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Improving International Comparisons of Real Income

The ICP 2005 Benchmark and Its Implications for the Gap Between the West and China

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Improving International Comparisons of Real Income: The ICP 2005 Benchmark and its Implications for the Gap Between the West and China

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Abstract:
The International Comparisons Program (ICP) compares the purchasing power of currencies and real income across countries, and plays a pivotal role in the construction of the Penn World Table. The much larger budget of the latest round (ICP 2005) has allowed far more data for more countries to be gathered than in previous rounds, which in turn has led to a number of methodological innovations. Using detailed price quote data from nine countries in the Asia-Pacific region, we evaluate some of these innovations and explore ways of further improving the ICP methodology. We then show how it can be extended in new directions, such as the estimation of rural-urban price differences. 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.

Keywords: International Comparisons Program; Penn World Table; Country-Product-Dummy Method; Price Index; Basic Heading; Rural-Urban Price Differences; Representative and Unrepresentative Products; Asia-Pacific Region
JEL Classification Codes: C43; O47; O53

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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 benchmark comparisons have been made in 1967, 1970, 1975, 1980, 1985, 1996 and 2005. The next is scheduled for 2011. ICP benchmarks play a pivotal role in the construction of the Penn World Table (probably the most widely used data set in academic research in the economics field).

ICP 2005 is different from earlier rounds in that it had a much larger budget. It is a huge undertaking coordinated by the World Bank in collaboration with the OECD, Eurostat, IMF and UN, with 146 participating countries. Its large budget allowed far more data to be gathered than in previous rounds. A number of methodological innovations were also introduced.

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).[1] More generally, 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 bigger than average for the Asia-Pacific region.

[1]The 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.

Insert Table 1 Here

These large revisions for China and India indicate that there may be a problem with either ICP 2005 or with the pre-ICP 2005 comparisons. The 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 is obtained from a regression extrapolation from the previous ICP round (since it was not an active participant in the previous round).

ICP 2005 by contrast has the advantage that it is a much more detailed comparison and that China and India both participated, although China's participation was on a limited scale and the price quotes were obtained from only 11 cities and their surrounding areas (see Blades 2007a).

It is tempting to conclude that the problems all lie with the pre-ICP-2005 results. It is worth pausing though to consider the extent to which the discrepancy might be attributed to problems with ICP 2005. We return to this issue after some preliminary discussion of the mechanics of ICP 2005.

ICP 2005 was broken up into two stages. Problems could have arisen at either stage. In stage 1, the world was divided into six regions (one of which was the Asia-Pacific) each of which made its own within-region comparison. In stage 2, a second comparison was made between 18 so-called ring countries drawn from the regions. The stage 2 comparison was used to link the regions together to obtain the overall global results (see Diewert 2008a, 2008b and Hill and Hill 2009).

A problem in stage 2 should affect all countries in the Asia-Pacific region in a similar way, while a problem in stage 1 should affect each country differently. The fact that per capita GDP in the Asia-Pacific region fell on average by 17.4 percent in ICP 2005 suggests that a fall of 22.1 (i.e., 39.5-17.4) in China's per capita GDP can be attributed to stage 1 of ICP (i.e., the within Asia-Pacific region comparison). The remaining 17.4 percent should be attributed to stage 2 (i.e., the ring comparison that linked the regions together).

The ICP 2005 aggregate results at the level of GDP for each region are obtained from 155 basic heading price indexes and corresponding expenditure levels (some of

the basic headings are listed in Table 2).[2,3] The basic heading price indexes, which are typically calculated using the Country-Product-Dummy (CPD) method, 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. It is here at this disaggregated level that the most pressing research problems can be found.[4]

Deaton and Heston (2008, 2010) argue that some countries in ICP 2005, notably China, may have priced more unrepresentative products or products purchased in urban locations than other countries (sees sections 2.2 and 2.3). These sampling asymmetries could cause the price level in these countries to be overestimated, and hence per capita income underestimated. This is because anecdotal evidence suggests that, other things equal, representative products tend to be cheaper than unrepresentative products, and the same product sells at a lower price in rural locations than in urban locations.

In the hope of reducing the magnitude of any biases that might arise from mismatches in the proportions of representative and unrepresentative products priced by countries, the ICP 2005 Technical Advisory Group (TAG), of which both Deaton and Heston were members, recommended that comparisons at the basic heading level should be made using an extended version of the CPD method which includes representative dummies (see Summers 1973 and Diewert 2010). Hence all participating countries were asked to identify which of the products they priced were representative.[5] However, this information was not actually used in the Asia-Pacific region comparison.

Our data set consists 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.[6]

[2]Actually only 142 basic headings were used in the Asia-Pacific region.

[3]A 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 2007b).

[4]Above 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 1999 and Neary 2004).

[5]Eurostat and the OECD have already been doing this for many years.

[6]Strictly speaking we should refer to economies rather than countries, given that two of our sample

While we do not have any data for China itself, we are able to quantify the potential impacts on measured GDP of an excessive focus on unrepresentative products or urban locations for our sample of countries. We then explore the extent to which such biases could explain the pre and post ICP 2005 discrepancy for China.

A second objective of this study is to assess whether the decision to omit representative dummies in the Asia-Pacific region was justified. Our findings are mixed. The inclusion of representative dummies undoubtedly increases the explanatory power of our CPD-type regressions. Most of the dummies are significant and have the expected sign. Hence the inclusion of representative dummies has the potential to at least partially alleviate the concerns of Deaton and Heston. However, at the same time it is clear that representative products were not identified in a consistent manner across countries. We show how the inclusion of representative dummies in this case could itself introduce noise and bias into the results.

More generally, ICP 2005 neglects some potentially important econometric issues. We find clear evidence of heteroscedasticity in the Asia-Pacific data set, and hence correct for it using feasible generalized least squares (FGLS). We also correct for semilogarithmic coefficient bias, which results from the fact that our basic heading price indexes are equal to the exponents of our estimated coefficients on the country dummies. For most of our 92 basic headings the heteroscedasticity and semilogarithmic coefficient bias corrections are small. However, for a few so-called 'comparison-resistant' headings they are quite large. We then check whether simultaneous estimation of the CPD model over a group of basic headings in a seemingly unrelated regression (SUR) type setting can improve the efficiency of the estimated price indexes.

We also consider the viability of further extending the basic CPD method to include urban and outlet-type dummies. ICP 2005, by contrast, averaged prices across outlets and across rural and urban areas within each country prior to application of the CPD method. While we find that the outlet-type data are not consistent enough to justify the inclusion of outlet-type dummies directly in a CPD-type model, we think the case for including urban dummies is rather stronger, although this may require a subsequent

(Hong Kong and Macao) are not countries. Nevertheless, for convenience we will henceforth use the term 'countries'.

adjustment to the results to prevent bias.

One advantage of estimating a CPD-type model directly on the individual price quotes is that it simultaneously generates estimates of the average price differential between urban and rural areas. The calculation of rural-urban price differences is very important for the construction of poverty lines and hence for the measurement of the number of people living in poverty (see Chen and Ravallion 2010 and Deaton 2010a, 2010b). We find that the price quotes on average are 11 percent higher in urban areas than in rural areas. However, when we quality adjust to ensure that we are comparing rural and urban prices of the same products, this differential falls to just 2.5 percent. This suggests that more of the price quotes in rural areas are for the cheaper (and presumably lower quality) products within each basic heading.

Our estimate of 2.5 percent is rather lower than most others obtained for the Asia-Pacific region (see section 2.3). We consider some reasons why our estimate might be too low. Supposing though that it is correct and applicable also to China, then the lack of rural price quotes in ICP 2005 for China can explain at best only about 1 percent of the pre and post ICP 2005 discrepancy (given that China was probably not the only country to undersample from rural areas and only about half of expenditure in China is in rural areas anyway).

We estimate the representative-unrepresentative price differential to be about 12.5 percent. The reliability of this figure is undermined by the fact that in our sample of nine countries only 6 percent of the price quotes with representative/unrepresentative identifiers are identified as unrepresentative (see Table 3). This is far too low. Also, the extent of understatement almost certainly varies across countries. Nevertheless, taking the data at face value and assuming that 50 percent of products priced in China are unrepresentative, then a 12.5 percent representative-unrepresentative price differential would imply a downward bias in China's GDP of around 6 percent (i.e., a little under half of 12.5 percent).[7]

Summing these two effects we obtain a bias of around 7 percent relative to the

[7] This figure should be treated as an upper bound. While China's sampling from high-end outlets in urban areas probably led it to price more unrepresentative products than most of the countries in our data set, to assume China's share was nearly 50 percent higher is probably excessive.

average in the Asia-Pacific region. In other words, we can perhaps attribute about one third of the total stage 1 (i.e., the Asia-Pacific within-region comparison) pre and post ICP 2005 discrepancy for China to an excessive focus in the Chinese data on unrepresentative products and urban outlets.[8]

2 Some Possible Sources of Bias in ICP 2005

2.1 The productivity adjustment for government services

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 (see Deaton and Heston 2010). The issue here is that while civil servant (including employees in the public health and education systems) wages tend to be much lower in poorer countries, the output of civil servants cannot be observed directly. If it is assumed that all civil servants are equally productive, this acts to inflate real output in the government services sector in poorer countries relative to richer countries to an implausible extent. To prevent this, the Asia-Pacific, West-Asia and Africa regions assumed that civil servant output in each country was proportional to its average capital per worker. Given that richer countries have more capital per worker this productivity adjustment acts to increase inequality across countries. This effect can be clearly seen in Table 1. The standard deviation of the logarithm of per capita income in the WDI-2007 results is 0.912. The corresponding standard deviation for ICP 2005 is 1.081. Determining the impact of this adjustment on the per capita income of Asia-Pacific countries measured in US dollars is made more complicated by the two-stage structure of ICP 2005. The OECD region did not make any such productivity adjustment. Nor was such an adjustment made in the stage 2 ring comparison used to link the regions together. In this situation the choice of ring countries plays a crucial role. The ring countries for the Asia-Pacific region in ICP 2005 are Hong Kong, Malaysia, the Philippines, and Sri Lanka. Linking the OECD to the Asia-Pacific region through Hong Kong (the second richest economy in the Asia-Pacific region after Singapore), given the combined impact of the productivity

[8]Given that we have data only for the Asia-Pacific region, we cannot measure the rural-urban and representative-unrepresentative price differentials arising out of the stage 2 ring comparison.

adjustment and fixity in the within-region Asia-Pacific results, acts to push down the per capita incomes of other Asia-Pacific countries measured in US dollars. This effect is partially offset by the inclusion of the other ring countries (i.e., Malaysia, the Philippines, and Sri Lanka). However, inspection of Table 1 suggests that these four countries are a richer than average sample from the Asia-Pacific region, and hence that the overall combined effect of the productivity adjustment and within-region fixity will be to lower the US dollar income of most countries in the Asia-Pacific region, while at the same time raising the US dollar income of the richest countries in the region. This effect is clearly discernible in Table 1. In fact, the interaction between the productivity adjustment and within region fixity can by itself probably explain most of the fall in average per capita income in US dollars in the Asia-Pacific countries arising out of ICP 2005. Given that West Asia and Africa also made productivity adjustments for government services, it is likely that their incomes in US dollars have also been distorted in similar ways.

The fact that China's per capita income in US dollars fell rather more in ICP 2005 than that of some other countries in the Asia-Pacific region with lower per capita incomes (e.g. Indonesia, Laos, Mongolia, Pakistan and Sri Lanka) suggests that we may have to look elsewhere for an explanation of why China's per capita income fell so much more than the Asia-Pacific average.[9] Alternative explanations include excessive sampling of prices of unrepresentative products or from urban areas in China (see below).

More generally, in our opinion, the productivity adjustment implemented in ICP 2005 is almost certainly justified. However, applying it to some regions but not to others, and not in the stage 2 ring comparison, inevitably leads to distortions in comparisons between countries in different regions. It is hoped that future rounds of ICP will harmonize these decisions better across regions.

2.2 Excessive sampling of prices of unrepresentative products

Deaton and Heston (2008) offer the following explanation for why there may be a problem with the ICP 2005 results for some countries (notably China):

[9] Again it should be remembered that the pre-ICP 2005 results for China are of dubious quality. Hence it is harder to explain the sources of the pre and post ICP 2005 discrepancy for China than for countries that participated fully in earlier rounds of ICP.

> "Many of the qualities available in poorer countries are not available in higher income countries, while more of the qualities available in richer countries can also be found in poorer countries. ... The consequence is that prices for the ICP were often collected in higher-end outlets, which has the effect of raising price levels of poorer countries. This was made more likely in 2005 than previously because of the much closer review of prices across countries so that, for example, international brands were priced in (say) China, because they were available, even if mainly in high-end outlets. To the extent this happened, it would have the effect of raising parities in poorer countries, making them appear to have less income and output than in fact they do." (Deaton and Heston 2008)

Furthermore, in the case of China, following Chen and Ravallion (2008), Deaton and Heston 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. (Deaton and Heston 2010)

In other words, China priced many products that were representative in richer countries but only available in high-end outlets in China, and hence were not representative there. Therefore, a higher proportion of the price quotes in China were unrepresentative as compared with richer countries. Interestingly, the same was probably true for China as compared with lower income countries as well, since the latter did not price as many of these unrepresentative products. This tendency of pricing a higher proportion of unrepresentative products than other countries could have caused China's price level to be overestimated and GDP underestimated in ICP 2005.

2.3 Excessive sampling of prices from urban areas

It is generally assumed that prices are higher in urban areas than in rural areas. Most empirical studies in the Asia-Pacific region confirm this finding. For example, Ravallion and van de Walle (1991) find that the rural-urban 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 (2010a) obtains a differential of 10 percent for food prices in India, while Dikhanov (2010) focusing on food and clothing finds it is 3 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.

It follows therefore that a country that samples prices disproportionately from urban areas should tend to have its price level overestimated and GDP underestimated. The fact that China sampled prices only from 11 cities and surrounding areas suggests that it could be a case in point. The fact that these 11 cities were richer than average in China further compounds this effect (since prices may also vary very significantly across regions).

3 The Country-Product-Dummy Method and its Extensions

In ICP 2005 the world was divided up into six regions, each of which was able to draw up its own product list for each basic heading. An additional comparison between a group of so-called 'ring' countries drawn from the regions was then used to link the regions together (again see Diewert 2008a, 2008b for further details).

Most regions, including the Asia-Pacific region, used the country-product-dummy (CPD) method to calculate the within-region basic-heading price indexes for each country.[10] The CPD model estimates the following regression equation separately for each

[10]One 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

basic heading:[11]

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

where p_{km} denotes the price of 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:

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

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. In ICP, p_{km} is an average of the price quotes obtained from all the outlets in country k. An alternative approach would be to include all the individual price quotes for product m directly in the CPD regression. We would then have multiple observations of p_{km}. In other words, p_{km} would be replaced by p_{kmr} where $r = 1, \ldots, R_k$ indexes the price quotes on product m available in country k. In the empirical comparisons later in the paper, this is the approach we use.

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 to the model as follows:

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

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).

[11] It 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. The reason for our slightly nonstandard formulation of the CPD model will become apparent when we discuss the problem of semilogarithmic coefficient bias.

where now we also include a dummy z that equals 1 if product m is representative in country k and zero otherwise.

The error term, $\hat{\varepsilon}_{km}$, for a product that is representative in country k should tend to be negative in the CPD model (since other things equal a representative product should be cheaper than an unrepresentative product). If representative products can be identified, this information can be utilized to correct for imbalances between the proportions of representative and unrepresentative price quotes within a basic heading across countries. In effect, either the prices of representative products can be adjusted upwards by a representativity factor or the prices of unrepresentative products can be adjusted downwards. The CPRD method estimates the adjustment factor simultaneously with the product and country factors.

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)

Unfortunately,

> "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 principle, the CPRD method can be further extended, when the individual price quotes are available to include urban and outlet type dummies [i.e., the country-product-representative-urban-outlet-dummy (CPRUOD) method] as follows:

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

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 $i = 1, \ldots, I$ 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 this extended model in an ICP context. We also consider the country-product-urban-dummy (CPUD) and country-product-representative-urban-dummy (CPRUD) models at various points in the paper. CPUD is obtained by setting all the z and u_i dummies to zero in (2), while CPRUD is obtained by setting only the u_i dummies to zero.

Econometrically the methods employed for estimating the CPD model in ICP could be improved. The CPD model in ICP 2005 is estimated using ordinary least squares (OLS). In the presence of heteroscedasticity the OLS standard errors will be biased. Our main focus here, however, is on the point estimates of the parameters of the model since the price indexes are derived directly from them. For this reason, our primary interest in heteroscedasticity is in its impact on the efficiency of our parameter estimates. In the presence of heteroscedasticity efficiency can be increased by using generalized least squares (GLS). We find clear evidence of heteroscedasticity in our CPD-type regressions and hence there is a strong case for using GLS.

The basic heading price indexes in CPD-type models are obtained from the exponents of the estimated β_k parameters. Goldberger (1968), under the assumption that the error term in the CPD-type regression equation is normal, shows that

$$E[\exp(\hat{\beta}_k)] = \exp\left[\beta_k - \frac{1}{2}\hat{\sigma}_k^2\right],$$

where $\hat{\sigma}_k^2$ is an estimate of the variance of $\hat{\beta}$. In other words, $\exp(\hat{\beta}_k)$ is a biased estimator of $\exp(\beta_k)$. To correct for this bias, Kennedy (1981) suggests the following estimator of $\exp(\beta_k)$, denoted here by $\tilde{p}_k = \widetilde{\exp}(\beta_k)$:

$$\widetilde{\exp}(\beta_k) = \exp\left[\hat{\beta}_k + \frac{1}{2}\hat{\sigma}_k^2\right]. \tag{3}$$

It is important when making this correction that none of the country price indexes are normalized. If the price index of country 1 is set to one, then by construction $\hat{\sigma}_1^2 = 0$ and hence the Kennedy correction reduces the price indexes of all countries except country 1. This will cause a violation of base country invariance. Given that the choice of base

country is arbitrary, use of the Kennedy correction here will cause the price level in the base country to be systematically overestimated relative to all other countries.

For this reason we specify a formulation of the CPD model in (1) that does not have a base country. In this specification, the Kennedy correction can be applied without creating any systematic biases in the price indexes. However, the results will now not be invariant to the choice of base product. One way to resolve this problem is to use each product in turn as the base, and then average the results. Given that the price indexes are relatively insensitive to the choice of base product, here we simply choose one as the base for each heading rather than using this averaging procedure.

Our last extension of the basic CPD-type model is to demonstrate how, rather than estimating a CPD-type model separately for each basic heading, we can pool headings in related categories and estimate the system of equations simultaneously. This has the potential to improve the efficiency of our parameter estimates, as well as allowing us to impose a common coefficient on the representative dummies, urban dummies or outlet-type dummies across groups of headings. Focusing on the case of the CPRUD model, letting $n = 1, \ldots, N$ index the basic headings included in the pool, the pooled version of the model is estimated as follows:

$$\ln p_{knm} = \sum_{n=1}^{N} \sum_{\mu=2}^{M_n} \alpha_{n\mu} x_{n\mu} + \sum_{n=1}^{N} \sum_{j=1}^{K} \beta_{jn} y_{jn} + \gamma z + \delta w + \sum_{i=2}^{I} \theta_i u_i + \varepsilon_{knm}, \tag{4}$$

Abstracting from the Kennedy correction, 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 can be compared across countries for the same basic heading (i.e., $\exp(\hat{\beta}_{kn} - \hat{\beta}_{jn})$) but should not be 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.

4 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. In total there are 142 basic headings in ICP 2005 for the Asia-Pacific region. Our price quotes are drawn from 92 of these headings, all of which belong in the Final Consumption Expenditure by Households category.[12] Our list of basic headings is shown in Table 2.

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.[13]

[12] In 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.

[13] A 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 agen-

Insert Table 3 Here

5 CPD-Type Regression Results

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

We consider first our most general CPD-type model. This 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 4. 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 results broadly support this hypothesis, with 54 coefficients being positive (and 33 statistically significant) and only 26 being negative (with 11 statistically significant).[14]

cies; 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.

[14]The 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.

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).

Insert Table 4 Here

We suspect that there may be serious inconsistencies with the ways 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. Hence our focus now is the country-product-representative-urban-dummy (CPRUD) model. The results are presented in Table 5. 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, 63 times positive (of which 45 are significant) and 21 times negative (of which 14 are significant). Also, shown in Table 5 are results for the CPRD method. The results for CPRD are similar to those obtained for the representative dummies in CPRUD.

Insert Table 5 Here

Given that out of the nine countries in our sample 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 in ICP 2005. In particular, the use of CPRD in this context would actually cause an upward bias in the 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. Nevertheless, at some point in the future (once countries identify representative products more consistently) the inclusion of representative dummies may be justified.

ICP 2005 already makes use of urban-rural identifiers in its calculation of country average prices prior to estimation of the CPD model. 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 practice based on average prices. We have serious doubts though whether the inclusion of outlet types, at least in the form available in ICP 2005, would improve the quality of the results.

5.2 Differences in estimated price indexes across methods

Our focus when comparing the results is on two issues. First, we assess the sensitivity of the results to the choice of method. Second, we check for evidence of systematic differences between the results generated by different methods. Taking the former first, the average change in the price indexes of each country as a result of switching from method x to method y is measured here as follows:

$$A_k(x,y) = \frac{1}{N}\sum_{n=1}^{N} \max(P_{kn}^x/P_{kn}^y, P_{kn}^y/P_{kn}^x),$$

where P_{kn} denotes the price index of country k for basic heading n (expressed as the number of units of currency that have the same purchasing power as 1 Hong Kong dollar). Also of interest is the maximum change in a basic heading price index, calculated as follows:

$$M_k(x,y) = \max_{n=1,\ldots,N}[\max(P_{kn}^x/P_{kn}^y, P_{kn}^y/P_{kn}^x)].$$

The average and maximum changes as measured by the A_k and M_k formulas are shown in Table 6 for the following pairs of methods:[15] (i) CPD-CPRD; (ii) CPD-CPRUD; (iii) CPRD-CPRUD; (iv) CPRD-CPRDhet; (v) CPRDhet-CPRDhetken; (vi) CPRUD-CPRUDhet; (vii) CPRUDhet-CPRUDhetken. For example, $A_k = 1.081$ for Bhutan in a comparison between CPD and CPRD. This means that the basic heading price indexes for Bhutan change on average by 8.1 percent as a result of switching from CPD to CPRD.

Insert Table 6 Here

One must be careful comparing the A_k and M_k coefficients across countries for a few reasons. First, the results depend on the choice of base country (here Hong Kong). Second, 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(CPD,CPRD) coefficient can be attributed largely to its complete omission of the more problematic headings. Third, often large values of $A_k(x, y)$ may be attributable primarily to differences in the underlying data sets rather 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. Fourth, 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

[15] CPRDhet and CPRDhetken denote, respectively, CPRD corrected for heteroscedasticity and CPRD corrected for heteroscedasticity and incorporating Kennedy's correction of semilogarithm coefficient bias.

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).

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.

The largest M_k coefficients in Table 6 are 3.35 observed in a comparison of CPD and CPRD for Fiji for basic heading 81 (Cultural services), and 3.33 and 3.55 observed in a comparison of CPD and CPRUD, respectively, for Fiji for heading 81 (Cultural services) and Sri Lanka for heading 86 (Accommodation services). In other words, the price index for Sri Lanka for the 'Accommodation services' basic heading changes by a factor of 3.55 as a result of including representative dummies. Again, most of these large differences are probably attributable to the small number of price quotes with representative-unrepresentative indicators available for this heading (only 30 out of 112 price quotes for Sri Lanka for heading 86 had representative-unrepresentative identifiers) and the large variations between these price quotes. The big differences, therefore, typically occur in difficult-to-measure or diffuse headings such as 18=Other edible oils and fats, 20=Frozen, preserved or processed fruit and fruit-based products, 30=Spirits, 39=Maintenance and repair of the dwelling, 72=Telephone and telefax services, 81=Cultural services, 82=Newspapers, books and stationery, 86=Accommodation services.

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. It remains to be seen whether the use of CPRUD and CPRUOD would be preferable to the current ICP methodology of constructing average prices for each heading by sampling from the available price quotes according to location. In principle, though, it does seem likely that CPRD would be an improvement on CPD at least for some headings (as long as the representative-unrepresentative indicators are identified in a reasonably consistent manner across countries).

5.3 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. Price levels are obtained by dividing each price index by its corresponding average 2005 market exchange rate, with Hong Kong again normalized to 1. Systematic changes in price levels as a result of switching from CPD to CPRD could arise if for example a disproportionate share of the price quotes in say country k, relative to the others in our sample, are unrepresentative. The use of the CPRD method should in this case lower the measured relative price level in country k.

Rather than comparing all possible bilateral pairings of countries, here we simply consider whether the spread of the price levels across all nine countries rises or falls as a result of adopting the CPRUD method. Our measure of spread is given by the standard deviation of the logarithms of the price levels for each basic heading as follows:[16]

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

where P_{kn} again denotes the price index for basic heading n in country k, MER_k denotes the market exchange rate for country k, and $\overline{\ln(P_{kn}/MER_k)}$ is the average log price level for basic heading n.

We find that σ_n is higher for the CPRD method than for CPD for 47 headings and lower for 38 headings, as shown in Table 7.[17] To see whether this difference is significant we use the normal approximation to the binomial distribution. Let X denote the number

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

[17] As was noted above, for 7 headings, only Hong Kong and Macao supplied data and for these headings

of basic headings for which the CPRD σ_n coefficient is larger than its corresponding CPD σ_n coefficient. X is approximately normally distributed with mean $N/2 = 42.5$ and variance $N/4 = 21.25$. A value of $X = 47$, implies 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.

Insert Table 7 Here

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, while Vietnam is the country with the lowest price level (see the price level indexes for the Asia-Pacific region in the ICP Global Results). The inclusion of Vietnam in this group acts to prevent a noticeable increase in price level dispersion.

The results from a comparison of CPD and CPRUD also shown in Table 7 are quite similar. The CPRUD price level dispersion σ_n is higher for 46 headings and lower for 39 headings. Using the normal approximation to the binomial, we obtain a test statistic of $Z = 0.759$ which is likewise not significant.

By contrast, in a comparison of CPRD with CPRUD, the CPRD σ_n coefficient is higher for 53 headings, and smaller for only 31 headings. In this case $Z = -2.400$ 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 the ICP Global Results), namely Fiji, Hong Kong and Macao, are urban. The inclusion of urban

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.

dummies acts to lower the relative price levels in these three countries, thus reducing overall price level dispersion.

5.4 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. 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.

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 generalized least squares (GLS) should improve the efficiency of our price indexes.

For the case of CPD run on country average prices, Rao (2004) argues that these averages should be more reliable for those countries that have more price quotes. Assuming the price quotes are identically and independently distributed the implied heteroscedasticity of the country average prices can be modelled directly. However, we cannot use such an approach here since we estimate the CPD model directly from the individual price quotes.

Hence we use feasible GLS (FGLS). Let $\hat{e}_{kmr}$ denote the residual $p_{kmr} - \hat{p}_{kmr}$ 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 $\hat{e}^2_{kmr}$ 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, and in addition we define $\hat{h} = \exp(\hat{g})$. The weights are given by the reciprocals of the square root of $\hat{h}$. 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.[18]

[18] We observe three different reasons why $\hat{e}_{kmr}$ could equal zero. First, in a few basic headings (e.g.

While zero estimated errors are easily identified, 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 in the first stage of FGLS we regress $\hat{e}^2_{kmr}$ instead of $\ln \hat{e}^2_{kmr}$, as is more usual, on the explanatory variables. In the second stage the weights are set equal to the reciprocal of the exponent of $\hat{g}$.[19]

The average and maximum changes as measured by the A_k and M_k coefficients from using FGLS on the CPRD and CPRUD models are shown in Table 6. The use of FGLS has the biggest impact on basic headings 29 (Mineral waters, soft drinks, fruit and vegetable juices), 52 (Non-durable household goods), 65 (Passenger transport by railway), 66 (Passenger transport by road), and 86 (Accommodation services). The impact across countries of correcting for heteroscedasticity on the basic heading price indexes ranges on average from 0.5 percent and 2.1 percent for both the CPRD and CPRUD methods.

With regard to price level dispersion, FGLS applied to the CPRD model generates larger σ_n coefficients than OLS for 32 basic headings, while for 60 headings we observe the opposite result (see Table 7). 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 $Z = -2.919$, which is significant at the 5 percent level. The results for CPRUD are similar. FGLS generates larger σ_n coefficients for 36 headings, and lower coefficients for

40=Water supply, 41=Electricity, 54=Pharmaceutical products, and 92=Other financial services n.e.c.) 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. This situation is observed for basic headings 61=Motor cycles and 68=Passenger transport by sea and inland waterways. 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. Such cases are observed for 54=Pharmaceutical products, 59=Paramedical services and 92=Other financial services n.e.c. 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.

[19]We experimented also with setting $\hat{h} = 1 + \hat{g}$. The results were almost identical to those obtained with $\hat{h} = \exp(\hat{g})$.

56 headings. Now $Z = -2.085$, which is again significant. 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.

5.5 Correcting for semilog coefficient bias

The average and maximum changes as measured by the A_k and M_k coefficients from implementation of the Kennedy correction in (3) on the CPRD and CPRUD methods estimated using GLS are shown in Table 6. It can be seen that the average impact of the Kennedy correction is very small. Its impact is biggest on Fiji for the basic heading 92 (Other services n.e.c.), where the correction changes the CPRD and CPRUD price index by 52 percent. The next highest change is 8 percent, which is observed for Indonesia 91 (Other financial services n.e.c). Basic headings that experience large Kennedy corrections imply that there are significant relative price differences across countries for the products in this heading. These price differences may be genuine, or they could signal the presence of poor quality data. Any heading that experiences a large Kennedy correction therefore should be closely scrutinized.

The Kennedy corrected price dispersion coefficients σ_n are larger for 66 and 65 out of 92 heading, respectively, for CPRD and CPRUD. The corresponding values of Z obtained from the normal approximation to the binomial are 4.170 and 3.962 both of which are highly significant.[20] This finding that the Kennedy correction increases measured price level dispersion across countries should probably not be taken too seriously given the negligible magnitude of the correction on the price indexes themselves. For the vast majority of headings, the Kennedy correction is so small that it can be safely ignored.

[20]The combination of correcting for heteroscedasticity and semilogarithmic bias seem to at least partially offset each other in terms of their impact on price level dispersion across the countries in our data set.

5.6 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 philosophical 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^k_{Urb} 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:

$$\tilde{P}^k_n = \left[\left(\frac{\text{Exp}^k_{Urb}}{\text{Exp}^k} \right) (P_{Rur,Urb} - 1) + 1 \right] P^k_n, \tag{5}$$

where P^k_n denotes the original CPUD price index for basic heading n in country k, $\tilde{P}^k_n$ is the adjusted index, and $P_{Rur,Urb}$ is the average CPUD rural-urban price differential derived from (7) below. [21] From (5) we can see for a totally urban population such as Hong Kong that $\tilde{P}^k_n = P_{Rur,Urb} \times P^k_n > P^k_n$, while for a totally rural population

[21] With 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.

$\tilde{P}_n^k = P_n^k$. 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. 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 (5). 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.

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.[22] 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.[23]

It does seem likely that expenditure in poorer countries is concentrated on a smaller range of products. If so, it follows that the proportion of representative products in the ICP product list will tend to be lower for poorer countries, and hence that the CPD method will tend to systematically underestimate price differences (and overestimate income differences) across countries. This is exactly the effect described by Deaton and

[22]Here we abstract from the issue mentioned above that a particular product may be representative in urban areas but not rural areas of the same country.

[23]One 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 could all three, along with all the products within each of these headings, 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.

Heston (2010). Methods such as CPRD and CPRUD, however, will only help to offset this bias if representative products are identified in a consistent way across countries (which does not seem to have been the case in ICP 2005 in the Asia-Pacific region).

5.7 Pooled estimation of CPD-type models

It 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 as shown in (4) for the case of the CPRUD model. Following ICP 2005 (see World Bank 2008, Appendix C), we sort the headings into 10 groups as shown in Table 8. 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).

Insert Table 8 Here

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. Consider, for example, the representative dummies. Though these dummies are common to all basic headings, the estimated coefficients differ across basic headings. In a SUR context, this means that the representative dummies across different basic headings are essentially different variables. The same holds for the urban and country dummy variables.

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 (see Table 8).[24] Similar results are obtained from a comparison of the CPRD pooled and un-pooled models. 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 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. It is something that might be worth considering for some groupings of basic headings in combination with equality restrictions on the representative and urban coefficients, particularly when a prior case can be made for imposing these restrictions. However, it should probably not be used on a regular basis.

6 Measuring Price Differences Between Urban and Rural Areas

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.

$$\frac{P_k^{Urb}}{P_k^{Rur}} = \frac{\left(\prod_{u=1}^{U} p_{ku}^{Urb}\right)^{1/U}}{\left(\prod_{r=1}^{R} p_{kr}^{Rur}\right)^{1/R}}, \tag{6}$$

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 9. The overall average differential is 11 percent (i.e., urban prices are 11 percent higher than rural prices).

Insert Table 9 Here

[24] 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.

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:

$$\ln p_{km} = \kappa + \sum_{\mu=2}^{M} \alpha_\mu x_\mu + \sum_{j=2}^{K} \beta_j y_j + \delta w + \varepsilon_{km}, \tag{7}$$

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. Abstracting from semilog coefficient bias, 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:

$$\ln p_{km} = \sum_{\mu=2}^{M} \alpha_\mu x_\mu + \sum_{j=1}^{K} \beta_j y_j + \gamma z + \delta w + \varepsilon_{km}, \tag{8}$$

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 9. 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 rural-urban 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:

$$\ln p_{km} = \kappa + \sum_{\mu=2}^{M} \alpha_\mu x_\mu + \sum_{j=2}^{K} \beta_j^{Rur} y_j^{Rur} + \sum_{j=2}^{K} \beta_j^{Urb} y_j^{Urb} + \varepsilon_{km}, \tag{9}$$

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. Again ignoring semilog coefficient bias, 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.[25] As shown in Table 9 the average differential now is 2.4 percent.

Our findings suggest 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 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 differential between rural and urban areas. When we quality adjust, we find that urban prices are only about 2.5 percent higher (taking a rough average of our three quality-adjusted estimates of 2.4, 2.6 and 2.7) than rural prices.

Standard deviations across all basic headings of the logged rural-urban price differentials are also provided in Table 9 for each country.[26] A striking feature of Table 9 is how much smaller are the quality-adjusted standard deviations than the quality-unadjusted standard deviations. Hence it follows that the quality-adjusted rural-urban price differentials are much more stable across basic headings. The lack of stability in the simple geometric mean rural-urban price differentials is probably attributable to their failure to quality adjust.

Nevertheless, we think our quality-adjusted price differential of about 2.5 percent is implausibly low. Certainly it is at odds with most of the existing literature for the Asia-Pacific region referred to in section 2.3. Part of the explanation for this difference 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 consumer in mind (as is typically done 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

[25] We thank Angus Deaton for suggesting this method to us.

[26] We take logs of the rural-urban price differentials prior to computing the standard deviation so as to make the result invariant to whether rural or urban areas are defined as the base.

price differential, while a rural product list generates a Laspeyres-type index that does the reverse. The Paasche analogy is applicable to ICP 2005.

The CPRD method recommended by the ICP TAG 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.

7 Measuring Price Differences Between Representative and Unrepresentative Products

A similar exercise can be undertaken to calculate representative-unrepresentative price differentials. The results are again shown in Table 9. 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 (9)), 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 9).

8 Conclusion

We have considered a number of ways in which the ICP methodology could be extended in future rounds. First, there is the issue of whether CPD-type methods should include representative dummies. Given that out of the nine countries in our sample 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

been desirable for the Asia-Pacific region in ICP 2005. Nevertheless, we think that at some point in the future (once countries identify representative products more consistently) the inclusion of representative dummies or something similar may be justified.[27]

ICP 2005 uses the location of purchases (i.e., urban/rural and outlet type) to calculate average prices for each country for each product within a basic heading. These average prices are then fed into the CPD-model to generate the basic heading price indexes. An alternative is to run CPD directly on the individual price quotes, and include urban and outlet-type dummies. The outlet-type data in ICP 2005 was so inconsistent as to make the inclusion of outlet-type dummies infeasible. The case though is less clear cut for the urban/rural data, although correction factors may be required if urban dummies are included in a CPD-type model. We have shown one way in which these correction factors could be calculated.

A strong case can be made on econometric grounds for correcting for heteroscedasticity and semilogarithmic coefficient bias in CPD-type regressions. In practice, however, the impact of these corrections is generally small. Pooling of CPD-type models during estimation as a means of increasing efficiency is an issue that perhaps deserves further attention. Given our preliminary analysis, we do not recommend doing this as a general rule. It may, however, be worth considering for certain groups of headings.

Finally, we have shown how CPD-type models can be used to quantify the price differential between rural and urban areas, and between representative and unrepresentative products. For our data set we find that prices in urban areas are about 2.5 percent higher than in rural areas (which may have implications for the measurement of poverty), while unrepresentative products are about 12-13 percent more expensive than representative products.

Our results have a direct bearing on the debate over the causes of the substantial downward revision in China's GDP arising out of ICP 2005. They suggest that at best one third of the revision attributable to the ICP stage 1 Asia-Pacific comparison can be explained by an excessive focus in the Chinese data on unrepresentative products and

[27] In ICP 2011 countries will be asked to identify 'important' rather than 'representative' products (where importance is defined in terms of expenditure shares). The fact that expenditure shares are more tangible should ensure that 'importance' is identified more consistently across countries.

urban areas.

The remaining two-thirds of the discrepancy may well be caused by the pre-ICP 2005 estimates simply overstating China's (and India's) GDP. Alternatively, problems with our data set could have caused us to understate the ICP stage 1 bias. First, the identification of representativity across countries in ICP 2005 may have been too inconsistent to allow a Deaton-Heston bias for China (i.e., China pricing a higher proportion of unrepresentative products) to be correctly measured. Second, a mismatch of representative and unrepresentative price quotes across urban and rural areas could have caused us to underestimate the rural-urban price differential. With a larger rural-urban price differential, the lack of rural price quotes for China could have a bigger impact on its estimated GDP.

In conclusion, we have raised a number of issues that we think should be investigated further, and that may be of interest to future rounds of ICP, and more generally to researchers interested in comparing income levels, prices and poverty across countries.

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), "China in ICP 2005." Mimeo.

Blades, Derek (2007b) GDP and Main Expenditure Aggregates. Chapter 3 in *ICP 2003-2006 Handbook*. Washington DC: The World Bank.

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 (2010), "China is Poorer than we Thought, But

No Less Successful in the Fight against Poverty." *Quarterly Journal of Economics*, forthcoming.

Cuthbert, Jim and Margaret Cuthbert (1988) On Aggregation Methods of Purchasing Power Parities. *OECD Economics Department WorkingPapers*, No. 56. Paris: OECD Publishing.

Deaton, Angus (2010a), "Using Unit-Values to Assess Rural to Urban Price Differences: Indian Evidence." Princeton University, Mimeo.

Deaton, Angus (2010b), "Price Indexes, Inequality, and the Measurement of World Poverty. *American Economic Review* 100(1), 5-34.

Deaton, Angus and Alan Heston (2008), "Understanding PPPs and PPP-Based National Accounts." NBER Working Paper No. 14499.

Deaton, Angus and Alan Heston (2010), "Understanding PPPs and PPP-Based National Accounts." *American Economic Journal: Macroeconomics* 2(4), 1-35.

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 (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. Erwin (2010), "Understanding PPPs and PPP-Based National Accounts: Comment." *American Economic Journal: Macroeconomics* 2(4), 36-45.

Dikhanov, Yuri (2010), "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.

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.

Goldberger, Arthur S. (1968), "The Interpretation and Estimation of Cobb-Douglas Functions." *Econometrica* 35, 464-472.

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. (1999), "Comparing Price Levels Across Countries using Minimum Spanning Trees." *Review of Economics and Statistics* 81(1), February 1999, 135-142.

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.

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

	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: This Table presents estimates of per capita GDP in US Dollars calculated at purchasing power parity exchange rates for 2005 derived from two sources. The first source is the World Development Indicators (WDI) Report of 2007. The second source is the official results of the International Comparisons Program. 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: Some Statistics on the Signs and Significance Levels of the Estimated Coefficients of the CPRUOD Model

Variables	Statistics	All coefficients	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 5: 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 6: Average and Maximum Differences in Price Indexes by Method

Average differences

A_k	CPD CPRD	CPD CPRUD	CPRD CPRUD	CPRD CPRDhet	CPRDhet CPRDhetken	CPRUD CPRUDhet	CPRUDhet CPRUDhetken
Bhutan	1.0814	1.0799	1.0057	1.0082	1.0020	1.0082	1.0020
Fiji	1.2570	1.2563	1.0041	1.0133	1.0129	1.0138	1.0130
Indonesia	1.0195	1.0328	1.0234	1.0069	1.0032	1.0075	1.0033
Macao	1.0112	1.0108	1.0021	1.0054	1.0003	1.0054	1.0003
Malaysia	1.0106	1.0123	1.0053	1.0072	1.0002	1.0075	1.0002
Philippines	1.0312	1.0324	1.0061	1.0108	1.0003	1.0110	1.0003
Sri Lanka	1.0829	1.0857	1.0157	1.0214	1.0007	1.0208	1.0008
Vietnam	1.0107	1.0211	1.0161	1.0086	1.0002	1.0090	1.0002

Maximum differences (worst performing basic heading in brackets)

M_k	CPD CPRD	CPD CPRUD	CPRD CPRUD	CPRD CPRDhet	CPRDhet CPRDhetken	CPRUD CPRUDhet	CPRUDhet CPRUDhetken
Bhutan	1.344 (82)	1.814 (82)	1.060 (86)	1.072 (66)	1.037 (81)	1.068 (66)	1.038 (81)
Fiji	3.348 (81)	3.329 (81)	1.033 (92)	1.487 (52)	1.521 (92)	1.510 (52)	1.523 (92)
Indonesia	1.075 (18)	1.207 (18)	1.081 (19)	1.046 (29)	1.084 (91)	1.053 (29)	1.088 (91)
Macao	1.095 (20)	1.136 (20)	1.021 (76)	1.083 (86)	1.004 (58)	1.082 (86)	1.004 (58)
Malaysia	1.075 (72)	1.079 (86)	1.028 (19)	1.068 (65)	1.004 (65)	1.070 (65)	1.004 (65)
Philippines	1.227 (30)	1.279 (30)	1.030 (30)	1.268 (52)	1.006 (65)	1.263 (52)	1.006 (65)
Sri Lanka	1.142 (86)	3.549 (86)	1.077 (92)	2.201 (86)	1.007 (65)	2.132 (86)	1.008 (65)
Vietnam	1.064 (30)	1.101 (30)	1.060 (19)	1.162 (66)	1.005 (65)	1.169 (66)	1.006 (65)

Table 7: A Comparison of Price Level Dispersion Across Methods

x	CPD	CPD	CPRD	CPRD	CPRDhet	CPRUD	CPRUDhet
y	CPRD	CPRUD	CPRUD	CPRDhet	CPRDhetken	CPRUDhet	CPRUDhetken
$\sigma x > \sigma y$	38	39	55	60	26	56	27
$\sigma x < \sigma y$	47	46	29	32	66	36	65
Z	-0.976	-0.759	2.837	2.919	-4.170	2.085	-3.962

Notes: σx denotes the standard deviation of the price levels for a particular basic heading (calculated using method x) of the countries in our sample. 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 σx) than for the CPRD method (denoted by σy). 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 8: Categories for Pooled Estimation of CPD-Type Models

		Number of basic headings		Pooling lowers
		ICP 2005	Our data set	standard error
1	Food and non-alcoholic beverages	29	29	No
2	Alcohol, tobacco	5	4	Yes
3	Clothing and footwear	5	5	No
4	Housing, water, electricity, gas, other fuels	7	5	No
5	Furnishings, household equipments, etc	13	10	No
6	Health	7	6	-
7	Transport	13	10	No
8	Communication, recreation and culture	16	14	No
9	Education	1	1	-
10	Restaurants, hotels, misc. services	12	8	Yes
	TOTAL	108	92	

Note: our list of basic headings here is restricted to those belonging to Final Consumption Expenditure by Households.

Table 9: 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 (6) or its rep-unrep variant. CPD-XXX denotes a price differential for country XXX calculated using equation (9) or its rep-unrep variant. CPUD is a price differential calculated using equation (7), CPRD is a price differential calculated using the rep-unrep variant on (7), and CPRUD is a price differential calculated using equation (8). 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.