with existing ICP methodology, their implications for international comparisons of real income, and some possible improvements and extensions that could be implemented in future rounds of ICP. Our analysis has been made possible by our unique data set consisting of over 600,000 individual price quotes drawn from nine countries in the Asia-Pacific region. Being the first study of its kind, we undertook a comprehensive analysis of the problems and potential improvements in the construction of the ICP basic heading prices indexes. This is important since these basic heading price indexes are the fundamental building blocks on which the price comparisons at the national level are constructed.

Our data set was actually used in the computation of national average prices, price indexes and real income for some of the countries in the Asia-Pacific Region in ICP 2005. While undertaking the research, we encountered a number of problems with the data, such as inconsistencies in the interpretation of important concepts across countries, and inadequate representation of some items in the samples. Some of these problems could introduce noise and bias into the official ICP purchasing-power-parity exchange rates and per capita income.

We have considered here some innovations that could correct or at least reduce the extent of some of these problems. Our innovations include the insertion of representative and urban dummies into the CPD model to account for unrepresentative products and urban-rural price differences, the estimation of CPD using the individual price quotes rather than average prices (as is currently done in ICP), the estimation of weighted CPD models, the insertion of outlet-type dummies, and attempts to improve econometric efficiency by correcting for heteroscedasticity and/or pooling the CPD model across basic headings. The paper contributes to our understanding of ICP in various ways. It allays some pre-existing concerns over possible biases while reinforcing others. It identifies in addition some topics for future research. The choice between running CPD on the individual price quotes or on average prices, in particular, warrants further investigation given our finding that this decision has quite a significant impact on the results.

Our extended CPD model also sheds light on the very significant downward revision

of China's GDP in ICP 2005. It has been argued (see for example Deaton and Heston 2010) that excessive sampling of unrepresentative and urban price quotes in China may have contributed to this revision. Our results are consistent with this finding.

Appendix: Improving the Efficiency of Price Indexes

1. Estimation of FGLS to correct for heteroscedasticity

The Breusch-Pagan (BP) tests for our basic headings in the CPRD and CPRUD models clearly reject the assumption of homoscedasticity. The BP F statistics are significant at the 1 percent level for most basic headings and at the 5 percent level for the remaining headings. As mentioned before, our primary concern here is with the efficiency of our point estimates rather than possible bias in the standard errors. If the variance of the OLS errors are functions of the explanatory variables, as indicated by the BP tests, then feasible generalized least squares (FGLS) should improve the efficiency of our price indexes.

Let \hat{e}_{kmr} denote the residual $\ln p_{kmr} - \widehat{\ln p}_{kmr}$ on price quote r on product m in country k obtained from the estimated OLS model for a particular basic heading in a CPD-type model. We regress \hat{e}_{kmr}^2 on the explanatory variables of the model. For the CPRUD models, the explanatory variables are country, product, representative and urban dummies. Let \hat{g} denote the predicted values of the dependent variable obtained from the above regression. Two different weights are considered: the reciprocal of the square root of $\exp(\hat{g})$ and $1 + \hat{g}$. The variables are transformed by multiplying all the variables of the models by these weights. The FGLS parameter estimates are obtained by applying OLS to the transformed variables.

One problem that can arise in the implementation of FGLS on the ICP data is that the estimated error \hat{e}_{kmr} could be zero or very close to zero for one or more observations. There may also be situations where the estimated error is close to zero. These observations may tend to get large weights under FGLS and may cause parameter instability in the resulting regression coefficients. It is to prevent such instability that \hat{g} is exponentiated or added by 1 in order to obtain weights. The results obtained from using the two weights are almost identical.

We observe three different reasons why \hat{e}_{kmr} could equal zero. First, in a few basic headings only a single price quote is available for one or more countries. Second, even if there are multiple price quotes from a country but these price quotes all relate to the same product and are all identical, then the estimated error on all these price quotes will be zero. Third, even if a country prices multiple products, but for one of these products it is the only country pricing it and all the price quotes on it are identical, then $\hat{e}_{kmr} = 0$ for these observations. The best solution for this latter case is deletion of the product in question, since a minimum requirement for inclusion in the comparison is that a product should be priced by at least two distinct countries. Diewert (2004) presented a detailed

analysis of this question in the context of CPD methods and reached the conclusion same to ours.

The average changes as measured by the A_k coefficients defined in (3) from using FGLS on the CPRUD model are shown in Table 4. The impact on the basic heading price indexes of correcting CPRUD for heteroscedasticity ranges on average from 1.1 percent (Bhutan) to 3.9 percent (Hong Kong).

With regard to price level dispersion, FGLS applied to the CPRUD model generates larger σ_n coefficients than OLS for 36 basic headings, while for 56 headings we observe the opposite result (see Table 6). In this case $N = 92$ rather than 85 since for seven headings where we could not identify the representative effect we replace CPRUD with CPD. The test statistic obtained from the normal approximation to the binomial is $Z = 2.085$, which is significant at the 5 percent level. Therefore, while its impact on the price indexes is generally quite small, correcting for heteroscedasticity nevertheless seems to slightly reduce measured price level dispersion across countries.

2. Pooled estimation of CPD-type models

Pooling has the potential to improve the efficiency of the estimated basic heading price indexes, a point that has been raised in an ICP context recently by Silver (2009). Following ICP 2005 (see World Bank 2008, Appendix C), we sort the basic headings (of similar type) into 10 groups. These groups are: food and non-alcoholic beverages; alcohol and tobacco; clothing and footwear; housing, water, electricity, gas and other fuels; furnishings, household equipments, etc; health; transport; communication, recreation and culture; education; restaurants, hotels and miscellaneous services.

Focusing on the case of the CPRUD model, letting $n = 1, \dots, N$ index the basic headings included in the pool, a pooled version of the model can be estimated as follows:

$$\ln p_{knm} = \sum_{n=1}^N \sum_{\mu=2}^{M_n} \alpha_{n\mu} x_{n\mu} + \sum_{n=1}^N \sum_{j=1}^K \beta_{jn} y_{jn} + \gamma z + \delta w + \sum_{i=2}^I \theta_i u_i + \varepsilon_{knm}$$

The country price indexes for each basic heading are obtained by exponentiating the estimated $\hat{\beta}_{kn}$ parameters:

$$\hat{p}_{kn} = \exp(\hat{\beta}_{kn}).$$

These indexes can be used to compare across countries for the same basic heading (i.e., $\exp(\hat{\beta}_{kn} - \hat{\beta}_{jn})$) but should not be used to compare across basic headings for the same country (i.e., $\exp(\hat{\beta}_{kn_1} - \hat{\beta}_{kn_2})$) even when they are derived from the same CPD-type pooled regression. Comparisons of the latter type are not meaningful since there is no overlap in the product lists in two different basic headings. In an ICP context, comparisons of the first type are all that are needed from CPD-type methods. Aggregation across basic headings is done using standard price index formulas.

A number of caveats, however, apply. First, if a fully flexible model is estimated that allows all the estimated coefficients, including the representative and urban dummies to

vary across basic headings, then pooling is equivalent to a seemingly unrelated regression (SUR) model (see Zellner 1962). Because there are no common variables across basic headings, however, the cross-equation correlations are zero and the estimated SUR coefficients collapse to the OLS coefficients.

For pooling to have an impact it is necessary to impose restrictions on the coefficients across basic headings. These restrictions may take the form of equality constraints – such as the equality of the representative or urban dummy coefficients – across basic headings. The key issues are, first, whether the imposition of such restrictions is conceptually plausible, and, second, whether their imposition actually reduces the standard errors of the estimated coefficients. Conceptually, it is not clear whether such restrictions are desirable. Empirically, we find that out of eight groups, pooling of the CPRUD models with equality constraints increases the mean of the estimated standard errors in six groups and lowers it for two groups. The groups where the standard errors decrease are alcohol and tobacco, and restaurants, hotels and miscellaneous services. Two groups, health and education, are excluded. This is because all the observations in the health category are representative and urban (since they are drawn only from Hong Kong and Macao), while for education we have only one basic heading.

The fact that pooling with equality restrictions increases the estimated coefficient standard errors for six of the eight groups indicates that there are significant differences between the unconstrained representative and urban dummy coefficient estimates across these basic headings. For example, in the food group, the estimated urban dummy coefficient ranges between -0.063 and 0.119 across basic headings with a mean of 0.032, while the estimated coefficient obtained from the pooled model is 0.035.

In summary, the case for pooling is at best mixed. Pooling is most likely transmitting all the measurement errors in the data to all equation. In the current state of data, it should probably not be used.

References

- Almas, Ingvild and Ashild A. Johnsen (2010), “Chinas Growth Miracle – Still Awaiting the Real Great Leap Forward.” Mimeo, Norwegian School of Economics and Business Administration, Bergen, Norway.
- Asra, Abuzar (1999), “Urban-Rural Differences in Costs of Living and Their Impact on Poverty Measures.” *Bulletin of Indonesian Economic Studies* 35(3), 51-69.
- Blades, Derek (2007a), GDP and Main Expenditure Aggregates. Chapter 3 in *ICP 2003-2006 Handbook*. Washington DC: The World Bank.
- Blades, Derek (2007b), “China in ICP 2005.” Mimeo.
- Brandt, Loren and Carsten A. Holz (2006), “Spatial Price Differences in China: Estimates

- and Implications.” *Economic Development and Cultural Change* 55(1), 43-86.
- Breusch, Trevor and Adrian Pagan (1979), “A Simple Test for Heteroscedasticity and Random Coefficient Variation.” *Econometrica* 50, 987-1007.
- Chen, Shaohua and Martin Ravallion (2008), “China is Poorer than we Thought, But No Less Successful in the Fight against Poverty.” World Bank Policy Research Working Paper 4621.
- Chen, Shaohua and Martin Ravallion (2010), “The Developing World is Poorer than we Thought, But No Less Successful in the Fight against Poverty.” *Quarterly Journal of Economics*, 125(4), 1577-1625.
- Cuthbert, Jim and Margaret Cuthbert (1988) On Aggregation Methods of Purchasing Power Parities. *OECD Economics Department Working Papers*, No. 56. Paris: OECD Publishing.
- Deaton, Angus (2005), “Measuring Poverty in a Growing World (Or Measuring Growth in a Poor World).” *Review of Economics and Statistics* 87(1), 1-19.
- Deaton, Angus (2010), “Price Indexes, Inequality, and the Measurement of World Poverty.” *American Economic Review* 100(1), 5-34.
- Deaton, Angus and Alan Heston (2010), “Understanding PPPs and PPP-Based National Accounts.” *American Economic Journal: Macroeconomics* 2(4), 1-35.
- Deaton, Angus and Olivier Dupriez (2011), “Using Unit-Values to Assess Spatial Price Differences: Evidence from India and Brazil.” Paper Presented at the ICP Technical Advisory Group Meeting in Washington DC, April 18-19, 2011.
- Diewert, W. Erwin (1999), “Axiomatic and Economic Approachest to International Comparisons,” in A. Heston and R. E. Lipsey, eds., *International and Interarea Comparisons of Income, Output, and Prices*. NBER Studies in Income and Wealth, vol. 61., Chicago and London: University of Chicago Press, 13-87.
- Diewert, W. Erwin (2004), “On the Stochastic Approach to Linking the Regions in the ICP.” Discussion Paper 04-16, Department of Economics, University of British Columbia, Vancouver, Canada.
- Diewert, W. Erwin (2008a), “New Methodological Developments for the International Comparison Program.” Discussion Paper 08-08, Department of Economics, University of British Columbia, Vancouver, Canada.
- Diewert, W. Erwin (2008b), “New Methodology for Linking the Regions.” Discussion Paper 08-07, Department of Economics, University of British Columbia, Vancouver, Canada.
- Diewert W. E., S. Heravi and M. Silver (2009), “Hedonic Imputation Indexes versus Time Dummy Hedonic Indexes,” in *Price Index Concepts and Measurement*, NBER, Studies

- in *Income and Wealth*, Vol. 70, W.E. Diewert, J. Greenlees and C.R. Hulten (eds.). Chicago: University of Chicago Press, pp. 161-202.
- Dikhanov, Yuri (2010a), "Income Effect and Urban-Rural Price Differentials from the Household Survey Perspective." Paper presented at the 2nd ICP Technical Advisory Group Meeting, February 17-19, 2010, Washington DC.
- Dikhanov, Yuri (2010b), "Assessing Efficiency of Elementary Indices with Monte Carlo Simulations." Paper presented at the African Development Bank Workshop, April 7-13, 2010, Washington DC.
- Eltető, Oded and Pal Köves (1964), "On a Problem of Index Number Computation Relating to International Comparison", *Statisztikai Szemle* 42, 507-518.
- Feenstra, Robert C., Hong Ma, C. Peter Neary and D. S. Prasada Rao (2010), "How Big is China? And Other Puzzles in the Measurement of Real GDP." Department of Economics, University of California Davis, Mimeo.
- Gini, Corrado (1931), "On the Circular Test of Index Numbers", *International Review of Statistics*, Vol.9, No.2, 3-25.
- Gong, Cathy H. and Xin Meng (2008), "Regional Price Differences in Urban China 1986-2001: Estimation and Implications." Economics Program, Research School of Social Sciences, The Australian National University, Canberra, Australia.
- Hill, Robert J. (2000), "Measuring Substitution Bias in International Comparisons Based on Additive Purchasing Power Parity Methods." *European Economic Review* 44, January, 145-162.
- Hill, Robert J. (2012), "Hedonic Price Indexes for Residential Housing: A Survey, Evaluation and Taxonomy." *Journal of Economic Surveys*, forthcoming.
- Hill, Robert J. and T. Peter Hill (2009), "Recent Developments in the International Comparison of Prices and Real Output." *Macroeconomic Dynamics* 13 (Supplement no. 2), 194-217.
- Hill, T. Peter (2007), Estimation of PPPs for Basic Headings Within Regions. Chapter 11 in *ICP 2003-2006 Handbook*, Washington, DC: The World Bank.
- Kennedy, Peter E. (1981), "Estimation with Correctly Interpreted Dummy Variables in Semilogarithmic Equations." *American Economic Review* 71 (4), 801.
- Maddison, Angus (2008), Background Note on "Historical Statistics."
 <<www.ggdc.net/Maddison>>.
- Neary, J. Peter (2004), "Rationalizing the Penn World Table: True Multilateral Indices for International Comparisons of Real Income." *American Economic Review* 94(5), 1411-1428.

- Rao, D. S. Prasada (2004), "The Country-Product-Dummy Method: A Stochastic Approach to the Computation of Purchasing Power Parities in the ICP." Paper presented at the SSHRC Conference on Index Numbers and Productivity Measurement, Vancouver, Canada, 30 June-3 July, 2004.
- Ravallion, Martin and Shaohua Chen (2007), "Chinas (uneven) progress against poverty." *Journal of Development Economics* 82(1), 1-42.
- Ravallion Martin and Dominique van de Walle (1991), "Urban-Rural Cost-of-Living Differentials in a Developing Economy." *Journal of Urban Economics* 29(1), 113-127.
- Rouen, Ren and Chen Kai (1995), "Chinas GDP in U.S. Dollars Based on Purchasing Power Parity." World Bank Policy Research Paper No. 1415.
- Silver, Mick (2009), "The Hedonic Country Product Dummy Method and Quality Adjustments for Purchasing Power Parity Calculations." International Monetary Fund Working Paper WP/09/271. International Monetary Fund: Washington DC.
- Summers, Robert (1973), "International Price Comparisons Based upon Incomplete Data." *Review of Income and Wealth* 19(1), 1-16.
- Szulc, Bohdan J. (1964), "Indices for Multiregional Comparisons", *Przegląd Statystyczny* 3, *Statistical Review* 3, 239-254.
- Tripllett, Jack E. (2004), *Handbook on Hedonic Indexes and Quality Adjustments in Price Indexes: Special Application to Information Technology Products*, STI Working Paper 2004/9, Directorate for Science, Technology and Industry, Organisation for Economic Co-operation and Development, Paris.
- Vogel, Fred (2010), "ICP Survey Framework." Paper presented at the 3rd ICP Technical Advisory Group Meeting, June 10-11, 2010, Paris, France.
- World Bank (2007), *World Development Indicators*. Washington DC.
- World Bank (2008), *Global Purchasing Power Parities and Real Expenditures: 2005 International Comparison Program*. International Bank for Reconstruction and Development/World Bank: Washington DC.
- Zellner, Arnold (1962), "An Efficient Method of Estimating Seemingly Unrelated Regression Equations and Tests for Aggregation Bias." *Journal of the American Statistical Association* 57, 348-368.

Table 1: Estimates of Per Capita PPP GDP in US Dollars of countries in the Asia-Pacific Region in 2005

Country	WDI-2007	ICP 2005	ICP05/WDI07
Bangladesh	2054	1268	0.617
Cambodia	2722	1453	0.534
China	6757	4091	0.605
Hong Kong	35053	35680	1.018
India	3452	2126	0.616
Indonesia	3842	3234	0.842
Iran	7962	10692	1.343
Laos	2047	1811	0.885
Malaysia	10902	11466	1.052
Mongolia	2070	2644	1.277
Nepal	1552	1081	0.697
Pakistan	2370	2396	1.011
Philippines	5135	2932	0.571
Singapore	29951	41478	1.385
Sri Lanka	4601	3481	0.757
Thailand	8682	6869	0.791
Vietnam	3072	2142	0.697
Average			0.826

Notes: The table presents estimates of per capita GDP in US Dollars calculated at purchasing power parity exchange rates for 2005 derived from two sources. WDI-2007 refers to the World Bank's pre-ICP 2005 estimates for 2005. This is obtained from the World Development Indicators (WDI) Report for 2007. ICP 2005 refers to the official result of the International Comparisons Program which is obtained from World Bank (2008). The final column divides each WDI result by its corresponding ICP result.

Table 2: Our List of ICP Basic Headings for Final Consumption Expenditure by Households

1	110111.1	Rice	47	110531	Major household appliances
2	110111.2	Other cereals and flour	48	110532	Small electric household appliances
3	110111.3	Bread	49	110533	Repair of household appliances
4	110111.4	Other bakery products	50	110540	Glassware/tableware utensils
5	110111.5	Pasta products	51	110552	Small tools and misc. accessories
6	110112.1	Beef and Veal	52	110561	Non-durable household goods
7	110112.2	Pork	53	110562.1	Domestic services
8	110112.3	Lamb, mutton and goat	54	110611	Pharmaceutical products
9	110112.4	Poultry	55	110612	Other medical products
10	110112.5	Other meats and meat prep	56	110613	Therapeutical appliances and equip
11	110113.1	Fresh, chilled or frozen fish	57	110621	Medical Services
12	110113.2	Preserved or processed fish	58	110622	Dental services
13	110114.1	Fresh milk	59	110623	Paramedical services
14	110114.2	Preserved milk and milk products	60	110711	Motor cars
15	110114.3	Cheese	61	110712	Motor cycles
16	110114.4	Eggs and egg-based products	62	110713	Bicycles
17	110115.1	Butter and Margarine	63	110722	Fuels/lubricants for transport equip
18	110115.3	Other edible oils and fats	64	110723	Maintenance of transport equipment
19	110116.1	Fresh or chilled fruit	65	110731	Passenger transport by railway
20	110116.2	Frozen, or processed fruit	66	110732	Passenger transport by road
21	110117.1	Fresh or chilled vegetables	67	110733	Passenger transport by air
22	110117.2	Fresh or chilled potatoes	68	110734	Passenger transport by sea/waterway
23	110117.3	Frozen or processed vegetables	69	110736	Other purchased transport services
24	110118.1	Sugar	70	110810	Postal services
25	110118.2	Jams, marmalades and honey	71	110820	Telephone and telefax equipment
26	110118.3	Confectionery, chocolate, ice	72	110830	Telephone and telefax services
27	110119	Food products n.e.c.	73	110911	Audio-visual/photographic equip
28	110121	Coffee, tea and cocoa	74	110914	Recording media
29	110122	Mineral waters, juices	75	110915	Repair of audio-visual/photo equip
30	110211	Spirits	76	110921	Durables for outdoor/indoor recreation
31	110212	Wine	77	110931	Other recreational items and equip
32	110213	Beer	78	110933	Gardens and pets
33	110220	Tobacco	79	110935	Veterinary and other services for pets
34	110311	Clothing materials	80	110941	Recreational and sporting services
35	110312	Garments	81	110942	Cultural services
36	110314	Cleaning, repair of clothing	82	110950	Newspapers, books and stationery
37	110321	Shoes and other footwear	83	110960	Package holidays
38	110322	Repair and hire of footwear	84	111000	Education
39	110430	Maintenance/repair of dwelling	85	111110	Catering services
40	110441	Water supply	86	111120	Accommodation services
41	110451	Electricity	87	111211	Hairdressing salons
42	110452	Gas	88	111212	Appliances/products for personal care
43	110453	Other fuels	89	111231	Jewellery, clocks and watches
44	110511	Furniture and furnishings	90	111232	Other personal effects
45	110512	Carpets and floor coverings	91	111262	Other financial services n.e.c
46	110520	Household textiles	92	111270	Other services n.e.c.

Table 3: Some Summary Information on Each Country

Countries	Outlet type	Urban price quotes (percent)	Rural price quotes (percent)	Rep price quotes (percent)	Unrep price quotes (percent)	Number of Headings	Number of Price Quotes
Bhutan	Yes	100.0	0.0	59.8	16.4	74	17085
Fiji	Yes*	100.0	0.0	18.8	0.0	70	9897
Hong Kong	Yes	100.0	0.0	100.0	0.0	92	45231
Indonesia	No	38.2	61.8	98.5	1.5	40	62972
Macao	Yes	100.0	0.0	95.9	4.1	91	28554
Malaysia	Yes	83.9	16.1	100.0	0.0	85	70683
Philippines	Yes	83.1	16.9	92.2	7.8	85	142379
Sri Lanka	No	58.2	41.8	53.3	7.3	84	72562
Vietnam	No	57.9	31.7	100**	0**	83	156635
TOTAL		71.9	25.5	89.8	3.5		605998

*Outlet type identifiers are missing for many of Fiji's price quotes

**Vietnam did not provide any rep/unrep identifiers. We have assumed that all Vietnam's price quotes are representative.

Note: Urban/rural identifiers are missing for 10.4 percent of price quotes in Vietnam. Rep/unrep identifiers are missing for 23.8, 81.2, and 39.4 percent of price quotes in Bhutan, Fiji and Sri Lanka respectively.

**Table 4: Average Differences A_k in the Price Indexes
Between Pairs of Method**

	CPD CPD(av)	CPD(av) CPD(w-av)	CPD CPRD	CPRD CPRUD	CPRUD CPRUDhet
Bhutan	1.173	1.006	1.105	1.011	1.011
Fiji	1.150	1.016	1.219	1.014	1.017
Hong Kong	1.135	1.032	1.077	1.038	1.039
Indonesia	1.162	1.013	1.044	1.023	1.013
Macao	1.131	1.031	1.078	1.037	1.038
Malaysia	1.134	1.021	1.066	1.026	1.028
Philippines	1.124	1.021	1.075	1.026	1.031
Sri Lanka	1.110	1.021	1.103	1.029	1.034
Vietnam	1.106	1.020	1.065	1.030	1.027

Notes: 'CPD' price indexes are calculated by running CPD using the individual price quotes, while 'CPD(av)' runs CPD on the country average prices. 'CPD(w-av)' calculates the price indexes using weighted least squares. CPRD, CPRUD and CPRUDhet are all calculated using the individual price quotes.

Table 5: Per Capita Incomes and Price Levels

	Per Capita Income	Price Level (USA=100)
Bhutan	3694	36
Fiji	4209	85
Hong Kong	35680	73
Indonesia	3234	41
Macao	37256	66
Malaysia	11466	46
Philippines	2932	39
Sri Lanka	3481	35
Vietnam	2142	30

Table 6: A Comparison of Price Level Dispersion Across Methods

x	CPD	CPD(av)	CPD	CPRD	CPRUD
y	CPD(av)	CPD(w-av)	CPRD	CPRUD	CPRUDhet
$\sigma_x > \sigma_y$	50	48	38	55	56
$\sigma_x < \sigma_y$	42	44	47	29	36
Z	0.834	0.417	-0.976	2.837	2.085

Notes: σ_x denotes the standard deviation of the country price levels for a particular basic heading (calculated using method x). For a pair of methods (say CPD and CPRD) we count how many basic headings have smaller standard deviations for the CPD method (denoted by σ_x) than for the CPRD method (denoted by σ_y). The total number of basic headings available depends on the pair of methods being compared. The Z values are derived from the normal approximation to the binomial distribution based on the null hypothesis that the probability that $\sigma_x > \sigma_y$ is 0.5.

Table 7: Some Statistics on the Signs and Significance Levels of the Estimated Coefficients of the CPRUOD Model

Variables	Statistics	All	Positive	Negative
Representative variable				
	Number of +ve/-ve sign coefficients		35	42
	Number of significant coefficients		21	27
	Simple average of coefficients	-0.1	0.148	-0.3
Urban variable				
	Number of +ve/-ve sign coefficients		54	26
	Number of significant coefficients		33	12
	Simple average of coefficients	0.018	0.075	-0.1
Outlet-type variables*				
Department stores	Number of +ve/-ve sign coefficients		28	27
	Number of significant coefficients		11	10
	Simple average of coefficients	-0.026	0.144	-0.201
Open markets	Number of +ve/-ve sign coefficients		32	47
	Number of significant coefficients		12	23
	Simple average of coefficients	-0.031	0.133	-0.143
Specialized stores	Number of +ve/-ve sign coefficients		27	60
	Number of significant coefficients		14	43
	Simple average of coefficients	-0.047	0.165	-0.143
Wholesale & discount stores	Number of +ve/-ve sign coefficients		12	22
	Number of significant coefficients		6	12
	Simple average of coefficients	-0.069	0.169	-0.198
Other stores	Number of +ve/-ve sign coefficients		36	56
	Number of significant coefficients		12	38
	Simple average of coefficients	0.005	0.139	-0.097

*The base outlet type is Supermarkets

Table 8: Some Statistics on the Signs and Significance Levels of the Estimated Coefficients of the CPRD and CPRUD Models

Model	Variable/S	All	Positive	Negative
CPRD Model	Representative variable			
	Number of +ve/-ve sign coefficients		30	47
	Number of significant coefficients		20	35
	Simple average of coefficients	-0.123	0.145	-0.294
CPRUD Model	Representative variable			
	Number of +ve/-ve sign coefficients		29	48
	Number of significant coefficients		20	43
	Simple average of coefficients	-0.123	0.148	-0.287
	Urban variable			
	Number of +ve/-ve sign coefficients		63	21
	Number of significant coefficients		45	14
Simple average of coefficients	0.026	0.052	-0.053	

Table 9: Difference in Fisher Price Indexes for Household Consumption

Country	CPD CPD(av)	CPD(av) CPD(w-av)	CPD CPRD	CPRD CPRUD	CPRUD CPRUDhet
Bhutan	0.858	0.988	1.022	1.001	1.000
Fiji	0.936	1.004	1.016	0.998	1.010
Hong Kong	1.000	1.000	1.000	1.000	1.000
Indonesia	0.878	1.007	1.005	0.985	1.001
Macao	0.933	0.999	0.997	0.999	1.005
Malaysia	0.970	1.002	1.002	0.998	1.007
Philippines	0.977	0.998	0.989	0.996	0.999
Sri Lanka	0.995	0.999	1.030	0.990	0.993
Vietnam	1.047	0.996	0.995	0.990	1.005

Notes: Each Fisher index is calculated over the list of headings available for that country. Data for Hong Kong is available for all 92 headings. In each bilateral comparison the expenditure shares are adjusted so that they sum to 1. Each column divides the top method's Fisher price index by the lower method's Fisher price index. For example, the first column of results provides $P[CPD]/P[CPD(av)]$.

Table 10: Rural-Urban and Rep-Unrep Price Differentials

	Rural-Urban Price Differentials		Rep-Unrep Price Differentials	
	Geometric Mean	Standard Dev of Logs	Geometric Mean	Standard Dev of Logs
GM-Bhutan	-	-	0.944	0.382
GM-Fiji	-	-	-	-
GM-Hong Kong	-	-	-	-
GM-Indonesia	1.022	0.377	1.526	0.717
GM-Macao	-	-	1.003	1.765
GM-Malaysia	1.148	0.431	-	-
GM-Philippines	1.185	0.420	0.812	1.067
GM-Sri Lanka	1.044	0.112	1.010	1.130
GM-Vietnam	1.159	0.292	-	-
GM-Average	1.110	-	1.034	-
CPD-Bhutan	-	-	0.946	0.096
CPD-Fiji	-	-	-	-
CPD-Hong Kong	-	-	-	-
CPD-Indonesia	0.991	0.082	1.022	0.062
CPD-Macao	-	-	0.771	0.231
CPD-Malaysia	1.069	0.065	-	-
CPD-Philippines	1.005	0.064	0.863	0.225
CPD-Sri Lanka	1.025	0.027	0.868	0.158
CPD-Vietnam	1.033	0.035	-	-
CPD-Average	1.024	-	0.890	-
CPUD	1.027	0.055	-	-
CPRD	-	-	0.883	0.365
CPRUD	1.026	0.073	0.883	0.363

Notes: The rural region and representative products are the numeraires, respectively. For example, a rural-urban price differential of 1.022 implies that urban prices are 2.2 percent higher than rural prices. Similarly, a representative-unrepresentative price differential of 1.526 implies that unrepresentative products are 52.6 percent more expensive than representative products.

GM-XXX denotes a price differential for country XXX calculated using equation (10) or its rep-unrep variant. CPD-XXX denotes a price differential for country XXX calculated using equation (13) or its rep-unrep variant. CPUD is a price differential calculated using equation (11), CPRD is a price differential calculated using the rep-unrep variant on (11), and CPRUD is a price differential calculated using equation (12). Columns 2 and 4 give the geometric means of the price differentials calculated across all basic headings for each country. Columns 3 and 5 give the standard deviations of the logarithms of the price differentials across all basic headings for each country.

All the means are weighted means, where weights are the expenditure share corresponding to basic headings and relative GDP shares corresponding to countries. See footnote 28.