Defining an Outlet: What Characteristics are Truly Price Determining?

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Abstract
In order to produce the Consumer Price Index, the Bureau of Labor Statistics collects its sample frame using a very narrow definition of the target sample unit – a retail establishment or 'outlet'. Specifically, an outlet is defined by the unique combination of operating name, mode (e.g. internet, brick-and-mortar), and if brick-and-mortar, the exact physical address of the store. While it is necessary to determine a precise location for pricing purposes, this definition of an outlet may not be ideal for sampling. This paper examines whether or not the definition of an outlet can be broadened in order to simplify data collection and to allocate the sample more efficiently, without introducing bias or nonsampling error. Specifically, the effect of both location and franchise status on price change is modeled and evaluated to determine which is more relevant in defining an outlet.

Key Words: Consumer price index, sample frame, outlet definition

1. Introduction

In order to produce the Consumer Price Index (CPI), the Bureau of Labor Statistics (BLS) collects its outlet sample frame using a very narrow definition of the target sample unit – a retail establishment or 'outlet'. Specifically, an outlet is defined by the unique combination of operating name, mode (e.g. internet, brick-and-mortar), and if brick-and-mortar, the *exact* physical address of the store.

The frames from which outlet samples are selected are defined by Point-of-Purchase (POPS) category, Primary Geographic Sampling Area (PSU),[2] and half-sample. A POPS category is a defined group of similar commodities or services; there are approximately 200 different POPS categories for which data are collected in the TPOPS. The CPI currently has 87 PSUs consisting mostly of metropolitan areas. Of those, the 31 with the largest populations[3] are designated "self-representing" or "A" sized PSUs; TPOPS respondents in these PSUs are divided into two or more[4] independent groups or half-samples, and independent samples are selected for each.[5] For the remaining PSUs (non-self-representing or "B" and "C" sized PSUs), an independent sample is drawn for each PSU, POPS category combination.

[1] Any opinions expressed in this paper are those of the author and do constitute policy of the Bureau of Labor Statistics.
[2] The PSU is defined by where the respondent lives, not where items are purchased.
[3] Except Anchorage and Honolulu which have smaller populations, but are still self-representing.
[4] The three largest cities, New York, Chicago and Los Angeles, each have four half-samples.
[5] See Bureau of Labor Statistics (2007). BLS Handbook of Methods.

The CPI calculates outlet sample selection probabilities for each outlet based on the expenditures reported in the Telephone Point of Purchase Survey (TPOPS).[6] If an outlet is reported by more than one household within a outlet sampling frame, ideally those expenditures are combined so that the outlet sample selection probabilities (expenditure shares at a given outlet compared to expenditures for all outlets within the frame) accurately reflect the outlet's market share; this is important to ensure representativeness of the selected CPI sample.

Under the current definition of an outlet however, we rarely see identical locations of the same chain reported *and* identified within the same sampling frame. In fact, in attempting to quantify how frequently this occurs, it was found that there is approximately a seven percent reduction in the number of outlets within a frame after expenditures are collapsed on average. While this is not entirely insignificant, the vast majority of the sample selection probabilities for a given outlet within a frame are based on one respondent's expenditure. This combined with the fact that the average number of outlets selected for a given frame is only 2.73, raises the question if the calculated probabilities of selection are that different from what they would be using equal probability of selection. Of course, equal probability of selection is not ideal because it does not reflect the actual retail environment.

However, by changing the definition of an outlet to outlet name only for the first stage of sample selection, identifying these newly defined outlets and collapsing their expenditure shares becomes much easier.[7] For simplicity, this paper will refer to the outlet-name-only definition as a "chain" although non-chain stores are also included. By reducing the non-sampling error associated with identifying duplicate outlets, the CPI would greatly increase the likelihood of being able to collapse expenditure records and likewise calculate more accurate expenditure shares at the chain level.

A convincing argument against redefining the outlets as chains is that price change is highly dependent on location. In other words, if Store X on Main Street changes prices independently of Store X (same operating name) on First Street, then the CPI needs to view these outlets independently when selecting a sample as it does now. However, if price change at the two stores is highly correlated, the CPI could view the outlets as the same at least for an initial stage of sample selection, and in a subsequent stage, select either store to price at with little bias on the index.

There is much anecdotal evidence that price levels for at least some items at different locations within a chain are not just similar, but identical. For example, many fast food chains have national advertisements for value menu items that include prices of those items, such as Subway's "$5 Footlong" ads or McDonalds's "Dollar Menu". While franchised locations may not be contractually obligated to charge these prices, hence the

[6] The TPOPS is a household survey conducted by the Census Bureau on behalf of the BLS. Households are asked whether or not select items were bought in a given timeframe and if so, to provide information about where items were purchased (including mode, name and address, if applicable) as well as how much was spent.

[7] The CPI uses a "national" concept of expenditure meaning that it measures the change in prices faced by consumers living in a particular area, i.e. regardless of where the purchase was made. Therefore for unless the CPI were to change to a "domestic" concept of expenditure, some geographical information is necessary.

common “participating locations” disclaimer, there is certainly incentive to do so.[8] If price levels are the same overtime, it follows that price change would also be identical.

Assuming price change is more correlated by outlet name than location, it can be argued that the CPI should consider focusing more on outlet name than location when selecting its sample. Under the current system, the sample is selected using a systematic probability-proportional-to size procedure which causes any outlet with a market share greater than or equal to 1/n, where n is the number of outlets being selected for that frame, to be a certainty selection. However, since outlets are defined very specifically, there tend to be very few certainty selections across all outlet sampling frames, let alone any given sampling frame.[9] If many TPOPS respondents in the same PSU report buying milk at a large grocery chain, but each one went to a different location, each location would have an independent probability of selection. Even if that chain store accounted for the vast majority of the expenditures for milk in the PSU, it is possible that not a single location of that chain would be selected.

Of course, for certain types of outlets it may not be the case that price and price change are consistent across different locations of a given chain (e.g. prices at gas stations seem to be more dependent on location than outlet name). While this paper focuses on the industries where it is reasonable to believe that prices and price change are more dependent on outlet name than the specific outlet location, it does not argue that two stage sample selection is appropriate for all sampling frames. It does suggest however, that for those goods and services where outlet name seems to be a major price determining characteristic, a two stage sample design (with the first stage target sample unit being defined by outlet name) may improve the CPI’s selected sample.

Using data collected in the TPOPS as well as CPI price data, this research will attempt to determine first the effect of moving to a two-stage sample selection on the resulting selected sample and then if price change within chain is actually correlated.

2. Literature Search

There is not much literature specifically considering whether or not price change is consistent across locations of a given store; however, there is ample literature that indirectly addresses this issue. While the evidence is mixed, Noel and Basker (2007) note that “many supermarket chains have a ‘uniform pricing’ policy whereby prices are set centrally for a broad geographic area”. In the world of fast food franchises, Ater and Rigbi (2007) argue that setting prices for value menu items (e.g. McDonald’s Dollar Menu) can be used “as a managerial tool to improve the chain’s control over its franchisees”. In addition to setting prices for such items, prices for substitute items fall substantially so that the franchisee’s price premium over the company-owned outlets is only 3.5% compared to 12.5% before the value menu existed. This finding implies that while the corporate level tries and to some extent succeeds in setting uniform prices, there remains some discrepancy. Additionally, over the seven years of this study price

[8]These advertising campaigns create consumer expectations which make it hard for franchisees to charge more; in fact in a 2008 press conference, McDonald’s CEO Jim Skinner reported that 90% of franchisees offer the double cheeseburger for $1.

[9] Of all outlets reported in a recent CPI sampling cycle, only 0.55% were certainty selections, 90% of these were cases where there was only one outlet reported within the frame.

change in franchised locations was quite different than company owned locations for given items.

While not specifically addressing the issue of uniform pricing in chains, Ellickson and Misra (2006) discuss two different pricing strategies: everyday low pricing (EDLP) and promotional or PROMO pricing. They find that pricing strategies within a given market actually match across chain, in other words instead of using a pricing strategy as a form of differentiation competing firms choose the same strategies.

Yang (2009) points out that pricing policies tend to vary across types of retailers, specifically noting that while gas stations do not exhibit uniform pricing, it “is used by many clothing and cosmetic retailers, as well as large department stores”.

Given much of the literature on chain store pricing suggests that, at least in some cases, prices are highly correlated by store name further suggests that changing the current CPI sampling methodology could potentially result in a more representative outlet sample.

3. The Data

The data used in this analysis come from the CPI’s Commodity and Services Pricing Survey (C&S). In order to isolate the effects of location and outlet name, relatively homogeneous items and services were targeted for evaluation. Also it was necessary to focus on goods where chain stores are prevalent market players. Specifically, two POPS categories were evaluated: limited service meals and snacks (fast food) and milk. Limited service meals and snacks are priced bimonthly in all but the three largest PSUs, whereas milk is priced monthly.

4. Empirical Analysis

4.1 Regressions on Price Change

The first basic regression model used in this analysis attempts to explain twelve month price change for like items within the same outlet. Twelve month price relatives were calculated using a geometric average at the outlet level. The first dataset was limited to prices for milk being sold in outlets in Los Angeles.[10] Prices were observed from 2005 through 2009. Given this paper is trying to determine the effect of both location and outlet name, variables representing both are included in the model. Differences in location were measured as the outlet’s distance from the center of the PSU.[11] Dummy variables were created to represent each of the six most common chains in this dataset, each of which had over 20 observations. Dummy variables were also created to represent year.

The first regression model used in this analysis was:

$$(1) \quad grel_i = \alpha_i + \beta X_i + \beta T_i + \beta D_i + \varepsilon_i$$

[10] Los Angeles is actually comprised of two distinct self-representing PSUs, Los Angeles County and the Los Angeles suburbs.

[11] The center of the PSU was generally identified as a major landmark within the PSU such as the tallest building, sports area or city hall.

where grel is the outlet level 12-month price relative of milk, X is the distance of the outlet from the center of the PSU[12] in miles, T represents a set of time dummy variables, and D represents a set of dummy variables for the six most prevalent chains (outlet names). The R-squared for this regression is 0.44, so this regression does explain 44% of the variance in year-over-year price change of milk in Los Angeles. The distance variable does not approach statistical significance using a 90% confidence interval. All three year variables are significant using a 99% confidence interval. Four of the six chain dummies are significant using a 90% confidence interval.
A similar regression was run for a different set of items, specifically fast food items; however due to sample size observations were not limited to a single city. In order to account for variation among cities, dummy variables were added to represent both region and city size. Again the dataset included price relatives based on observed prices from 2005 to 2009.

The model used was:

$$(2) \quad grel_i = \alpha_i + \beta X_i + \beta R_i + \beta S_i + \beta T_i + \beta D_i + \varepsilon_i$$

where R represents dummy variables for three of the four CPI regions (North, Midwest, West and South) and S represents a set of dummy variables indicating city size.[13]

While several of the variables in this model are significant, unfortunately this model does not do a good job of explaining differences in price change (R^2 = 0.04). Again, the variable for distance is not statistically significant, while several of the dummy variables for chain are.

Limiting the previous dataset to observations in LA, created a much better model (R^2 = 0.19). Distance is now significant using a confidence interval of 90%; the negative coefficient suggests that as you move away from downtown LA, price change decreases though very slightly. Only two of the chain dummies are statistically significant, both using a confidence interval of 95%.

Several different models were tested, but few were able to explain much if any of the variation within the model. The failure to create models to explain the variation in price chance could be in large part due to the very small sample size.

4.2 Hedonic Regressions on Price Level

Given the amount of unexplained variation in the previous models; another approach was taken. Assuming that price *level* is often determined by chain, models were run using level as the dependent variable, instead of price change. This allowed for more data to be included in the regression models because an item need only be available in a given month in order to be included in the dataset. Additionally, given these observations were at the item level rather than the outlet level, variations across different types of items could be addressed within the models by introducing dummy variables for different item characteristics.

The basic hedonic model used was:

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[12] In this dataset "city center" for both PSUs was defined as the U.S. Bank Tower in downtown LA.

[13] The 31 self-representing cities are designated as A-sized PSUs while non self-representing are designated as B or C-sized indicating metropolitan or non-metropolitan, respectively.

$$(3) \quad lnp_i = \alpha_i + \beta X_{\ i} + \beta R_i + \beta C_i + \beta D_i + \varepsilon_i$$

where lnp is the log price of observation *i* and C represents a set of dummy variables for product characteristics including menu type (such as children, senior or breakfast), item type (combo meal, or ala carte items including main courses, soups, or drinks) and if the meal was purchased to go or for delivery.

The model was run first including distance and then excluding distance for observations in December, 2005.

Nearly half of the variation in price level is explained by this model (R^2 = 0.4976). All but one of the dummy variables for product characteristics are significant using a 90% confidence interval (most are significant with 99% confidence), with the one exception being the variable representing a senior's menu, and even its p-value of 0.12 is close to being considered statistically significant with 90% confidence. All but one of the coefficients for these variables exhibit the expected sign: negative for items on the children's and senior's menu, negative if for items that are not labeled "combo" meals and positive if the price is for a delivered item. The only coefficient that displays the opposite sign of what one would hypothesize is the coefficient for takeout. One could reasonably expect that takeout would be less, not more, expensive than food purchased as eat-in. Five of the six dummy variables are significant using a 99% confidence interval with the sixth being significant with 95% confidence.

The same regression model was run excluding distance resulting in a slightly lower R^2 of 0.4944; all coefficients were nearly equal to those listed above and all maintained the same sign. Also, no variables went from being insignificant to significant. This provides evidence that distance from the city center is not a good predictor of price level. When the dummy variables for chain are removed however, the R^2 drops to 0.38 reinforcing the hypothesis that chain may play a larger role in determining variation across price level. Knowing that distance from the city center may not be the best way to determine differences in specific locations, another test was necessary. The dataset was limited to a specific chain and PSU. This way instead of using distance to look at geographical differences, dummy variables for each specific outlet could be used. This approach attempted to evaluate if prices differed based on specific outlet location. Unfortunately, limiting the data to such a specific group of observations within a PSU decreased the sample size to 24.

The model used in this regression was:

$$(4) \quad logp_i = \alpha_i + \beta X_i + \beta O_i + \varepsilon_i$$

where O is introduced to represent the set of dummy variables for specific outlet. Unlike the previous example, none of the product attributes are significant using a 99% confidence interval; however the item type variables are all significant with a 90% confidence interval. None of the outlet variables approach statistical significance using a 90% confidence interval. While the small sample size makes it difficult to draw any real conclusions from the previous regression, the fact that none of the outlet dummy variables were significant may provide some evidence that specific location of a given chain within a PSU is not a price determining characteristic.

The results of these regressions illustrate that the differences in the product attributes explain much of the variance in price and therefore, perhaps it is these differences that are accounting for most of the variance in price change over time, in the CPI.

4.3 Regressions on Price Change-Combo Meals

To test this theory, the data sets were limited to observations with similar product attributes-specifically “combo menus” from a standard menu purchased for eat-in. Again this limited the amount of observations available so dummy variables were only created for the top four chains. Hypothesizing that long-term pricing trends might be both easier to see and more telling, a three year price change was calculated for all applicable observations, nationwide.

The model used was:

$$(5)\quad prel_i = \alpha_i + \beta R_i + \beta D_i + \mu_i$$

The following table presents the regression results for this model:

Variable	Parameter Estimate	Std Error	t-stat	Pr > |t|
Intercept	1.023	0.039	26.15	<.0001
NORTH	0.108	0.042	2.57	0.016
MIDWEST	0.104	0.056	1.88	0.071
WEST	0.089	0.047	1.90	0.068
Chain A	0.073	0.029	2.50	0.018
Chain B	0.070	0.048	1.45	0.159
Chain C	-0.060	0.044	-1.35	0.188
Chain D	0.034	0.053	0.63	0.533

Only one of the chain dummy variables is significant using a 95% confidence interval whereas all of the region dummies are significant using a 90% confidence interval. However, the R^2 of 0.45 shows that this model better explains the variance in price change than all other models.

To independently examine the variation in price change that can be explained by outlet name the same regression was run omitting the variables for region.

While the R^2 did fall substantially, the new value of 0.32 suggests that chain alone does account for almost a third of the variation in price change. Furthermore, another chain dummy variable is now significant using a 90% confidence interval. This evidence that multicollinearity existed in the previous model can be expected due to the small sample size and the fact that certain chains may be limited to specific regions (either in reality or in the sample).

Given these results, it seems reasonable to believe that both geographical location and outlet name play some part in price change; however, more research is needed to determine what level of geography is price determining. In other words, a fast food chain on the west coast may exhibit different pricing behavior than one on the east coast, but two fast food chains in downtown Manhattan may not. Likewise, different locations of the same chain operating in the same metropolitan area may all offer the same prices and sales; in fact these prices and sales may persist nationally. Unfortunately, small sample sizes make this difficult to determine using the CPI data.

4.4 Sample Selection Probabilities Based on Outlet Name

This research suggests that outlet location may be less important than an outlet name when it comes to prices and price changes for a specific item within an item category. Therefore, it is interesting to examine the effect on sample selection if the CPI did in fact, choose to redefine outlets.

A single frame, specifically limited services meals in the Washington, DC area, was examined. Four outlets were selected for this frame. Using current sample selection methodology, no single outlet location was a certainty selection. In fact, the highest probability of selection for any outlet was 3.6%, nowhere near the 25% needed to be a certainty selection. When the sample units were redefined by outlet name only, one chain had a 30% probability of selection making it a certainty first-stage sample selection. This particular chain had 31 locations reported in the original frame, but not one was selected to be priced in the CPI.

Given the current definition of a sample unit, no outlet reported for limited service meals and snacks has been a certainty selection in the CPI since 2007. This is probably not surprising given the large number of outlets and varying locations of these outlets, within each frame. Even the big market players in this category are unlikely to be certainty selections as most fast food chains have several different locations within a PSU. For example, according to www.insiderpages.com, the two most popular[14] fast food chains, McDonald's and Burger King, have 396 and 137 locations respectively within 50 miles of Washington, DC.[15]

In order to see what effect collapsing records based on outlet name would have, the same outlet sampling frames (those for limited service meals and snacks beginning in 2007) were examined using the broader definition of a sampling unit, i.e. chain. Using this definition would have resulted in six certainty selections in this timeframe rather than the zero that actually occurred. .[16] While six certainty selections within three years[17] is a small number, defining a first-stage sampling unit by name clearly has an impact. In each of these six frames, the CPI could have guaranteed the selection of a chain that clearly was a large market player in the given PSU, rather than leaving it to chance. Again, the reason why we don't see a large number of certainty selections even when using a much

[14] http://www.marketingcharts.com/topics/behavioral-marketing/top-10-favorite-fast-food-chains-mcdonalds-still-1-8667/

[15] Not all of these locations are necessarily within the CPI's definition due to the large radius; however, four of the five locations 49 miles or more from DC were determine to be within the CPI's definition of Washington, DC. The fifth was in the definition for Baltimore and given Baltimore is approximately 45 miles away from downtown Washington, DC many of these locations may not be located in DC, but rather Baltimore.

[16] This requires some manual review of the frame data, which is time consuming, so efforts were mainly limited to identifying large chains and therefore not all records were accurately collapsed; however as most misspellings of large outlets were identified, the number of certainty selections is most likely accurate.

[17] Sample selection had only taken place for data collected through the third quarter of 2009 when this study was done.

broader definition of a sampling unit is because even when defining outlets by name only the average number of records in these frames is approximately 43, the smallest frame even contains 19 different chains, which is relatively high especially when taking the CPI's fairly small sample sizes into account. The average and minimum number of records in a frame were 95.7 and 31 respectively when using the CPI's current definition of a sampling unit.

This example illustrates another, possibly more important point, which is small outlet samples can lead to large sampling error. The average number of outlets selected per frame is only 2.83 which leads to small probabilities of selection when combined with the larger frames that are a product of the current sampling unit definition. In fact, when observing all the outlet sampling probabilities from the past three years, the mean probability of selection is 0.0302.

5. Conclusion

How the BLS chooses to define outlets has important implications in the CPI. The current definition of an outlet reflects the theory that the exact location of an establishment is ideal for sampling purposes. While not specifically addressed by this research, both the literature and anecdotal evidence suggest that it may be the case that location is more of a factor for some goods and services than others. For example, neighboring gas stations almost always charge identical or near-identical prices for the same grade fuel. For other types of items, like fast food, there may be some sort of national pricing and customers are more likely to have a preference for the food of a particular chain (or non-chain). Differences like these may warrant different definitions for different outlet sampling frames, but their expected existence certainly requires more research be done before any change could be recommended.

As suggested by this initial research, for certain items including limited service meals, price and price change seem to be correlated within chain. To the extent that this is the case, redefining a sampling unit could be beneficial. Defining a first-stage sample selection unit by outlet name would ensure that more chains with large market shares are included in the CPI outlet sample. While redefining the CPI sample unit would increase the number of chains in a sample, current stratification procedures[18] would guarantee that smaller stores are still included in the sample. The costs of accurately identifying identical sampling units would fall as a sample unit is defined more broadly. While some costs would increase, specifically a second-stage of sample selection would be needed, these are unlikely to outweigh the cost savings. Given the potential for lower operating costs and possible improvements to the CPI's representativeness, changing the definition of an outlet warrants further investigation to guarantee doing so would not increase bias in the index.

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