Panel Price Index Construction
with Chinese Scanner Data on Non-Alcoholic Beverages

Soye Shin
Department of Agricultural and Applied Economics
The University of Georgia
Conner Hall, Athens GA 30602
syshin@uga.edu

Chen Zhen
Department of Agricultural and Applied Economics
The University of Georgia
Conner Hall, Athens GA 30602
czhen@uga.edu

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Abstract

Conventional price indexes provide time-series cost of living or cross-sectional cost of living, failing to capture both spatial and temporal variations in price level and ignoring product heterogeneity which reflects quality and variety or, consumer heterogeneity such as income. This paper considers the variety and quality of the products in each market, the combination of region and year, and constructs panel price indexes at different income level. We use three years (2011-2013) of Kantar Worldpanel barcode-level purchase data on non-alcoholic beverages for two income groups in 24 Chinese provinces and municipalities covering 40,000 Chinese households. We estimate demand systems using a modified nested logit and a nested random coefficient logit model that are relatively free from a dimensionality problem and provide flexible patterns of consumption. We find that price indexes are very different from market to market, which is in line with a great fluctuation of product varieties across/within provinces over a short time periods in China. We also find a large discrepancy in price indexes across three models, implying the importance in choices of appropriate models in price indexes constructions.

Keywords: panel price index, quality and variety biases, non-alcoholic beverages, Chinese scanner data

JEL: Q11, R12, R22, D12, D31

1. Introduction

The cost-of-living indexes are key factors to measure real income and expenditures of household living in different locations. These are critical in welfare analysis because household real income and expenditures are used for estimating degrees of poverty and of income inequality. Despite their importance, most of the commonly used price indexes provide time-series (see, e.g., Broda and Weinstein, 2010) or cross-sectional cost of living (see, e.g., Jolliffe, 2006; Albouy, 2009), both of which do not allow price comparisons between locations in different time periods. For instance, the US Bureau of Labor Statistics and Bureau of Economic Analysis releases national price indexes (CPI) based on the long time series data and the official regional price parities (RPPs) since 2006, but not the combination of both. Also, most of the standard cost-of-living indexes are criticized in that they fail to capture the true spatial price variation by ignoring consumer and product heterogeneities such as incomes, quality and varieties (Bils and Klenow 2001; Brandt and Holz 2006; Broada and Weinstein 2010; Khandelweal 2010; Sheu 2014). Some studies show evidence suggesting that product availability varies across regions (Handbury and Weinstein, 2015) and over time (Broda and Weinstein, 2010). Also, Handbury (2013) finds that the income specific price indexes vary widely within and across cities in the U.S. This implies the importance of handling aforementioned heterogeneities in the construction of price indexes. However, neither CPI nor RPPs carefully address these issues. The U.S. CPI accounts for product entry and exit yet in a very limited way by looking at the particular store being surveyed *only*, and RPPs have also partially addressed product heterogeneity.

These problems become even severe in large developing countries such as China where a comprehensive expenditure data is not readily available and, spatial heterogeneities in consumer preferences and product availabilities along with quality are likely to be substantial over time. China does not have official and available price indexes that reveal the cross-regional price level differences. Responding to this gap, Ingvild and Åshild Auglænd (2012a, 2012b) construct spatial price indexes using Engel's law and apply them to measure poverty. Due to data limitations, however, they have to lean on this simple approach, failing to address heterogeneity problems at product levels. The recent study (Feenstra et al., 2017) on cost-of-living indexes in China overcomes this limitation by using detailed barcode level data but is limited to fully consider varieties of Chinese-origin products (e.g., tea) in the market. Despite some limitations, all these studies consistently show that accounting for varieties of products are significantly important in establishing Chinese spatial price indexes. We could not find a paper addressing products quality in Chinese cost-of-living indexes but, the previous studies provide evidence that even the absence of heterogeneity in variety itself could largely bias the true cost-of-living price indexes across locations, especially in large countries such as China.

This paper overcomes the limitations shown in the previous literature by leveraging large-scale retail scanner data of Chinese non-alcoholic beverages with panel structure. There are seven sub-groups of the beverages: Carbonated soft drinks (CSD), Juice, Ready-to-drink(RTD) tea, Functional drinks, Packaged water, Ready-to-drink coffee, and Soybean milk. This dataset records households' weighted volume and expenditure of barcode level products consumed for each 4-week period of year 2011 to 2013 (i.e., 13 quad-weeks per year). The 40,000 households are represented by four different income levels living in four municipalities and 20 provinces which are part of the first tier of administrative divisions in China directly under the central government.

The primary benefit from this rich data is to be able to explicitly obtain barcode product fixed effects that reflect unobserved (by econometricians) consumer tastes and quality of the products. Recovering the estimates of the fixed effects is straightforward once we obtain the within estimator. Secondly, within transformation of panel data rules out an endogeneity of one of the two regressors (i.e., the share of expenditure for product j in group g) in a demand equation because unobserved quality of the products correlated with within-group sales are removed by the data within transformation. This leaves us only one endogeneous variable to take care of. Third, we construct a strong instrument variable for price of product j which is usually suspicious to be endogenous, using the prices of the same product in a cross section of different provinces. Fourth, we can estimate separate demands by households' income given that tastes vary with income (Handbury, 2013). Finally, we can clearly identify demand parameters of our interests including price using sufficient variations in detailed product-level data at relatively high frequency across regions and over time. This variation is driven by three dimensions: cross-sectional differences across products, across 24 provinces, and time series changes over 39 periods.

We estimate a demand system using two flexible models based on Sheu (2014) as the basic functional forms. These are relatively free from a dimensionality problem and more capable of capturing the heterogeneity in consumer tastes compared with conventional demand systems. One is a modified nested logit (NL) model and the other is a nested random coefficient logit model (NRCL), both of which are modified slightly to be in line with the nested constant elasticity of substitution, CES (Anderson, de Palma, and Thisse, 1992). This equivalence between two models allow us to build CES price indices developed in Feenstra (1994) using estimates from modified NL or NRCL demand models. The modification also allows a consumer to purchase more than 1 unit of the chosen good instead of restricting to buy 1 unit of the good that gives the highest utility, which aligns with consumer behaviors in our data.

This paper proceeds as follows. In Section 2 we describe the data for analysis. Section 3 discusses the details of the underlying model, followed by Section 4, which addresses estimation. The results are shown in Section 5. Finally, we conclude in Section 6.

2. Data overview

The barcode-level data come from Kantar Worldpanel database. Similar to Nielsen HomeScan data, consumers participating in the Kantar's household scanner data program are asked to scan beverage products they purchased using handheld scanners. The households earn points in return for their participation that can be used to redeem products that the World panel does not track. This reward system was designed not to generate confounding factors interfering with households' purchase decisions on products in interests. Although one could argue the home-scan data may underestimate consumers' actual purchases and that could be the actual case, this approach has shown to be effective for measuring purchasing patterns at household level (Bryant et al., 2011) given that there is no alternative to obtain such a detailed micro data. In addition to purchasing information, Kantar collects the demographic information of the household that is used for calculating sampling weights. The sampling weights apply to all bar-coded beverage product purchases to include demographically representative information in 24 areas across China between 2011 and 2013. One could argue about a sample size bias that occurs when more households in large cities are sampled so that more varieties tend to be observed. The barcoded product level purchases data do not allow us to address this bias with Handbury and Weinstein (2015) method. Therefore, we assume that the sample size bias is miniscule, as what Handbury and Weinstein (2015) show with Nelsen HomeScan data.

For each barcode product, scanner data measure weighted expenditure in the Chinese national currency, the RMB, and weighted volume by liters purchased by 4 different income groups (monthly income less than 3,000 RMB /3,001-5,000 RMB/5,001-7,000 RMB/over 7,000 RMB) for every 4- week period. We integrated these four income categories into two groups (less than or equal to 5,000 RMB and over 5,000 RMB) due to intrinsic features of the model we use, which will be further explained in the next part. For our analysis, we also limit to use three sub-groups of beverages, CSD, Juice and RTD tea out of seven to construct panel price indexes comparable in both dimensions: region and time. The details will be discussed in the next part. We also calculate price as RMB/liter by dividing total expenditure by total purchase volume, and observe that households from different income groups face different prices for the same good j in region i at period p. This could happen when households with specific characteristics tend to more actively use price-cutting strategies available for them such as coupons and vouchers, compared to households without the characteristics. This would make the price variable endogenous even though we control for unobserved time-invariant effects of the products. We average prices over regions and periods to reduce the degrees of endogeneity so that prices would be the same for every household living in the same provinces at the same time period. Table 1 shows summary statistics for the sample we use to estimate demand. The number of unique UPC varies widely across provinces and periods.

[Table 1 about here]

3. Model

In this section, we discuss the framework that forms the basis of the panel price indexes and the estimating demand equation. We model consumer demand using a modified logit preferences aligned with the nested CES framework. The modification has been made by entering the indirect utility equation in log forms as opposed to levels, by which consumers are allowed to purchase multiple quantities of the good that gives them the maximum utility. The specific models are the multinomial logit (MNL), the nested logit (NL) and the nested random coefficient logit (NRCL). Unlike the MNL where only one parameter for elasticity of substitution in beverages (γ) is specified, NL model allows to impose more realistic substitution patterns by assuming that the elasticity of substitution of products within the same nest (σ) is different from across nests (γ). That means we can impose a substitution pattern in such a way that juice product A is a closer substitute for juice product B compared to a RTD tea product. The discrepancy between two elasticity of substitution in the beverages market may not be large compared to high-tech industries such as printers, yet our data shows that the difference is significant and affects the panel price indexes. We use NRCL model with the aim of introducing systematic heterogeneity in preference for product characteristics among households from different income groups. Since these three models can be easily constructed from one another, we will describe the NRCL model only.

1) Consumption Utility

For simplicity, we define market t as a combination of region and period. Then, we can specify utility for household i of income type r who purchases product j in market t as

(1) $u_{ijt}^{r} = \ln\left(a_{jt}^{r} m_{ijt}^{r}\right) + ln\xi_{j} + \xi_{igt}^{r} + \varepsilon_{ijt}^{r}$

where a_{jt}^{r} is unobserved (by econometricians) product-specific quality and/or tastes measured by households of income type r at market t, m_{ijt}^{r} is the quantity of product j in market t that household i of income type r chooses to buy, ξ_{j} is the national mean valuation of the unobserved product characteristics of product j, and ξ_{igt}^{r} , ε_{ijt}^{r} describe i.i.d. random draws from a logit distribution with scales μ_{1}^{r} , μ_{2}^{r} respectively for each household, one for each product j $\in$ τ_{gt}^{r} (the bundle of goods in group g purchased by income type r at market t) and the other for each group g $\in \{\text{Broda}, 2010, \text{RTD TEA}\}$. The last two terms fall into the error terms.

Substituting the budget constraint, $y^{r} = p_{jt} m_{ijt}^{r}$, we can obtain indirect utility for the household as

(2) $v_{ijt}^r = \ln(a_{jt}^r) - \ln(p_{jt}) + \ln(y^r) + ln\xi_j + \xi_{igt}^r + \varepsilon_{ijt}^r$

We control for the unobserved characteristics a_{jt}^r and ξ_j such as vertical component (e.g., national brand is at least as preferred as generic brand), horizontal component (e.g., 100% organic juice vs. orange flavored juice) or region (and type) specific consumer tastes (e.g., strong tendency towards particular types of products in some regions) by including barcoded-product-specific dummy variables in the regressions. This is an extension of Nevo (2000a)'s work advocating the use of product's brand fixed effects, focusing on variation between brands within a group in estimating ready-to-eat cereal demand at brand levels. We assume that a_{jt}^r could be different across regions but are remained to be equal over time within a region. This is possible because three years of time window is relatively short for this to be changed dramatically. For instance, beverages manufacturers rarely change product characteristics once the products are released to the market, which may not be the case in high-tech industries. Also, changes in characteristics unless they are minor, should cause new barcodes to be assigned[1].

By combining product-specific measures, $\ln(a_{jt}^r)$ and $ln\xi_j$, as $\ln(Q_{jt}^r)$ and the two error components as ω_{ijt}^r, (2) can be rewritten as

(3) $v_{ijt}^r = \ln(Q_{jt}^r) - \ln(p_{jt}) + \ln(y^r) + ln\xi_j + \omega_{ijt}^r$

We obtain the following expenditure shares by integrating over the remaining logit random shocks and substituting some terms for corresponding elasticity of substitution.

(4) $s_{jt}^r = \dfrac{b_{jt}^r {p_{jt}}^{1-\sigma^r}}{(\sum_{j\in\tau_{gt}^r} b_{jt}^r {p_{jt}}^{1-\sigma^r})^{\frac{\gamma^r-\sigma^r}{1-\sigma^r}} \sum_{g\in\{CSD,JUICE,TEA\}}(\sum_{j\in\tau_{gt}^r} b_{jt}^r {p_{jt}}^{1-\sigma^r})^{\frac{1-\gamma^r}{1-\sigma^r}}}$

[1] GTIN Allocation Rules,2007

where $b^r_{jt}(= {Q^r}_{jt}^{\frac{1}{\mu_2^r}})$ is a measure of quality or tastes, $\sigma^r(= 1 + \frac{1}{\mu_2^r})$ is the elasticity of substitution of type r between beverages in the same group, and $\gamma^r(= \frac{1}{\mu_2^r} + 1)$ is the elasticity of substitution of type r between groups. We derive our logit demand estimation from (4).

2) Price Indices

Based on a strong connection between NCES and NL, we can use estimates from three modified logit demand models and form an index with CES structure. Note that demand parameters are estimated at the 'region-period' levels, but the price indexes are calculated at the 'region-year' levels. Therefore, unlike the previous definition about 'market' in the utility part, we newly define a market as a combination of a region and a year for this discussion. The price index will be interpreted as how much prices on a set of products in the base market would have to fall to make consumers in the market obtain as much welfare as consumers in a comparison market with broader set of products have. Suppose we choose one base market which has the least number of product varieties in terms of 1) the broad category, non-alcoholic beverages, and 2) the three sub-groups of the beverages (i.e., CSD, Juice, and RTD tea). Denote the base market c^0y^0, the combination of region c^0 and year y^0 and the comparison market cy in the same manner. Then, the NRCL price index is given by

$$(5)\quad \pi^{NRCL}_{cy} = \prod_{r\in\{income\ 1, income2\}} \left(\frac{\left(\sum_{g\in\{CSD,JUICE,TEA\}}\left(\sum_{[j\in\tau_{gcy}{}^r]} b^r_{jcy}{p_{jcy}}^{1-\sigma^r}\right)^{\frac{1-\gamma^r}{1-\sigma^r}}\right)^{\frac{1}{1-\gamma^r}}}{\left(\sum_{g\in\{CSD,JUICE,TEA\}}\left(\sum_{[j\in\tau_{gc^0y^0}{}^r]} b^r_{jc^0y^0}{p_{jc^0y^0}}^{1-\sigma^r}\right)^{\frac{1-\gamma^r}{1-\sigma^r}}\right)^{\frac{1}{1-\gamma^r}}} \right)^{f^r_{cy}}$$

where f^r_{cy} is a fraction of expenditure on the products in the comparison market cy. Note that this is simply the geometric average of the NL price indexes for each income type. We set that Chong qing-year 2012 as the base market because this has the smallest varieties in both two categories: 1) beverages in total and 2) each of three sub-groups of beverages. The way we construct the comparable panel price indexes is to calculate each NRCL price indexes for comparison markets by anchoring Chong quing-2012 market as the fixed base. We use only data on CSD, Juice and RTD tea among seven groups, because there is no single base market, the number of varieties of which is the smallest in all seven sub-groups.[2]

This allows us to compare any two markets in a consistent way. For example, if one wants to compare the cost of living price indexes of two provinces, she can simply calculate the ratio of two corresponding NRCL price indexes and see how much prices of a market with fewer varieties would have to decrease in order to achieve the same level of welfare of consumers from a market with more varieties.

4. Estimation

In order to avoid an aggregation bias in estimation, we do not aggregate cross-sectional observations by year. The observation units for estimation, therefore, are the ‘region-period’, which will be denoted by market t. First, we need to choose a reference good in the non-alcoholic beverages (i.e., inside good) to rescale estimation inputs to be in units relative to those of the reference good. Therefore, the reference good should be an inside good that appears in every market t for MNL and NL analysis, and appears in every market t as well as every income type r for NRCL analysis. The treatment of the reference good is different from other logit demand applications with quantity shares where researchers set an outside of good as a reference good allowing for the no purchase option. This difference is driven by the perfect convertibility between NCES and the modified logit models. In the NCES framework, the allocation of expenditure is modeled conditional on a given amount of budget tied to the set of goods we pay attention to. This implies that expenditure will be used up across these goods. We can obtain expenditure shares for the reference good from (4), assuming that the quality index for the reference group, b_{0t}^{r}=1 for all consumer types and all markets. The demand model is obtained by taking the log of the expenditure shares of each product and of the reference good and subtracting the latter from the former.

[2] The three groups account for 80.4% of total expenditure and 70.22% of total volume of the data we observe.

$$(6)\ \ln\left(\frac{s_{jt}^r}{s_{0t}^r}\right) = \frac{\gamma^r-1}{\sigma^r-1}\ln\left(b_{jt}^r\right) - (\gamma^r - 1)\ln\left(\frac{p_{jt}}{p_{0t}}\right) + \frac{\sigma^r-\gamma^r}{\sigma^r-1}\ln\left(s_{jt|g}^r\right)$$

The s_{jt}^r and s_{0t}^r are the share of expenditure for product j and for the reference good amongst income type r consumers. $s_{jt|g}^r$ is the share of expenditure for the product j within the product's corresponding group g, implying that $s_{0t|g}^r$ equals to one.

There is only one product satisfying the reference good criteria for MNL and NL, which is a functional drink product (i.e., NongFuShanQuan fiber drink 550ml). However, we do not find a single product meeting the reference good criteria for NRCL analysis, which means that we cannot calculate s_{0t}^r for every observation, thereby being left with many missing values on dependent variables. If we use the same functional drink product as the reference good, we would lose observations on purchases by type r in the markets where the reference good was not purchased by that type of households in that markets. When we use original 4 income groups we lose observations in more than 400 markets out of 936 markets, covering 32,201 purchases. This may distort the estimates for the demand[3]. We get around this problem by combining income groups by two. The number of markets we lose reduces to 40 (4.27% of total markets), including 7,123 observations (1% of total sample size).

We could estimate the product specific measure of quality/tastes, b_{jt}^r, with product characteristics like Sheu (2014) did. However, the choice of product characteristics tends to be arbitrary and is also suspicious to effectively capture time-invariant differences across goods in different provinces. Moreover, a failure in controlling for this term would cause endogeneity problems in demand estimation because an increase or decrease in unobserved quality can lead changes in prices and group shares. Instead of leaning on using some product characteristics, we use panel fixed effects techniques to estimate main parameters in demand and recover the estimates of time-invariant fixed effects (u_{jt}^r) for b_{jt}^r. Based on this discussion, we can specify an estimating demand equation as

[3] If we use 4 income groups in the analysis, the coefficients on prices are not negative and significant in certain income groups even when we use an instrument variable for prices.

$$(7)\ \ln\left(\frac{s_{jt}^r}{s_{0t}^r}\right) = -(\gamma^r - 1)\ln\left(\frac{p_{jt}}{p_{0t}}\right) + \frac{\sigma^r - \gamma^r}{\sigma^r - 1}\ln\left(s_{jt|g}^r\right) + u_{jt}^r + \varepsilon_{jt}^r$$

5. Results

We define a panel individual as a product in a region. Under this definition, the product A in region 1 is considered as a different product from the same product A in region 2, while it is to be the same product within region 1 over periods.

1) Estimated Coefficients

We usually need to find good instrument variables in order to estimate a demand system due to many unobservable (by econometricians) components falling into the error terms. For instance, differentiated-products pricing models assume that prices are a function of marginal cost and a mark-up term. The mark-up term is a function of the unobserved product characteristics and region-income specific consumer tastes on the products, which is in the error terms. Analogously, unobserved quality or tastes can increase within group sales. However, it would be expected that our demand estimation does not to suffer from the endogeneity after controlling for significant amount of endogeneity by barcode product fixed effects. We provide panel fixed effects (FE) estimates in Table 2. To correct for correlation across observations of the products in the same province, we cluster standard errors at the province level.

[Table 2 about here]

The first column uses the pooled sample, while second and third columns show the results from two different income groups respectively. The coefficients on log group shares is highly significant and less than one, suggesting that a nested model is appropriate and an instrument variable is not required. The coefficients on log prices, however, are positive and very significant across all columns, suggesting that this variable still suffers from the endogeneity. This may be driven by the way we obtain prices indirectly from data on the weighted volume and the expenditure. As explained before, the calculated prices are different by income groups in each market. These may contain time-varying heterogeneous information on households' income specific tastes, which cannot be removed by fixed effects technique. Although we average the calculated prices over two income groups, the unobserved tastes would not be completely removed from the variable, being correlated with the error term where market-specific shocks are included. Therefore, we need an instrument for this variable.

We exploit the panel structure of the data (Hausman et al.; 1994, Nevo; 2000a, 2000b). Our identifying assumption is to assume that the region-specific valuations of the product are independent across provinces but are allowed to be correlated within a province over time once we control for product-specific fixed effects. Under this assumption, the prices of the same barcode product in other provinces are valid instruments. Specifically, for product j in a region c at period p, we generate a regional average price of product j in the same period p excluding the region c. We take the log of each instrument because the logarithmic instruments explain the endogenous variable better than the level data. The method we use is panel fixed effects instrumental variable (FEIV) where two-stage least squares are applied to within transformation data. The main parameter estimates from FEIV along with the F-statistics from the first stage estimates appear in Table 3. As for the FE analysis, standard errors are clustered at the province level.

[Table 3 about here]

The coefficients on log group shares are similar to the ones in OLS and also highly significant, supporting our choice of the nested model. The coefficients on log prices now turn to be negative and significant throughout all samples, implying that the instrument variable removes a positive bias on the log price variable. Indeed, the regional period average prices strongly explain the log prices and the F-statistics for the excluded instruments are significantly large.

We also calculate two elasticities of substitution within (σ) and across groups (γ) using the estimated parameters from FEIV. Overall, the difference between σ and γ is not large but within group elasticity of substitution is the biggest among the lower income group. This would be the case when households in the lower income group are more sensitive in prices so that are more likely to substitute their choices for others within the groups of non-alcoholic beverages, relative to households in the higher income group. We also retrieve barcode product fixed effects[4] using FEIV estimates and obtain b_{jt}^{r} for each product j purchased in market t (region-period combination). Then, we recalculated these values and prices at the yearly level in each region to use them to build yearly panel price indexes.

2) Price Indexes

We construct NRCL price indexes by substituting parameters from the previous section along with prices into equation (5). The NR price indexes are simply the inside formula of the most outside bracket of the NRCL price indexes, and MNL price indexes are made by setting $\sigma = \gamma$ and aggregating price and quality components over sub-groups of the beverages from NRCL price indexes. Let us re-define the market for price indexes. Here, the market is the combination of region and *year*. In the end, we obtain 72 panel price indexes for 72 markets (24 provinces * 3 years) for each of the three different models. As shown in the model section, the price indexes can be comparable one another because they share the same market, Chong qing-2012, as the basis. The results are presented in Table 4. Chong qing-2012 is market number 8 which is standardized as 1.

[Table 4 about here]

One would have to multiply the prices of goods available in the basis market by the index number in order to make households as well off as they were with the choice set of the corresponding comparison market. For instance, 0.375 NL index for Chong qing-2013 market (market ID number 9) means that the basis market prices would have to decrease by 62.5% in order to give the same levels of welfare in market 9 to the households in the basis market. If we want to compare one market with broader choice set to the other market with smaller choice set, we simply divide the former by the latter. For example, if the comparison province is Hei Long Jiang-2012 (market ID number 32) and the basis province is Hei Long

[4] The individual fixed effects are inconsistent but unbiased in a large sample size with a fixed time.

Jiang-2011 (market ID number 31), the NRCL price index will be 0.583 ($\pi^{NRCL}_{HLJ,2012}/\pi^{NRCL}_{HLJ,2011}$), meaning that the prices of Hei Long Jiang-2011 would have to fall by 41.7% in order to make consumers as well off as they were in Hei Long Jiang-2012.

We can see that price indexes are very different from market to market, which is in line with a great fluctuation of product varieties across/within provinces over a short time periods in China. We also find a large discrepancy in price indexes across three models. This implies that model specifications highly affect the magnitude of price indexes, emphasizing the importance in choices of appropriate models in price indexes constructions. The difference between MNL and NL price indexes suggests that one needs to carefully consider the structure of the goods to design reasonable patterns of elasticity of substitution. On the other hand, the gap between NL and NRCL indicates a need for accounting for consumer heterogeneity such as income in cost-of-living indexes, which is shown in another research as well (Handbury, 2013). We also separate NRCL into two income groups concluding that there are large differences between high and low income households of perceived prices and varieties available even in the same market.

6. Discussion

This paper builds panel price indexes that account for differences in available varieties and quality of detailed barcoded products in China using purchases on non-alcoholic beverages by two income groups. The significance discrepancy among price indexes across region and time provides evidence of a need for spatial deflation in measuring cross-province income differences for a large and dynamic country such as China.

This paper fills the gap of the literature on regional price indexes in developing countries. Specifically, this study contributes to extending the knowledge on costs of the non-alcoholic beverage in China, one of the largest countries in the world experiencing diverse and rapid economic as well as cultural changes. The distinct features of this paper are as follows; 1) panel price indexes allow price comparisons across geographic space in different point of time and a spatial coverage is large enough, 2) the elasticity of substitution is directly obtained from an estimated demand, 3) different functional forms are used to see how sensitive the price indexes are to the various functional forms.

Next task is to decompose the constructed panel price indexes into three components—price, quality and variety—using a unique sampling method used in Sheu (2014) and see how much each component contributes to improving welfare of consumers. Also, we are going to magnitudes of the biases from not considering varieties and quality of products by comparing our panel price indexes to conventional superlative price indexes such as Törnqvist index and Fisher index.

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Table 1: Summary Statistics for Kantar Worldpanel Data Used in Analysis

(Total sample size:684,054)

UPC counts

	Minimum	Median	Maximum
UPC per Subgroup	2422	14305	14305
UPC per Province	1211	3085	4816
UPC per Period	3789	5029	5865
UPC per Province &Period	114	469	1129

UPC counts within Subgroup by Province & Period

	Minimum	Median	Maximum
CSD	23	90	214
JUICE	50	298	639
RTD TEA	22	80	323

Table 2: Results from Logit Demand Equation by FE

	Pooled sample		Income group 1		Income group 2	
Variable	FE		FE		FE	
ln(price)	0.150***	(0.071)	0.238***	(0.075)	0.182**	(0.096)
ln(group share)	0.914***	(.018)	0.885***	(0.019)	0.917***	(0.020)
Observations	400,923		220,038		305,354	
Individual fixed effects (u_i)	0.907		0.991		0.965	

Notes: Standard errors are clustered at the province level (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$).
Singletons are automatically omitted in the fixed effect analysis.

Table 3: Results from Logit Demand Equation by FEIV

	Pooled sample		Income group 1		Income group 2	
Variable	FEIV		FEIV		FEIV	
ln(price)	-0.111 ***	(0.046)	-0.218 ***	(0.060)	-0.090 *	(0.053)
ln(group share)	0.919 ***	(0.017)	0.892 ***	(0.019)	0.921 ***	(0.019)
γ	1.111***	(0.046)	1.219***	(0.060)	1.090***	(0.053)
σ	2.376***	(0.734)	3.020***	(0.722)	2.142***	(0.818)
F-statistics for instrument	794.49		1732.28		524.04	
p-value	0.000		0.000		0.000	
Observations	377,213		220,038		305,354	

Notes: Standard errors are clustered at the province level (*** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$).
Singletons are automatically omitted in the fixed effect analysis.

Table 4: Panel Price Indexes

Province	Year	Market ID	MNL Model	NL model	NRCL model	NRCL income1	NRCL income2
Bei Jing	2011	1	3.552E-14	9.332E-10	7.401E-12	3.830E-06	2.715E-13
Bei Jing	2012	2	1.932E-15	1.736E-11	7.040E-12	5.877E-07	3.678E-13
Bei Jing	2013	3	1.608E-17	2.255E-15	6.165E-17	6.781E-08	9.456E-19
Shang Hai	2011	4	4.834E-13	4.925E-09	6.084E-10	1.648E-04	2.533E-11
Shang Hai	2012	5	5.188E-13	4.569E-09	5.036E-11	8.778E-05	1.765E-12
Shang Hai	2013	6	2.806E-15	2.620E-11	1.542E-14	9.636E-06	2.464E-16
Chong Qing	2011	7	8.295E-06	2.312E-06	1.997E-07	1.141E-03	1.150E-08
Chong Qing	2012	8	1	1	1	1	1
Chong Qing	2013	9	1.040E-01	3.751E-01	1.599E-05	3.311E-02	1.409E-06
Tian Jin	2011	10	1.762E-15	5.543E-12	2.247E-13	1.993E-06	1.262E-15
Tian Jin	2012	11	3.927E-13	3.866E-10	5.413E-15	5.442E-06	8.533E-18
Tian Jin	2013	12	1.116E-14	4.515E-12	3.786E-12	1.867E-07	1.411E-13
An Hui	2011	13	5.388E-10	1.485E-09	1.592E-10	6.391E-06	3.256E-13
An Hui	2012	14	1.787E-08	2.753E-08	1.135E-08	2.075E-03	3.070E-12
An Hui	2013	15	4.572E-09	6.417E-08	3.720E-08	2.506E-04	8.774E-10
Fu Jian	2011	16	6.712E-15	7.334E-16	1.234E-13	5.604E-07	9.826E-17
Fu Jian	2012	17	1.688E-12	8.136E-13	1.970E-11	1.086E-06	4.573E-13
Fu Jian	2013	18	7.969E-10	1.207E-06	2.022E-09	4.520E-04	4.831E-11
Guang Dong	2011	19	1.195E-13	2.249E-08	4.228E-12	3.649E-05	5.447E-14
Guang Dong	2012	20	2.837E-13	1.877E-07	1.699E-17	1.676E-04	1.353E-20
Guang Dong	2013	21	2.062E-13	1.778E-06	1.354E-08	3.684E-04	7.480E-10
Guang Xi	2011	22	1.710E-15	3.330E-18	2.951E-18	1.522E-07	4.649E-28
Guang Xi	2012	23	1.787E-10	5.466E-08	9.283E-10	4.058E-05	2.354E-12
Guang Xi	2013	24	7.551E-12	8.064E-09	2.323E-10	7.771E-06	1.959E-12
Gui Zhou	2011	25	1.656E-07	1.249E-08	8.709E-09	1.589E-05	1.436E-09
Gui Zhou	2012	26	1.954E-09	3.274E-12	4.481E-10	9.258E-06	3.283E-12
Gui Zhou	2013	27	3.035E-08	1.165E-06	1.081E-07	5.468E-04	4.586E-09
He Bei	2011	28	4.440E-14	1.331E-10	1.112E-11	1.824E-05	4.065E-16
He Bei	2012	29	9.765E-13	6.402E-10	3.746E-11	7.845E-06	1.188E-14
He Bei	2013	30	6.946E-13	6.146E-09	2.169E-11	5.231E-05	3.639E-17
Hei Long Jiang	2011	31	3.005E-11	3.666E-09	5.713E-09	8.785E-05	6.991E-12
Hei Long Jiang	2012	32	2.135E-10	3.289E-06	9.794E-09	1.625E-04	2.578E-11
Hei Long Jiang	2013	33	4.021E-11	3.511E-07	3.235E-10	2.913E-06	2.673E-12
He Nan	2011	34	6.834E-15	6.713E-12	4.967E-13	1.944E-07	1.640E-16
He Nan	2012	35	2.827E-15	6.319E-13	1.213E-14	7.171E-09	6.601E-18
He Nan	2013	36	1.981E-12	2.362E-09	4.953E-10	1.992E-05	3.146E-12
Hu Bei	2011	37	3.642E-08	4.475E-08	1.848E-09	4.125E-04	3.985E-12
Hu Bei	2012	38	1.628E-06	1.728E-05	6.359E-07	5.168E-03	2.117E-08
Hu Bei	2013	39	1.204E-07	1.067E-05	4.596E-06	7.675E-03	5.384E-07
Hu Nan	2011	40	5.328E-10	1.077E-09	1.277E-10	3.026E-05	2.225E-14
Hu Nan	2012	41	6.831E-10	4.596E-12	1.011E-10	5.475E-06	2.328E-13
Hu Nan	2013	42	1.078E-10	4.681E-13	1.669E-11	2.308E-06	2.177E-14
Jiang Su	2011	43	1.510E-08	8.249E-05	1.479E-06	1.262E-02	8.327E-08
Jiang Su	2012	44	7.031E-08	4.874E-05	7.265E-06	1.750E-03	1.276E-06
Jiang Su	2013	45	6.691E-09	4.599E-04	2.727E-09	5.712E-03	2.350E-11
Jiang Xi	2011	46	2.447E-10	2.039E-10	3.579E-09	5.886E-05	1.182E-11
Jiang Xi	2012	47	5.435E-08	2.983E-06	7.563E-07	6.759E-03	8.016E-09
Jiang Xi	2013	48	7.512E-09	1.057E-05	7.105E-08	2.026E-02	7.589E-12
Ji Lin	2011	49	9.770E-14	1.812E-13	1.125E-13	1.841E-06	5.859E-21

Ji Lin	2012	50	1.146E-10	1.489E-07	6.388E-08	1.707E-04	5.257E-09
Ji Lin	2013	51	1.404E-10	1.746E-08	4.037E-11	2.393E-05	4.978E-15
Liao Ning	2011	52	8.479E-15	2.051E-11	2.692E-13	9.490E-07	1.788E-17
Liao Ning	2012	53	8.365E-13	3.571E-08	1.579E-11	4.056E-04	7.544E-16
Liao Ning	2013	54	1.370E-14	4.587E-11	1.331E-14	2.364E-07	7.171E-19
Shaan Xi	2011	55	9.644E-09	9.151E-09	1.598E-10	1.863E-06	5.211E-12
Shaan Xi	2012	56	6.854E-08	1.020E-06	7.553E-07	7.441E-03	2.875E-08
Shaan Xi	2013	57	3.872E-09	3.781E-09	1.966E-09	4.494E-05	3.293E-11
Shan Dong	2011	58	2.289E-13	5.582E-10	9.924E-16	6.803E-07	2.228E-20
Shan Dong	2012	59	7.847E-14	1.478E-09	2.248E-11	2.040E-06	2.921E-13
Shan Dong	2013	60	7.268E-14	5.183E-10	5.457E-12	1.761E-07	1.212E-13
Shan Xi	2011	61	8.768E-12	1.285E-08	4.886E-11	4.562E-05	5.179E-16
Shan Xi	2012	62	4.052E-09	2.621E-06	2.957E-08	2.386E-04	4.654E-10
Shan Xi	2013	63	3.053E-09	1.118E-06	1.594E-07	2.057E-04	3.116E-08
Si Chuan	2011	64	1.308E-07	4.746E-06	4.189E-07	2.387E-03	1.532E-08
Si Chuan	2012	65	3.839E-06	1.763E-02	5.182E-06	1.545E-02	3.941E-07
Si Chuan	2013	66	4.176E-06	1.232E-01	2.588E-04	1.105E-01	6.811E-05
Yun Nan	2011	67	3.736E-10	1.270E-08	1.392E-09	8.546E-05	1.192E-11
Yun Nan	2012	68	3.412E-09	2.026E-05	2.872E-10	7.750E-04	1.955E-13
Yun Nan	2013	69	1.020E-10	1.464E-05	2.104E-10	3.445E-05	7.620E-13
Zhe Jiang	2011	70	1.102E-07	1.245E-04	2.245E-06	9.035E-03	1.675E-07
Zhe Jiang	2012	71	2.460E-08	1.002E-06	9.572E-08	7.009E-03	3.625E-09
Zhe Jiang	2013	72	2.143E-09	9.881E-06	2.649E-08	2.063E-04	1.726E-09

Appendix

<Kantar Worldpanel Household Sample Size by Province>

Province	Household Sample Size
BEI JING	2000
SHANG HAI	2000
CHONG QING	650
TIAN JIN	1000
AN HUI	1250
FU JIAN	1150
GUANG DONG	4620
GUANG XI	1170
GUI ZHOU	800
HE BEI	1260
HEI LONG JIANG	1220
HE NAN	1840
HU BEI	1750
HU NAN	1150
JIANG SU	2860
JIANG XI	870
JI LIN	810
LIAO NING	2430
SHAAN XI	1230
SHAN DONG	2610
SHAN XI	810
SI CHUAN	2860
YUN NAN	1330
ZHE JIANG	2330