Distribution as Expenditure*

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Abstract

Online price data provide a new and rich source of information. Yet, in the absence of information on quantities or on expenditure, researchers that use such data are (equally) averaging prices and price behavior across all products within a product group. In doing so, they introduce significant measurement error and potential bias. In this paper we address this challenge by presenting a simple methodological innovation that allows researchers to obtain information on expenditure when expenditure is not known. Specifically, we argue that measures of retail distribution – which can be computed solely from prices -- provide a good proxy for expenditure.

Through a series of simulations that use scanner-level price and quantity information on about 85% of the Fast Moving Consumer Goods (FMCGs) sold in the GCC countries, we show that treating all products equally introduces substantial measurement error and bias in the calculation of the frequency of price changes, of inflation, and of international price differences. But we also show that adding information on retail distribution reduces this error by 71%, 73%, and 75%, in the above estimations, respectively. Our findings also have implications for the work of the International Comparison Program (ICP).

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I. Introduction

Online price data offer a promising and rich new source of information for informing economic studies. Better exemplified by the work of Cavallo and Rigobon (2016) in The Billion Prices Project (BPP), these data are being increasingly used to answer questions on price behavior, market structure, and on the cost of living across time and space.[1] Because these data are up to date, easy to obtain, and they cover a very large number of retailers, locations, and products, their use in empirical work can be found across several economics disciplines.

For all their promise, these data scraped off from retailers' web sites face a major limitation: they offer no information on expenditure or on quantities. Researchers can potentially get access to prices of all products sold (and of some not sold) from a retailer's web site, but they do not know what consumers actually buy and how much. Because expenditure data is not available, at the product group level these studies treat each price observation equally by implicitly assuming that spending per product is evenly distributed within a product group.

But not all goods are made equal. While consumers purchase a variety of products, they exhibit strong preference for only a small subset of the available products and brands within any narrowly defined product group. The sales distribution is so skewed, that based on our own calculations total sales of the top 2% of grocery products per product category - in terms of sales – can account for as much as the total sales of the bottom 96%.[2] For these products, we observe that (i) sales are

[1] For information on the Billion Prices Project see Cavallo and Rigobon (2016). Cavallo and Rigobon (2011) and Cavallo (2012) use the data to study the distribution of price changes. Gorodnichenko et al. (2016) study sources of price rigidity using online price data while Cavallo (2013) uses data collected online to compare estimated inflation measures with official statistics. Cavallo (2017) finds that online and offline price data are similar in most countries and have similar behavior patterns. References within those studies provide information on additional work that uses online price data to study price behavior.

[2] Computations are based on sales of Fast Moving Consumer Goods (FMCGs) between 2006 and 2011, inclusive, in Qatar, United Arab Emirates, Oman, Bahrain, Kuwait, and Saudi Arabia. Scanner price and quantity data for 30 product categories provided by Nielsen are used for computations. A detailed description of the data follows in *Section 3*.

hundreds of times higher than sales of other products in the same category, (ii) prices are less sticky (change two to three times more often), and (iii) price differentials across retailers are much smaller due, perhaps, to the fact that consumers easily recognize them.

Since leaders and followers do exist in every product category, the practice then of averaging prices and price behavior across all products introduces significant measurement error and potential bias.

The unavailability of expenditure data at the basic heading level is also an issue that has come up in the work of the International Comparison Program (ICP). Labeled as "the largest and most complex international statistical activity in the world", the ICP aims to measure the cost of living across the world by computing purchasing power parity parities (PPPs).[3] In the 2011 round, its latest, the ICP collected price data from across 199 countries and regions. These data are used to provide direct comparisons of well-being, to compare growth rates by sector, to report price levels, and to assess poverty rates. Moreover, PPP-based GDP is used by the IMF to determine voting rights, quota subscriptions, and financing amounts for its county members. It is also used by the IMF to produce the World Economic Outlook.

Because in the data collection exercise of the ICP only prices are reported, which are then averaged to produce price aggregates at the basic heading level, measurement error is introduced. Similar to the studies that use online price data, in the ICP no weight information is collected to reflect the quantities of products sold, so all products within the same basic heading are treated equally.[4]

In this paper we propose a simple methodological innovation that enables researchers to back out expenditure shares when only prices are observed so that price observations can be weighted by importance. The methodology is easy to

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[3] http://blogs.worldbank.org/opendata/world-bank-publish-purchasing-power-parities-december013.

[4] In both the ICP and in studies that use online data, expenditure data from surveys and from the CPI are used *across* categories to aggregate data up. Our focus here is the aggregation that takes place *within* a basic heading where no weight is applied.

implement and it does not require additional resources in terms of time and cost. Additionally, it can be applied retroactively to existing price data collected online, such as those collected by Cavallo and Rigobon (2016) in the BPP. Therefore, we anticipate that the benefits from adopting the proposed approach will be significant for the ICP and for scholars working with online price data to conduct empirical work.

To see how the approach works, let us assume that we have collected prices of products across several retailers, but not quantities or expenditure. The resulting dataset will contain multiple prices per product but it will not be balanced as some products are sold in some retailers while others are not. Using only price information we can construct a metric for retailer distribution by dividing the number of outlets carrying a particular product over the total number of outlets in our sample. We call this metric numeric distribution (ND). We can also construct a measure of distribution that takes into account the size of each retailer, where the count of price observations at a given point in time (i.e. products) per retailer is used to proxy for size. We call this metric weighted distribution (WD).

Next, we project market shares for each product based on either of the two computed distribution metrics. We assume an exponential relation between market share and product distribution. That is, we assume that products available in more retailers have higher sales, and that any additional distribution point gained raises market share by more than a point. We discuss convexity parameter selection later in the paper. These projected market shares are finally used as weights in various estimations or computations of interest.

As it turns out, retail distribution is a very good proxy for expenditure. For over half a century marketing studies have documented the presence of a strong and convex relation between product market share and product distribution. Products or brands sold in more stores have higher sales. So, by knowing the number of outlets that carry a product, we claim that researchers can obtain a very good proxy for market share, even when expenditure or quantities are unknown.

We illustrate this approach and evaluate its performance in terms of reducing measurement error through a series of experiments. For these experiments, we use scanner data on Fast Moving Consumer Goods (FMCGs) sold across the Gulf Cooperation Council (GCC) countries between 2006 and 2011.

In each experiment we first compute or estimate a measure of interest using both prices and quantities. We set the outcome of this estimation to be the benchmark because it is based on actual prices consumers pay and actual quantities they purchase.

We then repeat the estimation by ignoring the expenditure information so that all products are treated (and weighted) equally. This approach reflects the approach taken by researchers working with online and with ICP data. By comparing the new estimate with the benchmark we are able to identify and quantify measurement error when expenditure or quantities are unknown and all products within a product group are treated equally.

Finally, to test whether by using information on retail distribution that is obtained solely from prices we can reduce measurement error and bring the estimate closer to the benchmark we repeat the exercise, but this time each observation is weighted by an estimated market share derived from retail distribution data.

We consider three main applications: (i) computing the frequency and magnitude of price changes, (ii) measuring inflation, and (iii) measuring PPPs across countries. We chose these applications because they span a big part of the empirical literature using micro prices, and because they cover topics of extreme importance to both policy makers and academics.

In the first application we document that the magnitude of price changes does not depend on market share, but frequency does. Products with higher sales experience more frequent price changes. As a result of this relation, we show that measuring the frequency of price changes using only price data introduces substantial downward bias. When we computed the average frequency of price changes by treating all products equally –which is the case when expenditure information is not known – we found that prices changed 21% (17% excluding sales) of the time. However, when we used actual expenditure data and weighted each product by importance, we found that prices changed 28% (23%) of the time. Not taking into account expenditure understated the frequency of price changes by a third because products with little sales and infrequent price changes were given the same importance in the calculation as products with high sales and frequent price changes.

To correct for this measurement error we repeated the exercise by discarding expenditure information (which would not have been known to researchers working with online price data), but used information on retail distribution collected from price data to proxy expenditure shares. We found that prices changed 26% (21%) of the time, which translates to a 71% reduction in measurement bias.

In the second application we measured price levels and computed inflation rates for each of the GCC countries between January 2006 and December 2011 for the FMCG product space. By not using expenditure information we understated inflation in each country by about 30%. Specifically, the democratic measure of inflation resulted in a 4.4% points lower inflation over the 6-year period than the plutocratic measure that took into account actual expenditure by consumers. However, when we computed inflation measures using prices and information on distribution, we found that prices were no longer understated, and that measurement error was reduced by 73%.

In the third and final application we computed PPPs for the six Gulf countries. Specifically, using information from the confidential World Bank ICP survey used to collect prices in 2011, we were able to simulate the ICP exercise using the scanner data without expenditure information, with expenditure information, and with information on prices and distribution but not expenditure. An interesting aspect of this exercise is that by setting a "lab experiment" we were also able to consider and evaluate several decision rules that are relevant to the ICP. For instance, we experimented with altering the number of outlets surveyed (10, 20, and 50). We also considered alternative practical rules when two or more items at a store fit the same product definition provided in the ICP product list (take the minimum, maximum, average, median, or a random price among all those products that fit the definition). We elaborate more on all these important aspects of the exercise in the main part of the paper.

In terms of measurement error, we found that using only prices at the basic heading level and excluding information on expenditure vastly overstated actual price differences across the GCC. Specifically, while we estimated prices to differ by 6% among the GCC countries when both prices and expenditure were included in the estimation, we estimated them to differ by 18% when expenditure information was excluded. In contrast, when information on numeric distribution and weighted distribution was used, we found prices to differ by 9% and 7%, respectively. Therefore, using distribution information to proxy for expenditure reduced measurement bias by 75%.

To summarize, in the absence of any information on quantities or on expenditure, using data on retail distribution, which can be computed solely from price observations on online data and data used in the ICP, can help us to identify the most important items within a product group. This works because of the convexity that characterizes the relation between market share and retail distribution. Even with noisy data, the convexity makes it easier to identify the most important products and attribute more weight on their in the estimations. And as the experiments show, the returns of such strategy in terms of reducing measurement error and potential bias and substantial.

In the following section we review the literature on retailer distribution and market share and illustrate their relation through a simple exercise. In Section III we present the data used in the applications and in Section IV we present the applications. We conclude in Section V.

2. Retail distribution and market share

Retail distribution is both a cause and a consequence of market share: higher distribution leads to increased sales, and increased sales lead to higher distribution. Nuttall (1965) attributed this relation to the market structure of retailers (few very large retailers, many tiny ones) and to their stocking decisions. Increased market share leads to higher retail distribution because many small stores with limited shelf space exist. In these stores, managers choose to carry brands with the highest market share. And retail distribution leads to higher market shares as increased product availability raises sales.

To measure retail distribution, the following metrics have been widely adopted in the marketing field:

$$\text{(1) Numeric or Physical Distribution (\%)} = \frac{\text{Number of outlets carrying product}}{\text{Total number of outlets}}$$

$$\text{(2) All Commodity Volume, ACV (\%)} = \frac{\text{Total sales of outlets carrying product}}{\text{Total sales of all outlets}}$$

$$\text{(3) Product Category Volume, PCV (\%)} = \frac{\text{Total category sales of outlets carrying product}}{\text{Total category sales of all outlets}}$$

Numeric distribution (ND), also known as *physical distribution*, reports the share of outlets carrying a particular product. It is the least data intense of the three metrics but it does not distinguish between stores with high sales and low. *All Commodity Volume (ACV)* and *Product Category Volume (PCV)* take into account variation in store size, but require more data, namely expenditure.

Several studies found strong evidence of a convex relation between retail distribution and market share, both in the cross-section and in the time-series. Nuttall (1965) studied confectionaries; Mercel (1991) cigarettes in England and Scotland; Farris, Olver, and de Kluyver (1989) tortilla chips and instant coffee in the US; Borin, Van Vranken, and Farris (1991) shampoo in Japan.

In 1995, Reibstein and Farris used scanner data from the IRI's 1988 Info Supermarket Review to test for convexity in 12 randomly chosen US grocery store categories. They first built a theoretical model to provide some conceptual foundation for the hypothesized convex relation.[5] They then tested the following logistic function that resulted from their model:

$$(4)\ \mathrm{MS} = \beta_0 ACV^{\beta_1} / (1 - ACV)^{b_2}$$

For all categories but frozen pizza they confirmed that a convex relation characterizes retail distribution and market share in the cross-section. In the time-series, the evidence were not as strong.

A decade later, Kruger and Harper (2006) from IRI expanded the Reibstein and Farris (1995) analysis by testing for the presence of convexity in 263 US product categories and 817 product groups over a period of 22 quarters between 2000:Q1 and 2005:Q2. They found evidence of convexity in 95% of the cases tested.

The evidence seem to suggest that in the absence of expenditure data, retail distribution can be used as proxy. However, for this approach to work on the datasets we have in mind - namely those that come from online sources and from the ICP price surveys -- a key prerequisite is to be able to produce measures of retail distribution solely from price data.

In the absence of expenditure data, Numeric Distribution (NUM) can be computed from online price data but ACV and PCV cannot. To account for variation in outlet size we propose an alternative metric that uses outlet product variety as indicator for outlet size. Specifically, we define Weighted Distribution (WD) as:

[5] Reibstein and Farris (1995) attributed convexity to the presence of customer loyalty, to search costs, and to uncompromised choice from the unavailability of competing brands. According to their model, distribution gives access to consumers loyal to a particular product/brand, but also to consumers whose preferred product/brand is not available. With perfect brand loyalty and/or no search costs, the relation between market share and distribution would be linear. But because search costs are non-negative and brand loyalty not perfect, the relation becomes convex.

$$\text{(5) Weighted Distribution, WD (\%)} \quad = \frac{\text{Total products of outlets carrying product}}{\text{Total products of all outlets}}$$

Counting the number of products offered by a store is a good indicator of its sales. As we show in the data section that follows, large stores carry more products, more brands, and more products per brand. Therefore, even if sales are not known, knowing the number of products sold is enough to help us distinguish between large and small stores.[6]

To illustrate how to compute the two retail distribution metrics from online data and to check whether they indeed provide a good proxy for actual market share, we conduct a simple experiment. We use an online application to collect offline prices and use those to build the two measures of retail distribution. We then use scanner data to compute market shares for each product. Finally, we merge retail distribution data and market shares and examine whether the relation between them is convex.

Feenstra, Xu, and Antoniades (2016) generously shared with us online price data for toothpaste, personal wash, shampoo, and laundry detergent products in China across 22 cities in 2014. The data come from an online application used in China to upload (offline) prices of products available in several stores in each city so that users can find which stores offer lower prices. More information on the dataset is provided in Feenstra, Xu, and Antoniades (2016).

There are several issues with these data. Firstly, there is no information on expenditure. Therefore, we do not know which products are important in terms of consumption and which are not. Secondly, there are data on about a dozen retailers or less reported in each city. The majority of retailers are not present in the app, and no information on retailer inclusion or exclusion exists. Thirdly, for each

[6] In the ICP price surveys it is not feasible to report the total number of products sold in each store. Nonetheless, price auditors can still report information on size based on store type (hypermarket, grocery, self-service) or simply the number of checkout counters.

retailer, we do not know if the reported observations provide a good indicator for the number of products sold. That is, if no price of a given barcode is reported by the app in a particular store, this either means that the product is not sold there or that it is sold but the price is not uploaded. Therefore, counting the number of products per store in the online app may not be a good proxy for actual store size.

Feenstra, Xu, and Antoniades (2016) also shared with us scanner data for these four categories provided by Nielsen. The scanner data provide barcode-level price and quantity information for each city, but prices are averaged across time (weeks) and space (retailers) in each city. Consequently, distribution cannot be obtained from the data.

We use the online price data to measure distribution (NUM and WD) for each product that appears on the app in each city. We use the Nielsen dataset to measure the category market share of each product in each city. Because prices in the Nielsen dataset are averaged across all retailers in the city, no information on distribution can be extracted. We then merge the two datasets, so that for the majority of the barcodes found in the online application we can observe both distribution and market share information. Finally, we allocate the products into bins based on market share, and take the median retail distribution (NUM or WD) across all products in each market share bin.

Scatter plots of distribution and market share for each product category are reported, first using the NUM measure (*Figure 1, left panel*), and then using the WD (*Figure 1, right panel*). The figure confirms a convex relation between the constructed retail distribution measures built from the online data and the market shares obtained from the barcode Nielsen data, for all the product categories. And we were able to confirm convexity despite the data issues discussed above that may have compromised our ability to measure retail distribution accurately.

The implications are significant. As in Feenstra, Xu, and Antoniades (2016) scholars can exploit the relation to predict market share from distribution information obtained only from prices, and then they can use the predicted market share to weight products based on importance. We elaborate more on this next as we consider several additional experiments. But first, we present the data that are used for the rest of the paper.

2. Data

The data come from AC Nielsen and cover sales of Fast Moving Consumer Goods (FMCGs) in six Gulf Cooperation countries (GCC): Bahrain, Qatar, Oman, Kuwait, United Arab Emirates, and Saudi Arabia. Price and quantity information for thousands of products (barcodes) across 30 product categories between the period January 2006 and December 2011 is provided.[7] The frequency is monthly or bi-month, and according to Nielsen, these data cover about 85% of all the FMCGs consumed in the Gulf Cooperation Council (GCC) countries.

Three important characteristics of the dataset are worth highlighting. First, the data is provided for *each* store, across thousands of stores. By analyzing the data at the store level we are able to provide stylized facts on retailers. We are also able to accurately measure retail distribution. Second, prices are reported during the day of the audit in each period. They are not averaged out across all days within a period. This allows us to measure the frequency and magnitude of price changes across periods without measurement error.[8] Third, most of the products we study are imported, many of the consumers in these markets are expatriates (as many as 85% in Kuwait and Qatar), and several international retailers operate in the markets. This suggests that the findings we present below could be generalized with some confidence to other economies outside the Gulf.[9]

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[7] The categories are: beans, blades, bullion, cereals, cheese, chewing gum, chocolate, cigarettes, cooking oil, carbonated soft drinks, deodorants, detergents, dish wash, energy drinks, fabric conditioners, insecticides, juices, liquid cordials, male grooming, milk, milk powder, powder soft drink, shampoo, skincare, skin cleansing, sun care, tea, toothbrush, toothpaste, and water.

[8] In many cases, Nielsen provides price data that are averaged across the period of interest (e.g. week or month). This practice prevents researchers from accurately measuring the frequency and magnitude of price change. For more on the time averaging measurement error in the Nielsen data, see Cavallo 2016c).

[9] Antoniades and Zaniboni (2016) make a similar point. The authors use a subset of this dataset to study retailers' pass-through into consumer prices in the United Arab

Descriptive statistics for the dataset are provided in *Table 1*. In total, the dataset provides price and quantity information on 203,719 products sold in 5,851 outlets over a period of six years. Qatar and Bahrain are the smallest economies in terms of population, and Saudi Arabia the largest. The majority of products do not exist across all periods and all outlets.

Sales of FMCGs are highly concentrated to a handful of products per category. The typical distribution of product market share per category is shown in *Figure 2a*.[10] In every product category a few products (on the left) account for the majority of sales, while a very large number of others (on the right) account for little sales.

Moreover, the relation between market share and retail distribution is convex in most product categories, regardless of which measure of distribution is applied. The relation is illustrated in *Figure 2b.*

In the previous section we made the assertion that counting the number of available products is a good proxy for store size. To provide support for this assertion, in *Figure 3* we plot average monthly sales by store in UAE in US dollars on the vertical axis with store ranking on the horizontal axis. Rankings are based on sales and stores are ranked from smallest to largest. Out of 976 outlets available in the sample, about a couple of dozen stores account for the majority of sales. The rest are tiny stores with little sales. Next, we plot the average number of products, brands, and products per brand sold by each store each month, while maintaining the size ordering of outlets (Table 2, remaining quadrants). We conclude that a substantial variation in store sales exist within a country, and that large stores offer more

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Emirates. They measure one-year pass-through to be 20%, which they find to be similar to estimates obtained using micro data in advanced economies.

[10] Because of data confidentiality, we are prohibited from disclosing any information at the product level. However, the convex relation documented in the Figure 2a is well known in the marketing literature and it can be replicated with any other scanner dataset that does not impose restrictions on its use.

products, brands, and products (varieties) per brand. The results for the other five countries are identical and omitted for brevity.[11]

4. Applications

So far, we have shown that product market share increases with retail distribution. Next, we illustrate how we can exploit this relation to obtain a proxy for expenditure when expenditure is not observed but prices are. We show this in three different applications: (1) measuring the frequency and magnitude of price changes, (2) measuring price levels and inflation, and (3) measuring PPPs.

While each application differs in nature, the core of the exercise is the same and consists of three steps. In the first step we use actual price and quantity (expenditure) information from the Nielsen dataset to compute or estimate a measure of interest, such as inflation or the frequency of price changes. Because this estimation uses the highest level of information, and because it takes into account differences in consumption (namely that some products are more popular than others), the outcome of the estimation will be the closest to the true measure of interest. Therefore, we set the outcome of this estimation to be the benchmark by which the results of the alternative estimations will be compared to.

In the second step we compute or estimate the same measure of interest but this time we use only prices and treat all observations equally. This estimation mimics the work of the ICP and of studies that use online price data, ignore expenditure data, and treat each product equally. We then compare these estimates with the benchmark case and attribute the documented differences to the presence of measurement error (or bias) that arises from assuming that all products matter the same.

Finally, in the third step we exclude any information on quantities or on expenditure but use measures of retail distribution extracted solely from price data to predict

[11] In our data, we also find evidence that product prices fall as outlet size increases. That is, we find that larger stores have lower prices.

market shares. We then use these predicted market shares as weights in the estimations. The outcome of this estimation allows us to see whether using retail distribution reduces measurement error and by how much.

To get predict market shares using NUM or WD, we impose the following two functional forms, respectively:

(6) Predicted Market Share = exp{-7.50 + 4.75*NUM}
(7) Predicted Market Share = exp{-7.90 + 114.7*WD}

The chosen functions capture convexity. In general, the coefficients will not be known to the econometrician. Here, however, we take advantage of the Nielsen data to compute both retail distribution and market share for each product and each period. We then pooled together all the data and regressed product retail distribution on log market share in order to obtain the coefficients of interest.

The results from these regressions are reported in *Table 2*. Columns 1 and 2 present results from regressing *ln(market share) on ND*, and Columns 3 and 4 on *WD*. Even columns include country-fixed effects.

The coefficients from the regressions that impose the least structure (namely columns 1 and 3) were chosen to calibrate *equations (6)* and *(7)* above.

For robustness, we replicated the analysis, but this time we ran a separate regression for each country-category combination. The results, which are available in *Appendix A*, allow us to observe how the two convexity coefficients changes across countries and product groups. We use this information for robustness check as we evaluate how sensitivity of our results are to alternative parameter specifications. We find that the that including measures of retail distribution reduces measurement error for a very generous range of coefficients, as long as the functional form used to link distribution and market share maintains convexity.[12]

[12] These results are important and will be added as a separate sections soon.

4.1 Frequency and magnitude of price changes.

We first compute the frequency and magnitude of price changes. We consider two methodologies for computing price changes: counting gaps in the price line, and carrying forward the last observed regular price through sale and stockout periods (for gaps of six months or less). We also consider estimates with or without sales included. For sales, we use a basic definition that identifies sales from a V-shape behavior in price. These measures are widely used in the literature. For more information, see Nakamura and Steinsson (2008).

We first plot the frequency and magnitude of price changes in UAE by allocating products into bins based on their market share. For each market share bin we take the average frequency, the average price change (conditioning on a price change taking place), the average price change for price increases, and the average price change for price decreases across all categories. We report these scatter plots for the non-sales, no-carry-forward case in *Figure 4*.[13]

We observe that the magnitude of price change does not depend on market share (*Figures 4b, 4c,* and *4d*) but frequency does (*Figure 4a*). Products with high sales experience more frequent price changes. This suggests that in the absence of any information on quantities or on expenditure that would allow us to distinguish between important and non-important products, averaging the frequency of price changes across all products overstates the degree of price stickiness in the economy.

Table 4 confirms that hypothesis. The frequency and magnitude of price changes in UAE is computed under three alternative specifications: (i) using expenditure information as weights (*column 1*; benchmark), (ii) excluding expenditure information and weight all products equally (*column 2*), and (iii) excluding expenditure information but use retail distribution to weight all products (*column 3*). *Panel A* reports computations for the frequency of price changes, and *Panel B* for

[13] Scatter plots for the other cases and countries are identical and omitted. Scatter plots are also identical when the median frequency in each bin is computed instead of the average.

the magnitude. *Columns 4* and *5* report the difference between the estimated number and the benchmark case.

When both prices and quantities are taken into consideration, we find that prices change 30% of the time. However, when information on expenditure is not known and all products are treated equally, prices appear to be stickier as they change only 23% of the time (a 23% drop in price variability from the benchmark case). Including retail distribution reduces measurement error (and the downward bias) substantially. With retail distribution information we find that prices change 27% of the time, a deviation of only 10% from the benchmark case. The results from alternative measures of frequency (*rows 2 ,3,* and *4*) provide the same conclusion: using retail distribution as a proxy for expenditure reduces measurement error and potential bias.

Unlike the case of the frequency, the magnitude of price changes does not depend on market share (see *Figure 4b*, *4c*, and *4d*). Therefore, we should not expect to see substantial variation in the estimation under alternative estimation methods. Indeed, this is confirmed in *Panel B* where the estimated magnitude of price changes does not change across columns.

4.2 Price levels and inflation

We measure inflation in each of GCC country using bi-monthly scanner data for 30 product categories of FMCGs between the periods January 2006 and December 2011. To measure inflation we estimate the model below with and without weights and we collect the time fixed effects:

(8) $\ln(\text{price})_{it} = a_0 + \mathbf{A}^*(\text{TIME FIXED EFFECTS}) + \mathbf{B}^*(\text{PRODUCT FIXED EFFECTS}) + \varepsilon_{it}$

where i identifies products; A is a vector of time fixed effects; and B a vector of product (barcode) fixed effects. In the version of the estimation that includes weights, we either use actual market shares, or we use predicted market shares based on retail distribution measures (ND and WD). Prices are averaged across outlets in each particular period.[14]

The estimated coefficients of the time fixed effects are plotted in *Figure 5* for all countries and cases. In each country, measuring inflation using only prices understates the true increase in prices over the sample period. In fact, the democratic measure of inflation that does not take into account expenditure weights understates prices by about 4.4% (a 30% deviation from the actual inflation rate over the five-year period). *Table 5* reports the root mean square error between each alternative measure of inflation and the benchmark case over each period (*columns 1*, *2*, and *3*). It also reports the end-of-period gap between each alternative measure and the benchmark (*columns 4, 5*, and *6*). In all cases, excluding weights understates the true level of inflation. However, including information on retail distribution reduces measurement error by about 73%.

4.3 The International Comparison Program

The International Comparison Program (ICP), a collaboration between the World Bank and national statistical agencies, is an initiative under the United Nations with the mandate to measure the relative cost of living across the world. Every few years, the World Bank puts together and distributes an extensive price survey to statistical agencies worldwide. The survey is broken down into product groups (e.g. "Bread and Cereals"; "Miscellaneous goods and services") and each product group into several basic headings (e.g. "Other cereals, flour, and other products"; "Appliances, articles and products for personal care"). Each basic heading contains a list of very detailed product definitions (e.g. " Cornflakes Kellogg's 500 gram, range 250-600 gram, milled corn (maize) pre-packed, ready to eat cereals, sugar and/or other ingredients"; "Tooth paste, tube, 80 mL, range 50-100 mL, Colgate, Classic Total, exclude whitening"). Its content varies by year and region and is highly confidential. Statistical agencies are asked to price each item in a number of stores and report back average price. Product prices are then used by the World Bank to

[14] We also experimented with taking the median, min, max, and random price across outlets. The results do not change (except for the case of the min price) and are available in the *Appendix* for review.

compute price levels for each basic heading, for each product group, and for the overall basket. At the basic heading level, because expenditure information for each product is not known, prices are averaged across all products by assuming identical weights. Then prices for each basic heading are aggregated up using expenditure information from the components that comprise the national CPI data.[15]

As straight forward as this exercise sounds, it presents an extremely daunting undertaking in terms of methodology and administration. There are issues that arise in the pre-survey (e.g. how to construct the baskets), during the survey (e.g. how to price), and the post-survey (e.g. how to aggregate) stages. Rightly, the World Bank characterizes the ICP as the largest and most complex statistical exercise in the world.[16]

In this third and final exercise, we consider the averaging of prices at the basic heading level and ask whether this practice introduces measurement error and potential bias. Because prices of the most important items may converge faster across retailers and across countries for consumers pay more attention, taking an unweighted average price across all items within the basic heading can bias measures of differences in the cost of living across countries upward.

To check this, we use the scanner data to simulate the ICP under alternative scenaria that are described below. We begin by extracting from the World Bank 2011 confidential ICP survey the product definitions that overlap with the Nielsen scanner FMCG data. These are: (i) blades – 2 definitions, (ii) cereals – 4 definitions, (iii) detergents – 2 definitions, (iv) juices – four definitions, and (v) toothpaste – 1 definition. Examples of definitions selected are "Cornflakes Kellogg's 500 gram,

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[15] I would like to thank the World Bank, especially Nada Hamadeh, for sharing with me a copy of the 2011 product survey. More information on the 2011 ICP survey is available at http://siteresources.worldbank.org/ICPEXT/Resources/ICP_2011.html.

[16] Two recent papers highlight key challenges in the ICP methodology. Deaton and Aten (2017) discuss the challenge of linking countries and regions together, while Inklaar and Rao (2017) compare and contrast alternative measurement methodologies. Antoniades (2016) succinctly captures key challenges in the collection of raw data with the 4Rs: the challenge finding: (i) the right product, (ii) the right weight, (iii) the right price/retailer, and (iv) the right variety.

range 250-600 gram, milled corn (maize) pre-packed, ready to eat cereals, sugar and/or other ingredients" and "Tooth paste, tube, 80 mL, range 50-100 mL, Colgate, Classic Total, exclude whitening". For confidentiality purposes, we omit to report the remaining eleven definitions.

While only 13 product definitions survive the matching, a total of 2,069 barcode products are selected. This happens because multiple varieties of the same product (barcodes) match the same ICP product description. Colgate Total 100ml, Colgate Total 100ml PD, Colgate Total 100ml Pump, Colgate Total 12 100ml, Colgate Total Fresh Stripe 100ml, and their 50ml variations all satisfy the ICP product definition "Tooth paste, tube, 80 mL, range 50-100 mL, Colgate, Classic Total, exclude whitening". For a full list of products that fit the same definition in the case of toothpaste and cereals see *Table 5*. The availability of multiple varieties of the same product, which we call variety bias, poses an important challenge for price auditors as they have to pick one of potentially several different prices. In the simulation, we experiment with alternative pricing rules. These are discussed below.

With the construction of the survey completed, the simulation is broken down into two parts: data collection and estimation. In the data collection part, we provide the simulation with a set of rules that mimick the actual process. Specifically, we first input the number of stores to be audited (*n=10, 20, or 50*). We then ask the simulation to pick those *n* stores out of the universe of outlets in our sample by selecting the largest stores first. If all supermarkets/hypermarkets are exhausted, the algorithm randomly picks the remaining from the population of groceries and mini-markets. This is an important stage as prices vary across stores, with the largest stores offering lower prices. Next, we ask the simulation to randomly pick a date for the audit out of the six bi-monthly periods in 2011. Finally, we give guidance as to which price must be quoted if multiple varieties of a product at a store satisfy the same definition. The six alternative rules are: (1) take an average price, (ii) take the median price, (iii) pick a price at random, (iv) pick the lowest price, (v) pick the highest price, and (vi) pick the price of the item you think is the most important based on sales (which can be asserted from shelf space). While the average and median rules are less practical, for the majority of cases where a handful of varieties exist, they can be easily computed on the spot.

Once prices are collected in each country, the country-product-dummy (CPD) regression

(9) $\ln(\text{price})_{ic} = a_0+\mathbf{A}^*(\text{CFE})+\mathbf{B}^*(\text{PFE})+\varepsilon_{ic}$

is estimated across the thirteen product definitions indexed by *i* in the countries indexed by *c*. *CFE* and *PFE* capture country and product fixed effects, respectively. PPPs, relative to the numeraire (in this case Bahrain) are obtained from the exponent of the CFEs. For example, if the exponent of the KSA coefficient is 1.2, then prices in Saudi Arabia are 20% higher than in Bahrain.

Three versions of the equation above are estimated. *Version 1*, the benchmark, considers both price and expenditure information so that each observation is weighted by importance. *Version 2* mimics the ICP by omitting expenditure information by treating all products equally. *Versions 3* and *4* omit expenditure information but use information on numeric (ND) and weighted (WD) distribution, respectively, to weight the data.

To ensure that the results are not sensitive to the random selection of time period and outlets, the exercise is repeated 50 times. Each time, average PPP difference across the GCC countries are collected, and the median difference across these 50 iterations is reported in *Table 6* for alternative specifications. The first column indicates the rule specified for dealing with variety bias (explained above). The second column lists the number of outlets audited. The next four columns report the estimation results under the four alternative methods.

For instance, the first row of the table lists average PPP differences for the scenario where 10 outlets are audited and price auditors are asked to report back average price in case multiple products satisfy the same PPP product description. When both prices and expenditure information is used (version 1 - benchmark), prices in the

GCC differ by 6%. However, when only prices are used and all products are treated equally, prices differ by 18%. Regardless of how many outlets are audited or which rule is used to deal with variety bias, excluding weights overstates PPP differences by a very large margin.[17]

However, when information on numerical and weighted distribution is used to project expenditure shares (versions 3 and 4), estimated average PPP differences are in line with the benchmark case.

To summarize, the main lessons from this exercise is that (i) treating all products equally overstates the true cost of living, (ii) increasing sampling size does not improve or worsen estimates, (iii) taking the lowest or median price is a better rule for dealing with variety bias, and (iv) projecting expenditure shares from retail distribution reduces measurement bias substantially.

5. Conclusion

The availability of data on prices that can be collected online presents a new opportunity for researchers to study prices and price behavior. Yet, as we documented in this paper, the unavailability of information on quantities or expenditure introduces substantial measurement error, and in many cases bias. By treating all prices equally, researchers may understate the cost of living, overstate price stickiness, and overstate price differences.

To overcome the challenge imposed by the lack of expenditure data we propose that researchers can use information on retail distribution to proxy for expenditure. By exploiting the convexity that characterizes the relation between retail distribution and market share, one can build measures of retail distribution solely from price data, and use these to back out expenditure shares. This approach helps identify the most important items within a product groups, and thus, it allows researchers to weight the data accordingly in the estimation.

We illustrate that the proposed approach works well by reducing measurement error by about 70% or more, when measuring the frequency of price changes, inflation, and international price differences.

[17] For robustness, we also report estimation results when the average (instead of the median) across the 50 iterations is computed. The results, which are available in the Appendix, are identical to those reported in *Table 6*.

Adopting the methodology will benefit those working with price data scrapped off from retailers' web sites or from online applications and will also benefit those working on the International Comparison Program.

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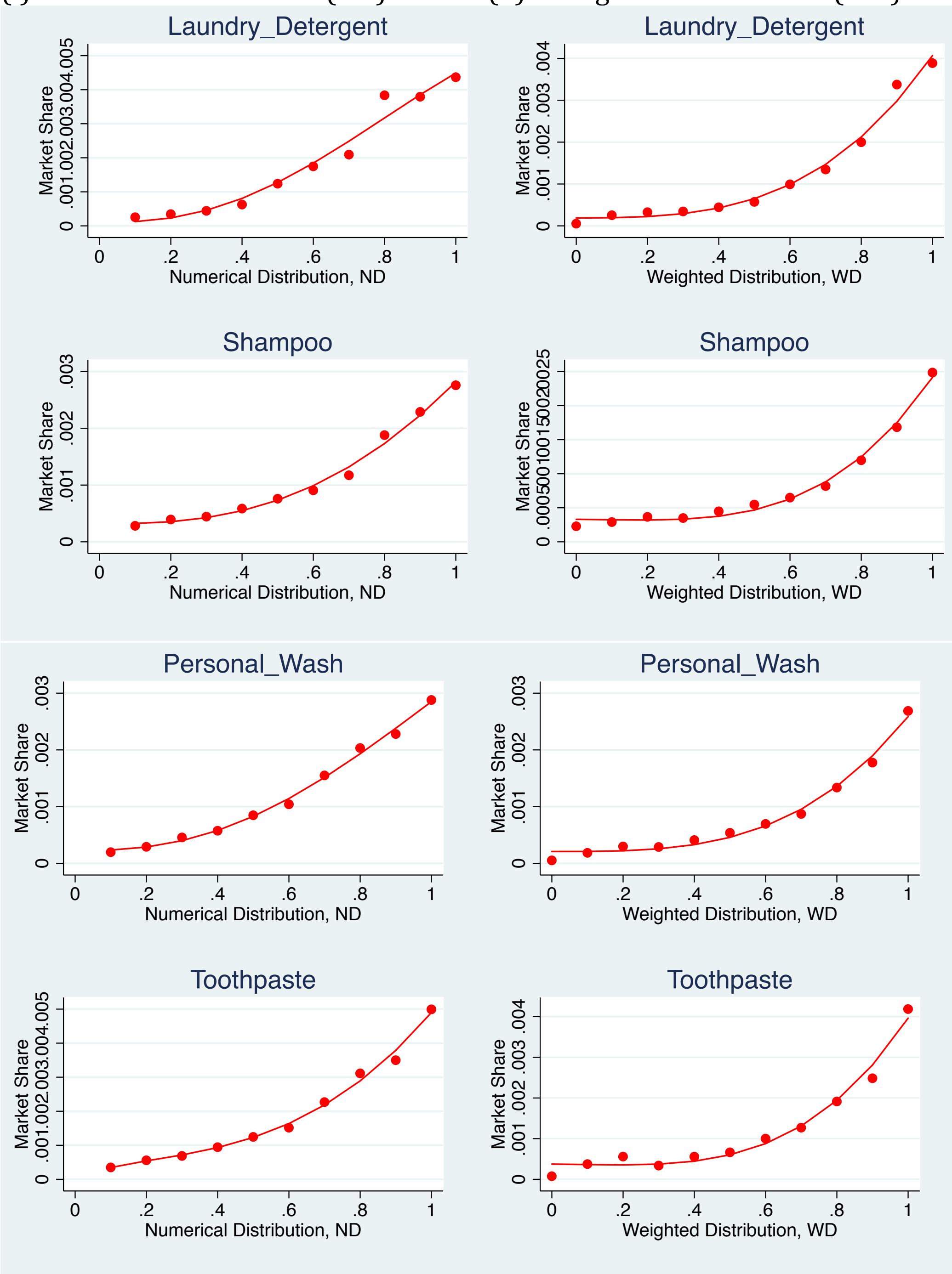
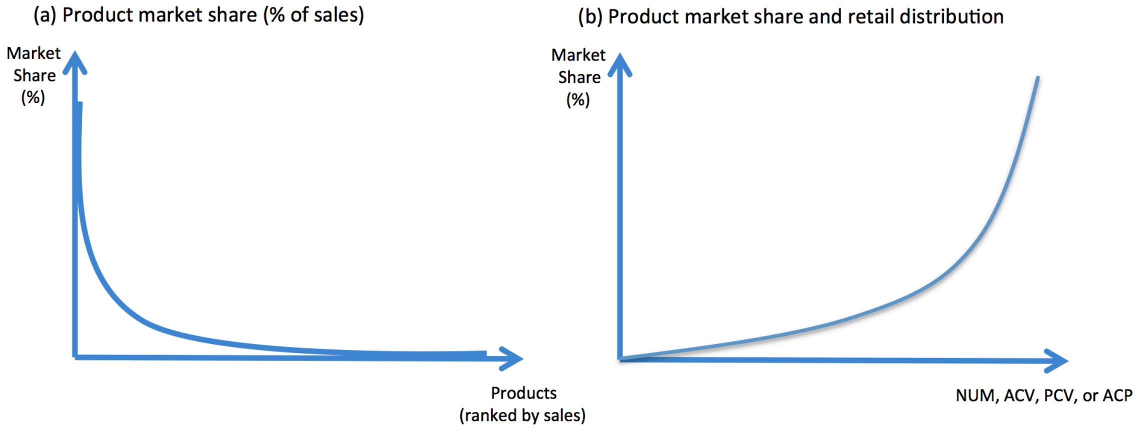
Figure 1 – Numerical Distribution and Market Share, Chinese data

(i) Numeric Distribution (ND) (ii) Weighted Distribution (WD)



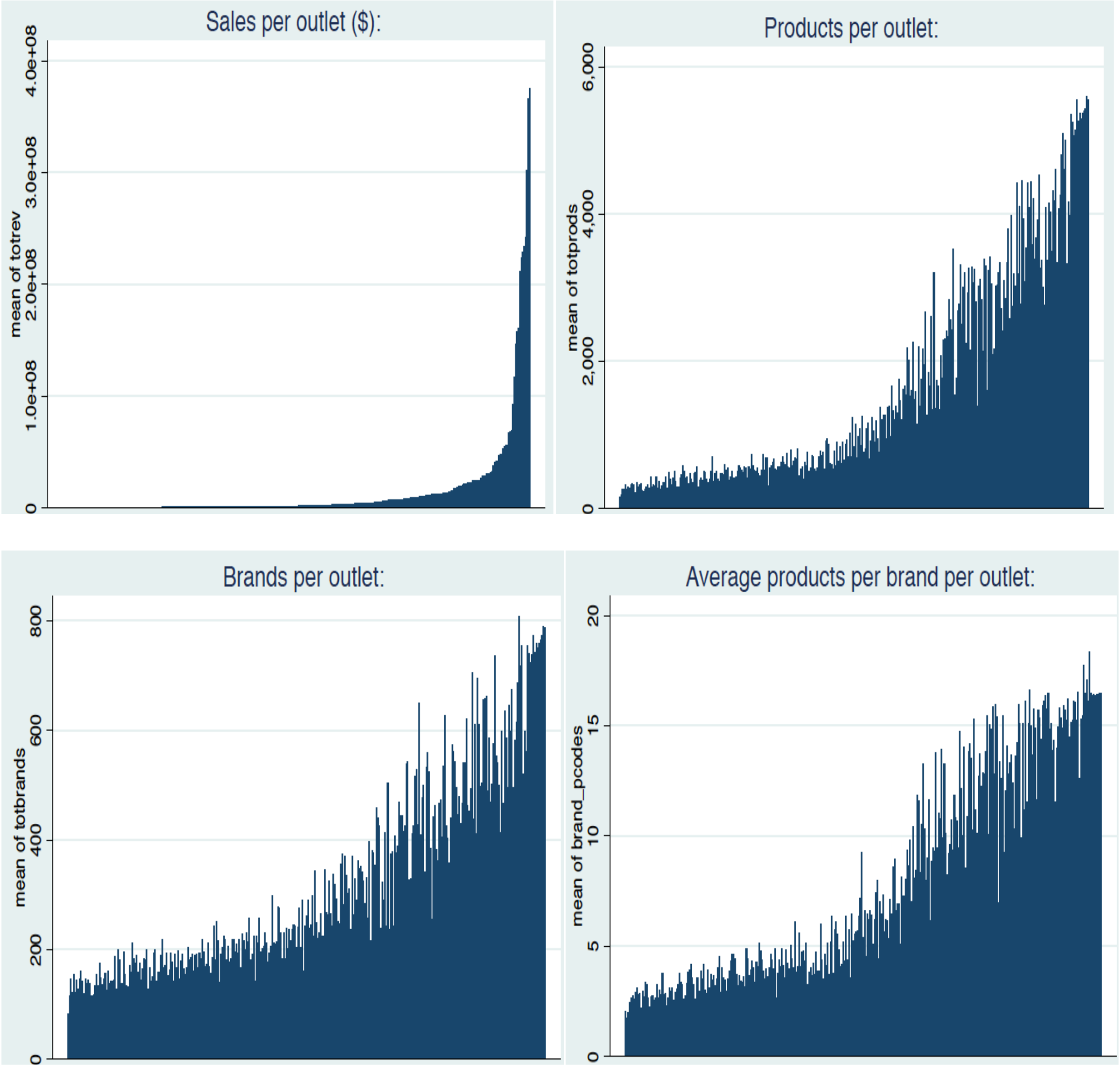
Notes:
We use price data from an online app in China to compute retail distribution (ND and WD) and Nielsen scanner data to compute market shares for products in laundry detergent, shampoo, personal wash, and toothpaste categories. Products are allocated into bins based on retail distribution (x-axis) and the average market share of all products within a bin is plotted on the graph, against measures of numeric distribution (ND; left), and weighted distribution (WD; right). From more info of the data, see Feenstra, Xu, and Antoniades (2016).

Figure 2 – Market shares and distribution



Notes:
The left graph illustrates a typical distribution of market shares for any product category of Fast Moving Consumer Goods (FMCGs) based on computations across 30 product categories in six GGG countries over a period of 6 years. In almost all cases, a small number of products account for the majority of sales, while the large proportion of products account for little sales. The right diagram illustrates the typical (convex) relation between product market share and alternative measures of retail distribution defined in *equations (1), (2), (3),* and *(5)* in the paper.

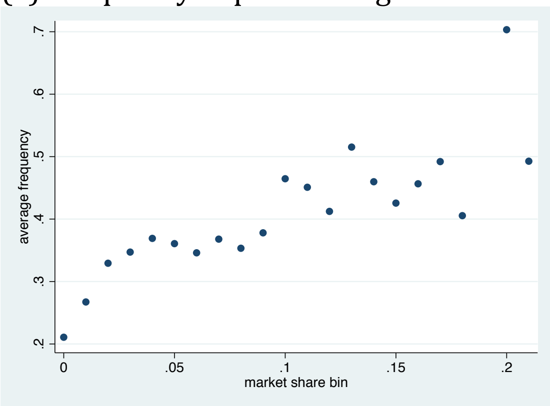
Figure 3 – Facts on retailers' heterogeneity, UAE



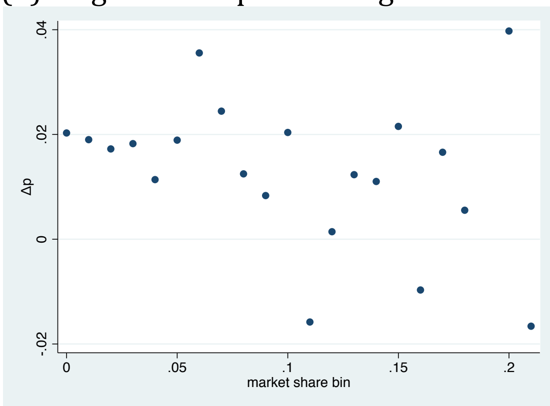
Notes:
Retail outlets in UAE are ranked based on average monthly sales (top, left). Monthly sales are computed from Nielsen scanner data across 30 product categories between Jan 2006 and Dec 2011. Products per outlet (top right), brands per outlet (bottom, left), and average products per brand per outlet (bottom, right) are shown for each retail outlet while maintaining the ranking.

Figure 4 – Frequency and Magnitude of Price Changes

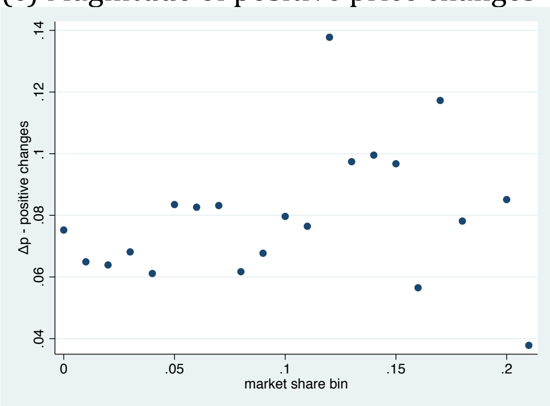
(a) Frequency of price changes



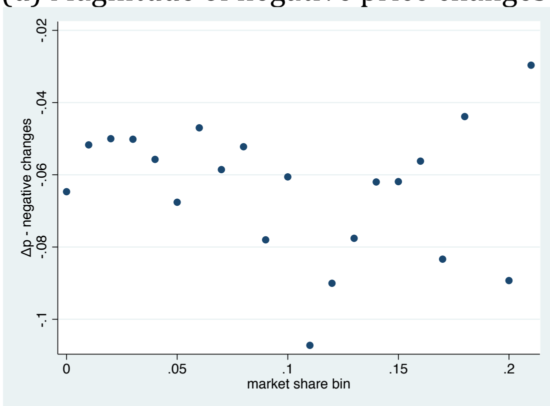
(b) Magnitude of price changes*



(c) Magnitude of positive price changes



(d) Magnitude of negative price changes

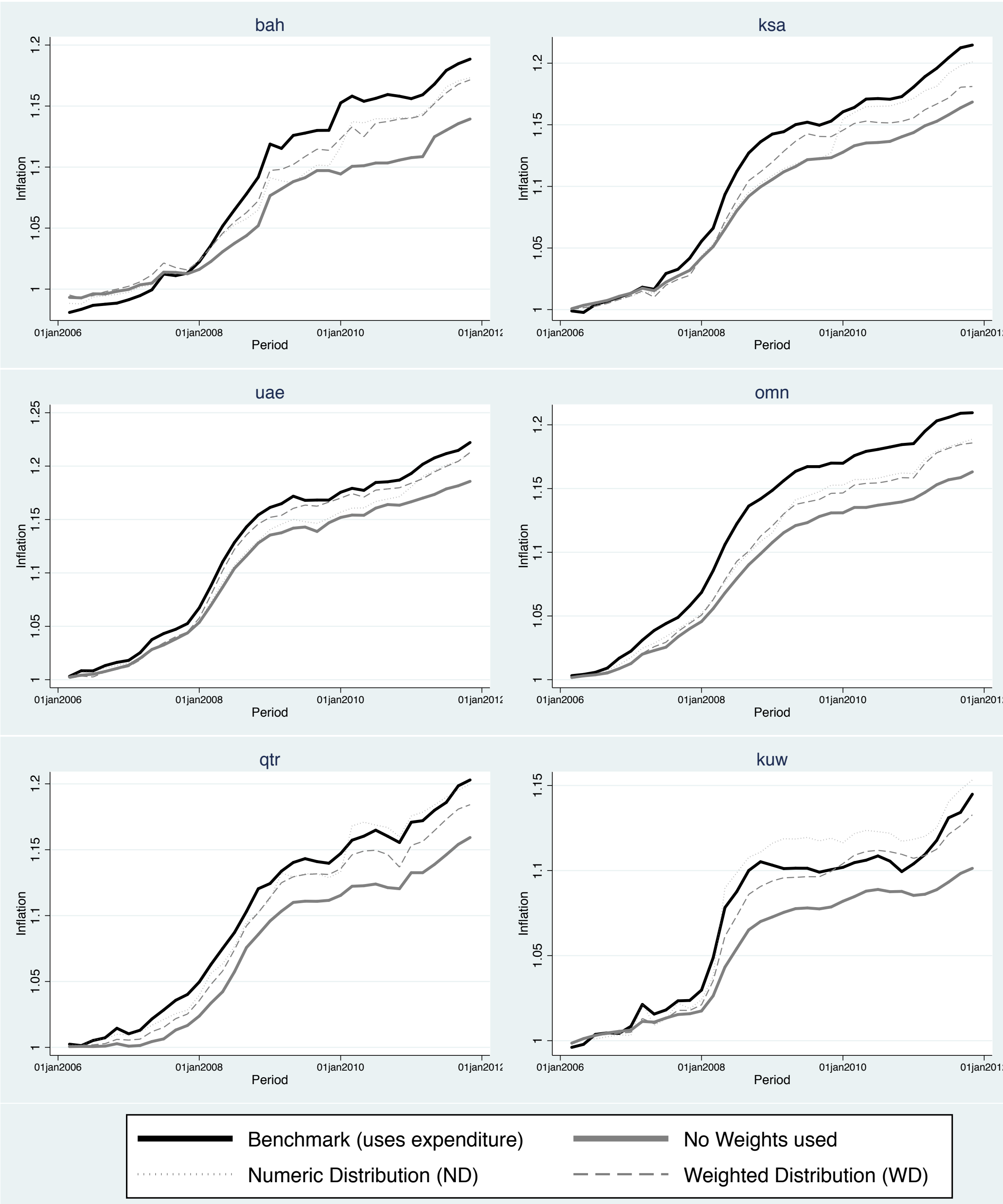


Notes:

*conditioning on a price change taking place.

We use Nielsen scanner data in UAE between Jan 2006 and Dec 2011 to compute the market share of each product in its product category and region. We also compute the frequency and magnitude of price changes for each product. Products are allocated into bins based on market share, and the average frequency and average magnitude of price changes in each bin are plotted. While the magnitude of price changes does not seem to depend on market share, the frequency does. Products with higher sales experience more frequent price changes.

Figure 5 – Inflation Measures



Notes:
We compute inflation measures between Jan 2006 and Dec 2011 for each of the GCC countries using four alternative specifications: (i) use prices and expenditure (solid black line), (ii) use only prices (solid grey line), (iii) use prices and information on numerical distribution (dotted grey line), and (iv) use prices and information on retail distribution (dashed grey line). In all cases, when information on expenditure is ignored and all products where treated equally, inflation was understated. Using, however, information on retail distribution obtained from prices reduces the measurement bias significantly.

Table 1 – Descriptive Statistics for the GCC Nielsen data

Country	Categories	Products	Brands	Retailers	Start Date	End Date
Bahrain	30	24,259	2,168	311	Jan-06	Dec-11
Kuwait	30	37,660	3,052	285	Jan-06	Dec-11
Oman	30	40,165	3,442	614	Jan-06	Dec-11
Qatar	30	24,150	1,474	267	Jan-06	Dec-11
Saudi Arabia	30	34,447	3,030	3,398	Jan-06	Dec-11
United Arab Emirates	30	43,038	3,650	976	Jan-06	Dec-11

Table 2 - Market Share and Distribution Regression Results

	Dependent variable: ln(market share)			
	(1)	(2)	(1)	(2)
Numeric Distribution, ND	4.753***	4.818***		
	(0.000706)	(0.000702)		
Weighted Distribution, WD			114.7***	131.9***
			(0.0186)	(0.0185)
Country FE	NO	YES	NO	YES
Constant	-7.499***	-7.252***	-7.900***	-7.569***
	(0.000263)	(0.000796)	(0.000333)	(0.000795)
Observations	68,882,587	68,882,587	68,882,587	68,882,587
R-squared	0.397	0.410	0.356	0.429

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3 – Frequency and Magnitude of Price Changes

	Measures			Measurement error (% change from benchmark case)	
	Benchmark (P&Q)	P	P & NUM	P	P & NUM
	(1)	(2)	(3)	(4)	(5)
	A. Frequency of Price Changes				
(i) With sales					
Continguous observations	0.30	0.23	0.27	-23%	-10%
Carrying regular price forward during sales and stockout	0.28	0.21	0.26	-25%	-7%
(ii) Without sales					
Continguous observations	0.24	0.19	0.22	-21%	-8%
Carrying regular price forward during sales and stockout	0.23	0.17	0.21	-26%	-9%
	B. Magnitude of Price Changes				
All changes*	0.024	0.026	0.027	10%	14%
Price increases	0.068	0.072	0.072	6%	5%
Price decreases	-0.055	-0.061	-0.059	10%	7%

* conditioning on a price change taking place.

Table 4 – Inflation measures

	Root Mean Square Error			Total Gap		
country	No WGT	ND	WD	No WGT	ND	WD
	(1)	(2)	(3)	(4)	(5)	(6)
Bahrain	0.13	0.03	0.01	-4.9	-1.5	-0.7
Saudi Arabia	0.08	0.03	0.02	-4.6	-1.4	-3.3
Kuwait	0.05	0.01	0.00	-4.4	0.8	-0.2
Oman	0.13	0.04	0.03	-4.6	-2.1	-1.3
Qatar	0.09	0.01	0.00	-4.4	-0.3	-0.6
UAE	0.05	0.02	0.00	-3.6	-1	0.1
Average	**0.08**	**0.02**	**0.01**	**-4.4**	**-0.9**	**-1**

Table 5 – Examples of products that fit the same ICP PPP product description

Cornflakes Kellogg's 500 gram, range 250-600 gram, milled corn (maize) pre-packed, ready to eat cereals, sugar and/or other ingredients"	Tooth paste, tube, 80 mL, range 50-100 mL, Colgate, Classic Total, exclude whitening
1 KELLOGG'S CORNFLAKES 375GR (F)(ARABIC)	1 COLGATE 100ml TOTAL
2 KELLOGG'S CORNFLAKES 500GR (F) (ARABIC)	2 COLGATE 100ml TOTAL PUMP
3 KELLOGG'S CRUNCHY NUT CORNFLAKES 500GR(F	3 COLGATE 50ML TOTAL 12 CLEAN MINT (FAC)
4 KELLOGG'S HONEYNUT CORNFLKE.375GR(F)(ARA	4 COLGATE 50ml TOTAL
5 KELLOGGS 375g CORN FLAKES	5 COLGATE 50ml TOTAL 12 CLEAN MINT
6 KELLOGGS 375g CRUNCHY NUT CORN FLAKES	6 COLGATE TOTAL 100 ML
7 KELLOGGS 375g HONEY NUT CORN FLAKES	7 COLGATE TOTAL 100ML
8 KELLOGGS 500g CORN FLAKES	8 COLGATE TOTAL 100ML PD
9 KELLOGGS 500g HEALTH WISE BRAN FLAKES	9 COLGATE TOTAL 100ML PD(M.BEN/FL)
10 KELLOGGS ALL BRAN FLAKES 375 GM PKT	10 COLGATE TOTAL 100ML PUMP
11 KELLOGGS C/F 250G (F)	11 COLGATE TOTAL 100ml PD
12 KELLOGGS C/F 375G (F)	12 COLGATE TOTAL 12 100ML PUMP
13 KELLOGGS C/F 500G (F)	13 COLGATE TOTAL 12 50ML
14 KELLOGGS CHOCO CF 375g (ARABIC)	14 COLGATE TOTAL 12 50ml
15 KELLOGGS CORN FLAKES 250GR PKT	15 COLGATE TOTAL 12 CLEAN MINT 50ML GUM
16 KELLOGGS CORN FLAKES 375GR PKT	16 COLGATE TOTAL 12 CLEAN MINT 50ML(FAC)
17 KELLOGGS CORN FLAKES 500 GR PKT	17 COLGATE TOTAL 12 CLEANMINT 50ML (COS)
18 KELLOGGS CORNFLAKES 375g ARABIC	18 COLGATE TOTAL 50ML
19 KELLOGGS CORNFLAKES 500g BOX ARABIC	19 COLGATE TOTAL 50ML (GUM)
20 KELLOGGS CRUMBS CORN FLAKES 595GR(A)ENG	20 COLGATE TOTAL 50ML CLEAN MINT PROT. GUM
21 KELLOGGS CRUNCHYNUT CORNFLAKES 375g ARAB	21 COLGATE TOTAL 50ML(GUM)
22 KELLOGGS FROSTED FLAKES 496GR (ENG)(C)	22 COLGATE TOTAL 50ml
23 KELLOGGS FROSTED FLAKES CORN 397GR(CRT)C	23 COLGATE TOTAL CLEAN MINT 50ml
24 KELLOGGS HONEY NUT C/F 375GR (A)	24 COLGATE TOTAL FRESH STRIPE 100ML
25 KELLOGGS HONEY NUT CORN FLAKES 375GR	
26 KELLOGGS HONEY NUT CORN FLAKES 375g BOX	
27 KELLOGGS M.GRAIN CORNFLAKES 375G(A)CRT(E	
28 KELLOGGS MULTIGRAIN C/FLAKES 375GR PKT	
29 KELLOGS C.F 250GM	
30 KELLOGS C.F 375GM	
31 KELLOGS C.F 500GM	
32 KELLOGS C.F ARABIC 250GM	
33 KELLOGS C.F ARABIC NEW 375GM	
34 KELLOGS C.F. ARABIC 375GM	
35 KELLOGS C.F. ARABIC 500GM	
36 KELLOGS CRUNCHY NUT C.F.500GM	
37 KELLOGS HONEY NUT C.F.375GM	

Table 6 –

Estimation Type	Outlets Audited	Average PPP difference among the GCC countries Weights used Expenditure (benchmark)	None	Distribution (ND)	Distribution (WD)
		(1)	(2)	(3)	(4)
avg	10	0.06	0.18	0.09	0.07
avg	20	0.05	0.17	0.06	0.06
avg	50	0.08	0.20	0.06	0.09
max	10	0.07	0.18	0.11	0.08
max	20	0.06	0.21	0.07	0.09
max	50	0.14	0.27	0.12	0.16
med	10	0.04	0.09	0.06	0.01
med	20	0.03	0.12	0.04	0.02
med	50	0.07	0.16	0.05	0.08
mii	10	0.12	0.15	0.06	0.08
mii	20	0.15	0.18	0.08	0.11
mii	50	0.09	0.17	0.05	0.07
min	10	0.04	0.11	0.05	0.05
min	20	0.06	0.11	0.04	0.05
min	50	0.03	0.07	0.05	0.03
random	10	0.02	0.12	0.05	0.06
random	20	0.06	0.13	0.06	0.09
random	50	0.08	0.16	0.04	0.10

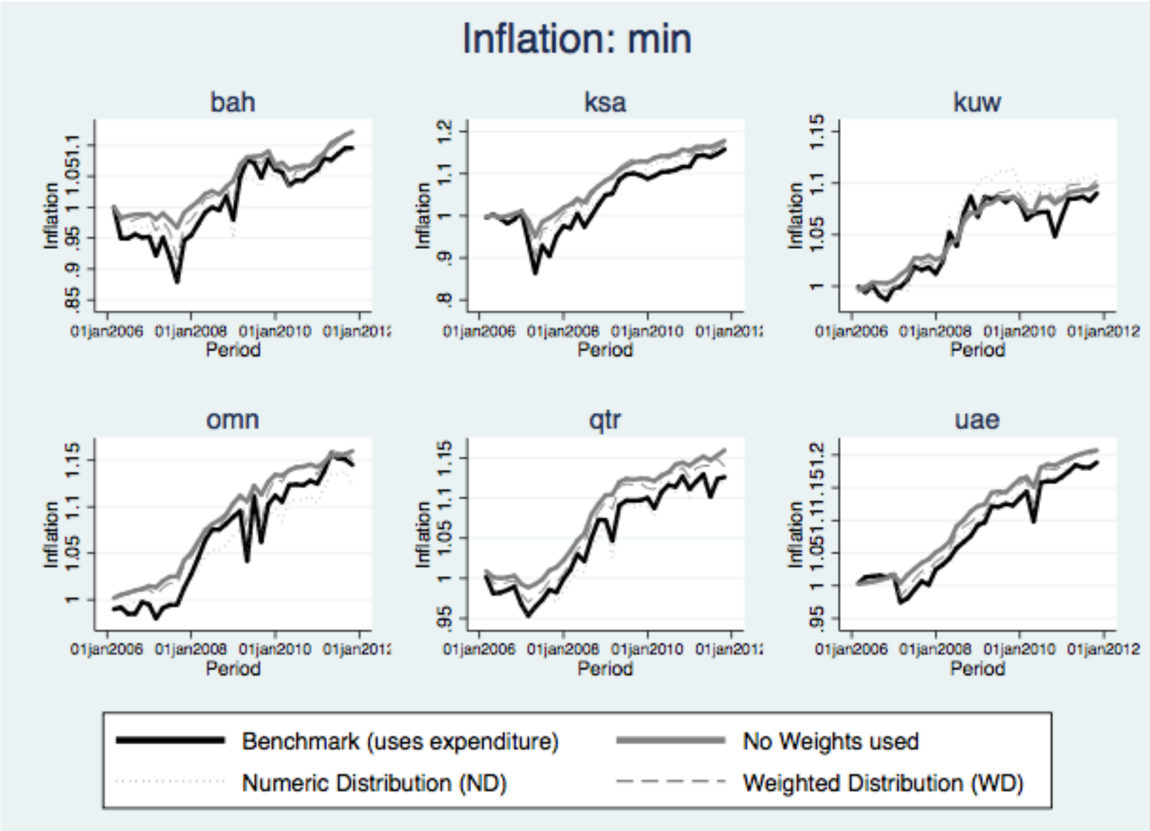
Table A1 – Regression estimates of ln(market share) = b0 + b1*Distribution by category

	(i) Distribution Measure: NUM Distribution													
	b0 (constant)						b1 (slope)						Average	
	KUW	QTR	BAH	OMN	UAE	KSA	KUW	QTR	BAH	OMN	UAE	KSA	b0	b1
Pooled data	-7.5	-6.9	-7.1	-7.4	-7.8	-7.5	4.8	3.8	4.5	5.1	4.8	5.0	-7.4	4.7
By Category														
Beans	-7.6	-6.2	-6.4	-6.6	-7.7	-7.2	7.0	4.7	8.7	7.4	7.0	5.5	-6.9	6.7
Blades	-7.6	-6.3	-6.2	-6.4	-7.0	-6.0	9.9	3.0	4.0	4.4	5.9	4.2	-6.6	5.2
Boullion	-5.1	-4.4	-4.0	-4.9	-5.6	-5.0	5.1	3.2	2.3	3.3	5.5	2.6	-4.8	3.7
Cereals	-7.5	-6.2	-6.7	-7.1	-7.3	-7.5	7.3	4.4	6.3	7.2	6.7	9.1	-7.0	6.8
Cheese	-7.7	-7.0	-7.1	-7.2	-7.5	-7.7	6.3	3.5	5.1	5.0	5.1	5.1	-7.4	5.0
Chewinggum	-6.4	-6.1	-6.9	-7.8	-7.9	-6.5	4.8	3.7	4.5	8.1	5.0	4.3	-6.9	5.1
Chocolate	-8.1	-7.1	-7.1	-8.2	-8.3	-7.9	5.6	3.3	4.6	6.4	4.5	5.1	-7.8	4.9
Cigarette	-7.5	-6.8	-7.3	-7.4	-8.4	-7.1	4.1	4.1	4.5	4.8	4.8	4.5	-7.4	4.5
Cookingoil	-8.1	-6.7	-7.0	-7.1	-7.6	-7.8	8.6	3.9	4.4	6.2	4.6	7.2	-7.4	5.8
Csd	-8.1	-7.2	-7.5	-7.8	-7.3	-7.9	4.2	3.5	4.7	4.3	3.6	4.1	-7.6	4.1
Deodorant	-7.9	-7.4	-7.6	-8.3	-8.7	-8.6	7.2	8.2	7.6	12.1	10.1	12.2	-8.1	9.6
Detergents	-7.1	-6.6	-6.5	-7.2	-7.3	-7.5	4.3	3.2	4.1	6.6	4.5	5.8	-7.0	4.8
Dishwash	-7.8	-6.3	-6.4	-7.4	-7.3	-7.5	8.6	4.2	4.9	11.5	6.1	8.3	-7.1	7.3
Energydrinks	-6.0	-5.5	-5.7	-6.1	-7.3	-5.5	5.4	4.2	4.7	5.5	5.7	4.6	-6.0	5.0
Fabricconditioner	-7.1	-5.9	-5.7	-6.9	-6.4	-7.1	6.2	4.5	3.6	8.2	4.4	7.8	-6.5	5.8
Insecticides	-5.7	-4.9	-5.3	-5.9	-5.9	-5.8	5.7	3.1	4.4	6.2	4.8	5.1	-5.6	4.9
Juices	-8.8	-7.9	-8.0	-8.4	-9.0	-8.6	4.6	3.8	4.5	5.5	5.5	5.9	-8.4	5.0
Liquidcordials	-6.7	-5.3	-5.9	-6.3	-6.2	-6.6	7.1	4.9	6.3	6.4	6.5	8.4	-6.2	6.6
Malegrooming	-6.6	-5.8	-6.1	-6.1	-7.3	-5.9	6.0	3.3	4.4	5.0	8.7	5.5	-6.3	5.5
Milk	-8.2	-6.9	-7.5	-7.8	-7.9	-7.5	5.7	4.0	4.8	5.2	5.3	4.3	-7.6	4.9
Milkpowder	-6.1	-5.6	-5.5	-6.4	-6.7	-6.5	4.7	3.5	3.4	6.1	5.0	5.1	-6.1	4.6
Powdersoftdrink	-7.4	-6.0	-5.8	-6.6	-6.4	-6.9	7.4	6.8	5.0	6.2	6.2	7.4	-6.5	6.5
Shampoo	-7.6	-7.1	-7.5	-7.6	-8.1	-9.0	6.3	4.5	5.6	6.3	5.7	11.0	-7.8	6.6
Skincare	-7.9	-7.3	-7.5	-8.0	-8.3	-7.7	5.1	3.5	4.5	6.4	6.0	7.8	-7.8	5.5
Skincleansing	-8.3	-7.7	-8.0	-8.3	-8.6	-8.3	7.5	4.5	5.5	6.6	5.7	6.3	-8.2	6.0
Suncare	-6.4	-5.3	-5.2	-5.3	-6.6	-4.7	7.8	4.4	4.4	3.9	6.4	4.6	-5.6	5.2
Tea	-7.9	-7.2	-7.1	-7.4	-8.0	-7.6	6.1	4.9	5.2	7.4	6.6	5.9	-7.5	6.0
Toothbrush	-7.9	-6.1	-6.5	-6.7	-8.1	-7.0	15.5	2.8	4.1	5.0	10.6	11.0	-7.1	8.1
Toothpaste	-7.1	-6.3	-6.7	-7.2	-7.5	-7.0	6.1	3.1	4.2	5.5	5.1	5.6	-7.0	4.9
Water	-6.9	-6.1	-6.2	-6.2	-7.3	-7.7	6.5	5.0	6.3	5.1	5.2	10.3	-6.7	6.4
Summary Statistics														
Min	-8.8	-7.9	-8.0	-8.4	-9.0	-9.0	4.1	2.8	2.3	3.3	3.6	2.6		
Max	-5.1	-4.4	-4.0	-4.9	-5.6	-4.7	15.5	8.2	8.7	12.1	10.6	12.2		
Mean	-7.3	-6.4	-6.6	-7.0	-7.4	-7.1	6.5	4.1	4.9	6.3	5.9	6.5		
Median	-7.5	-6.3	-6.6	-7.1	-7.4	-7.3	6.1	4.0	4.6	6.2	5.6	5.7		

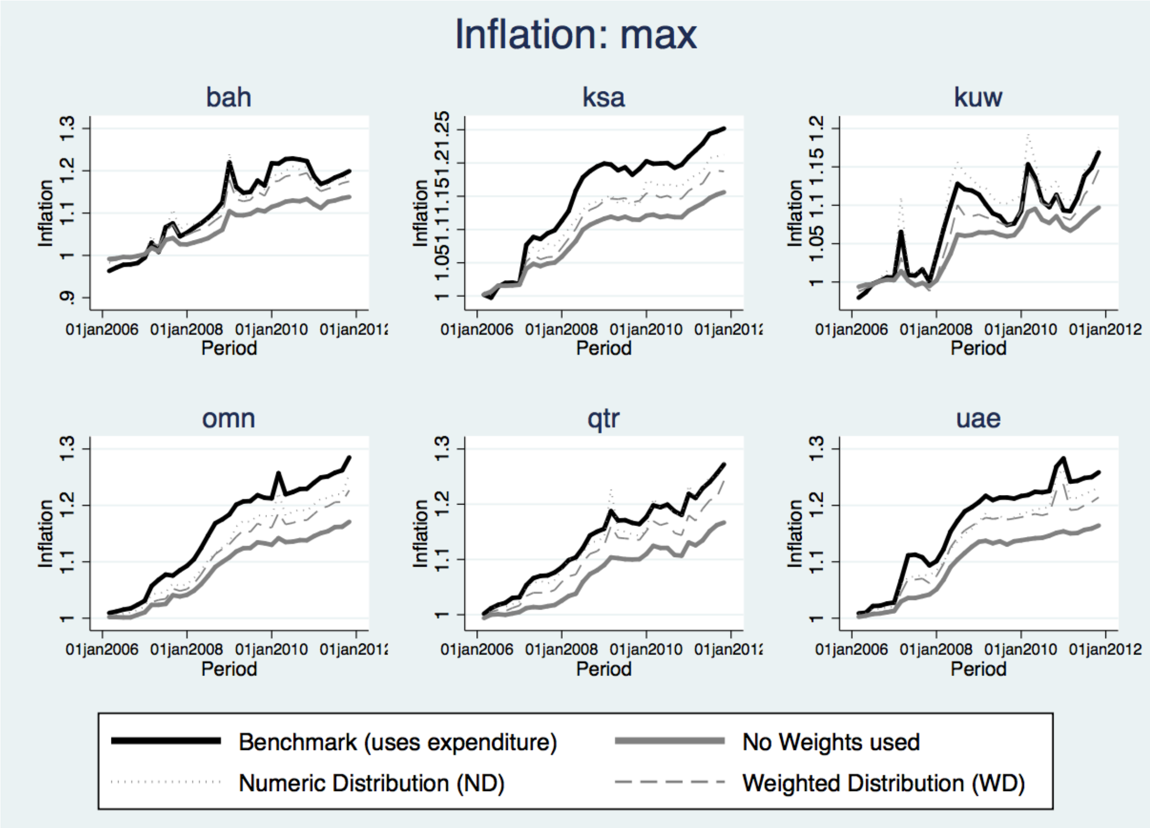
	(i) Distribution Measure: ACP Distribution													
	b0 (constant)						b1 (slope)						Average	
	KUW	QTR	BAH	OMN	UAE	KSA	KUW	QTR	BAH	OMN	UAE	KSA	b0	b1
Pooled data	-8.4	-7.6	-7.8	-7.9	-8.6	-7.7	150	143	150	137	152	92.9	-8.0	137
By Category														
Beans	-8.6	-6.9	-7.0	-6.8	-8.4	-7.6	207	166	188	141	205	116	-7.5	171
Blades	-8.4	-7.2	-7.4	-7.1	-8.3	-7.4	247	165	248	190	256	278	-7.6	231
Boullion	-6.3	-5.3	-4.7	-5.7	-6.7	-5.8	218	146	112	115	113	96.7	-5.7	134
Cereals	-7.9	-7.7	-7.5	-7.8	-8.0	-7.2	147	154	162	130	142	122	-7.7	143
Cheese	-8.4	-8.1	-8.2	-7.4	-8.4	-8.1	142	157	154	106	148	113	-8.1	137
Chewinggum	-7.2	-6.2	-7.4	-7.6	-7.6	-6.6	162	103	171	174	138	108	-7.1	143
Chocolate	-9.2	-8.4	-7.4	-8.7	-8.9	-8.5	178	164	121	166	151	126	-8.5	151
Cigarette	-7.3	-6.0	-7.0	-5.9	-6.9	-7.2	121	80.9	127	59.9	70.1	139	-6.7	100
Cookingoil	-8.7	-6.9	-7.7	-7.4	-8.4	-8.4	187	107	177	128	170	169	-7.9	156
Csd	-7.8	-7.3	-7.7	-7.9	-7.8	-8.0	107	125	146	150	140	136	-7.7	134
Deodorant	-7.7	-8.0	-8.4	-8.3	-8.8	-8.2	89.2	138	177	128	137	112	-8.3	130
Detergents	-8.3	-7.2	-7.5	-7.7	-8.2	-8.4	191	144	180	161	162	166	-7.9	167
Dishwash	-8.7	-7.1	-7.8	-7.6	-8.2	-8.5	224	182	273	192	198	200	-8.0	212
Energydrinks	-6.5	-3.8	-5.8	-5.8	-7.5	-5.4	162	34.7	143	118	172	136	-5.8	128
Fabricconditioner	-8.2	-7.0	-6.5	-7.0	-7.5	-7.2	175	120	54.7	115	146	109	-7.2	120
Insecticides	-6.1	-5.4	-5.9	-6.4	-6.7	-6.7	140	122	157	150	163	155	-6.2	148
Juices	-9.5	-8.5	-8.3	-8.4	-9.4	-7.9	162	148	144	139	167	54.4	-8.6	136
Liquidcordials	-7.7	-6.1	-6.9	-7.6	-7.2	-6.4	206	183	188	221	200	153	-7.0	192
Malegrooming	-7.6	-6.5	-6.4	-7.2	-8.2	-6.5	176	129	89.3	154	199	114	-7.1	144
Milk	-9.2	-7.3	-7.8	-7.7	-8.7	-7.1	189	139	154	124	177	48.2	-8.0	139
Milkpowder	-6.4	-6.3	-6.4	-7.1	-7.9	-7.1	96.6	142	149	182	119	128	-6.9	136
Powdersoftdrink	-8.2	-6.9	-6.8	-7.1	-7.5	-7.0	165	218	149	168	192	114	-7.3	168
Shampoo	-8.4	-7.8	-8.3	-7.8	-9.0	-9.8	143	153	170	108	155	130	-8.5	143
Skincare	-8.6	-8.4	-8.6	-8.8	-9.6	-8.6	115	140	165	141	166	136	-8.8	144
Skincleansing	-9.0	-8.7	-9.0	-8.6	-9.5	-8.9	149	180	198	136	174	125	-8.9	160
Suncare	-5.9	-4.8	-4.5	-6.4	-6.6	-4.9	86.3	69.3	9.86	125	111	119	-5.5	87
Tea	-9.0	-8.4	-7.9	-8.1	-9.0	-8.4	204	194	195	157	213	162	-8.4	187
Toothbrush	-8.2	-7.1	-7.5	-7.6	-8.6	-7.4	178	187	103	161	190	121	-7.7	156
Toothpaste	-7.9	-7.5	-7.6	-7.8	-8.8	-7.8	141	173	179	147	195	127	-7.9	160
Water	-7.8	-6.6	-6.7	-6.3	-7.5	-7.3	175	163	190	142	145	158	-7.0	162
Summary Statistics														
Min	-9.5	-8.7	-9.0	-8.8	-9.6	-9.8	86	35	10	60	70	48		
Max	-5.9	-3.8	-4.5	-5.7	-6.6	-4.9	247	218	273	221	256	278		
Mean	-7.9	-7.0	-7.2	-7.4	-8.1	-7.5	163	144	156	144	164	132		
Median	-8.2	-7.1	-7.4	-7.6	-8.2	-7.4	164	147	159	141	164	126		

Table A2 -

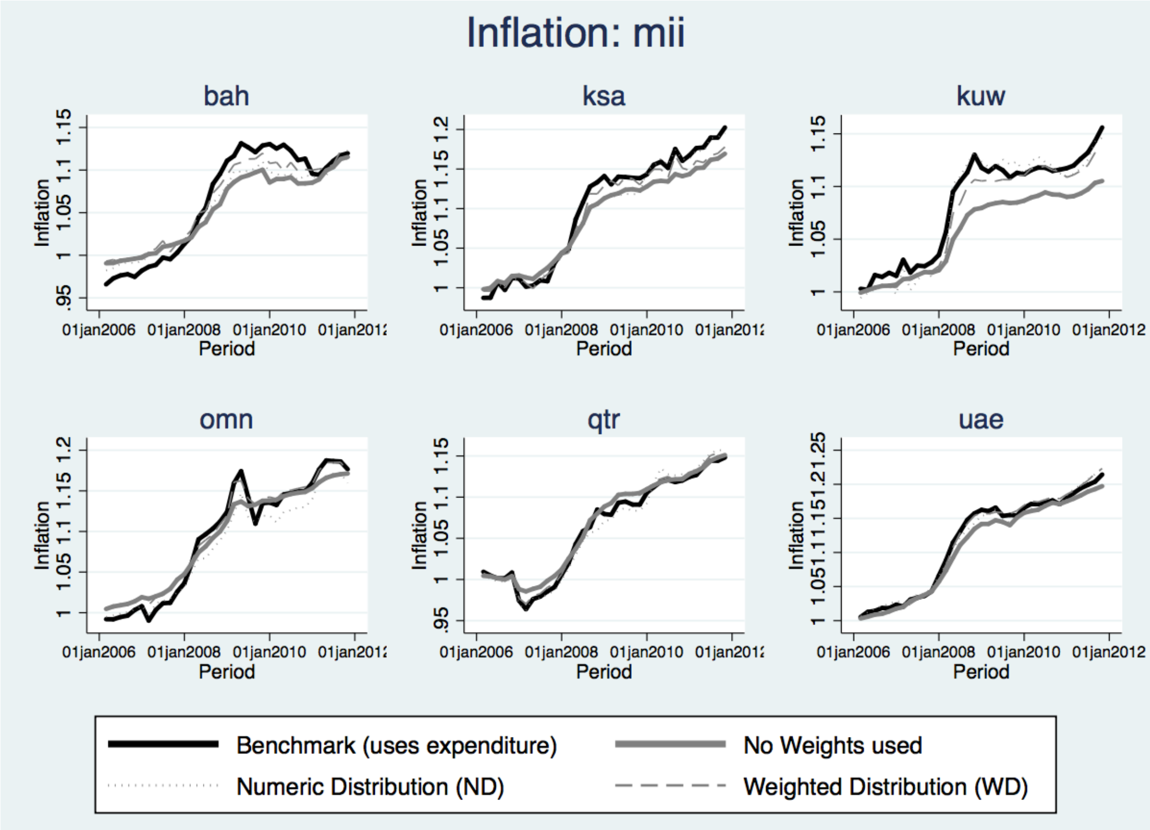
Estimation Type	Outlets Audited	Average PPP difference among the GCC countries			
		Weights used			
		Expenditure (benchmark)	None	Distribution (ND)	Distribution (WD)
		(1)	(2)	(3)	(4)
avg	10	0.06	0.17	0.09	0.07
avg	20	0.05	0.18	0.06	0.07
avg	50	0.08	0.20	0.06	0.09
max	10	0.07	0.19	0.11	0.08
max	20	0.06	0.22	0.07	0.08
max	50	0.14	0.27	0.13	0.16
med	10	0.03	0.10	0.05	0.01
med	20	0.02	0.13	0.04	0.03
med	50	0.07	0.16	0.05	0.08
mii	10	0.13	0.16	0.07	0.10
mii	20	0.14	0.20	0.07	0.12
mii	50	0.10	0.17	0.07	0.11
min	10	0.04	0.10	0.05	0.04
min	20	0.04	0.11	0.04	0.04
min	50	0.02	0.07	0.05	0.03
rnd	10	0.02	0.12	0.05	0.06
rnd	20	0.06	0.14	0.05	0.09
rnd	50	0.08	0.16	0.03	0.10



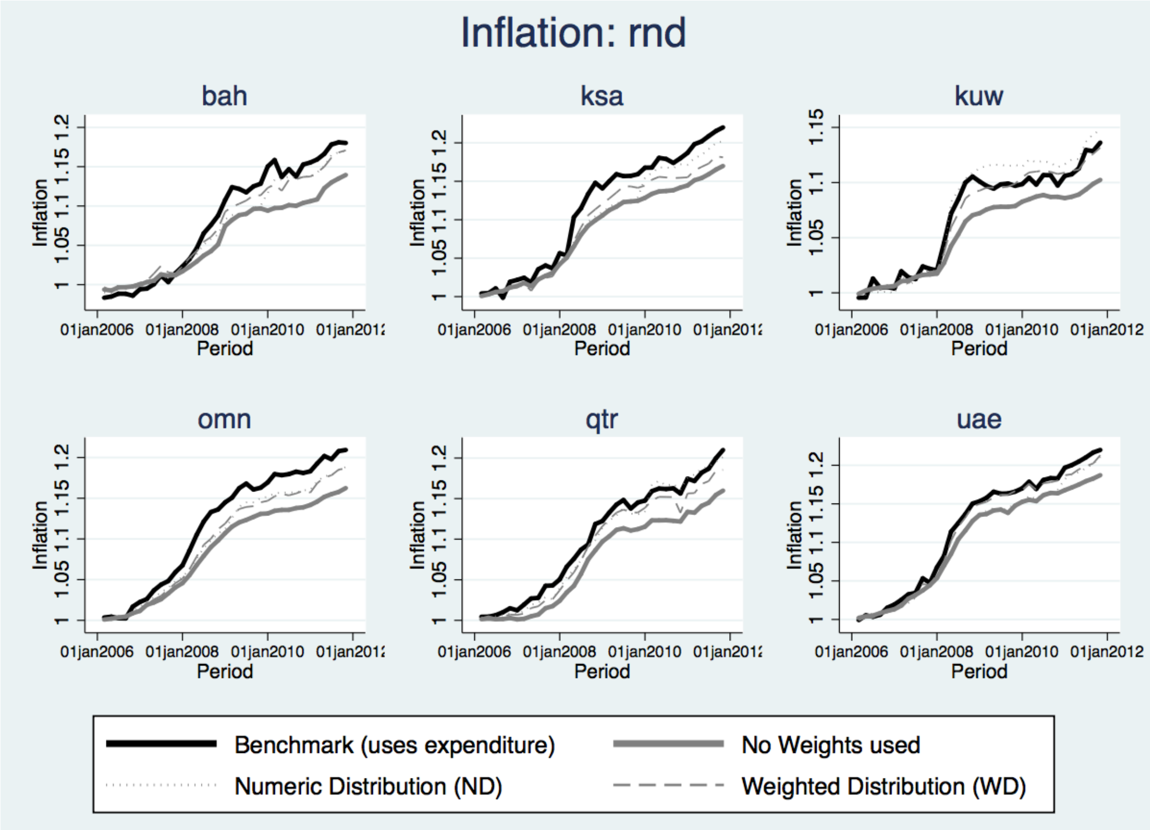
Inflation: min
bah
ksa
kuw
omn
qtr
uae
Inflation
Period
01jan2006
01jan2008
01jan2010
01jan2012
Benchmark (uses expenditure)
No Weights used
Numeric Distribution (ND)
Weighted Distribution (WD)



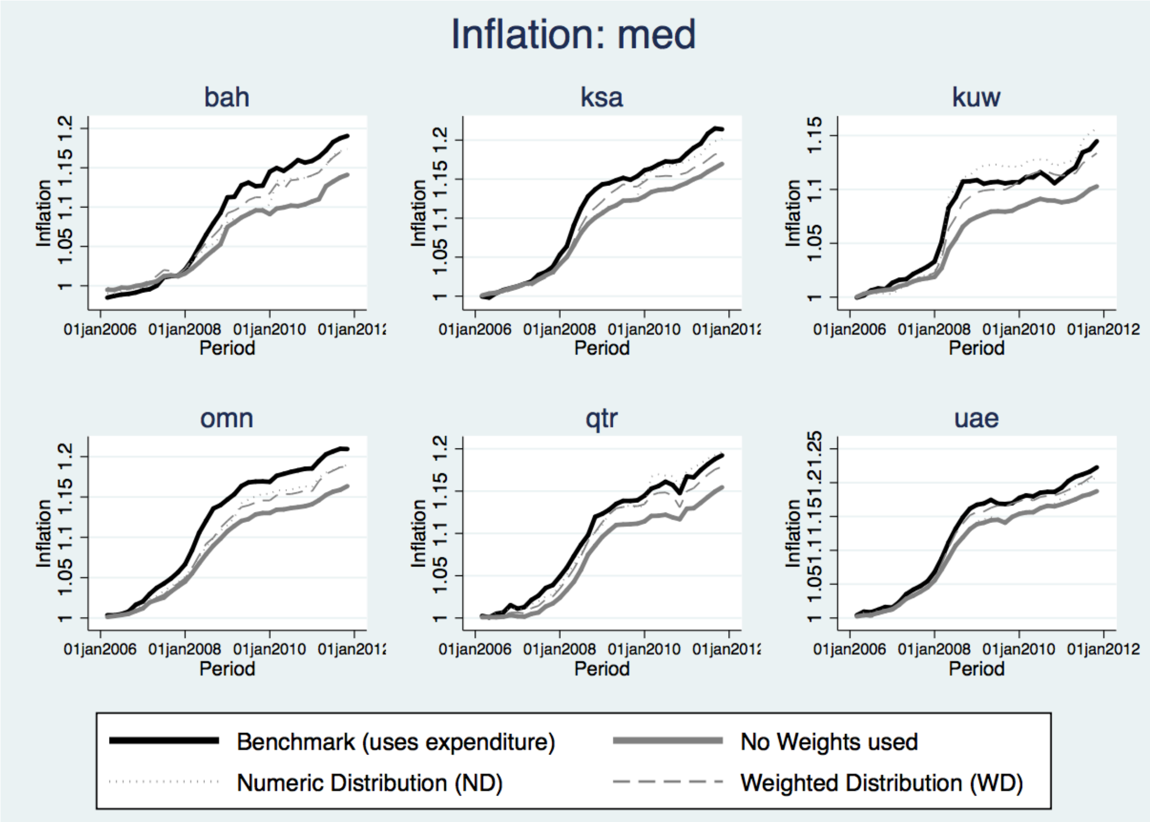
Inflation: max
bah
ksa
kuw
omn
qtr
uae
Inflation
Period
01jan2006
01jan2008
01jan2010
01jan2012
Benchmark (uses expenditure)
No Weights used
Numeric Distribution (ND)
Weighted Distribution (WD)



Inflation: mii
bah
ksa
kuw
omn
qtr
uae
Inflation
Period
01jan2006
01jan2008
01jan2010
01jan2012
Benchmark (uses expenditure)
No Weights used
Numeric Distribution (ND)
Weighted Distribution (WD)



Inflation: rnd
bah
ksa
kuw
omn
qtr
uae
Inflation
Period
01jan2006
01jan2008
01jan2010
01jan2012
1
1.05
1.1
1.15
1.2
Benchmark (uses expenditure)
No Weights used
Numeric Distribution (ND)
Weighted Distribution (WD)


Inflation: med
bah
ksa
kuw
omn
qtr
uae
Inflation
Period
01jan2006
01jan2008
01jan2010
01jan2012
Benchmark (uses expenditure)
No Weights used
Numeric Distribution (ND)
Weighted Distribution (WD)