Price Discounts and the Measurement of Inflation

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Abstract

Consumers are very responsive to sales, yet statistical agency practice typically under-weights sale prices in the Consumer Price Index (CPI), with some agencies excluding sale prices completely. Evidence is lacking on how this may impact on both the representativeness of prices included in the CPI and on estimates of inflation. We use high-frequency scanner data from US supermarkets to explore if there is any systematic directional impact. The key finding is that the exclusion of sales prices introduces a systematic effect. We also find that even when sales prices are included they are systematically under-weighted, but the under-weighting remains fairly stable over time so that inflation measurement is not significantly affected.

Keywords: Cost-of-living, CPI, Regular prices, Retail sales, RYGEKS, Scanner data

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1 Introduction

Price discounts are a frequent and prevalent part of the consumer shopping experience. Consumers tend to buy in large quantities during sales, yet the methods used by national statistical agencies for constructing key inflation measures, such as the Consumer Price Index (CPI), typically do not reflect this fact. There is little information on how the resulting under-weighting of sale prices may impact on both the representativeness of prices included in the CPI and on estimates of price change. Our interest is specifically whether there is any systematic directional impact when sale prices are under-weighted in the measurement of inflation.

There has been significant attention to price dynamics over recent years, particularly given the advent of researcher access to large scanner data sets. In particular, the question of whether temporary price changes should be included in "sticky price" models for the purpose of drawing macroeconomic implications has come under much scrutiny in recent years (e.g. Bils and Klenow 2004; Kehoe and Midrigan 2008; Nakamura and Steinsson 2008; Eichenbaum, Jaimovich and Revelo 2011). However the impact of the treatment of sales on inflation measurement has been relatively overlooked.

A product is on sale when there is a temporary price reduction, i.e. the price of an item drops from its pre-sale price only to return to its pre-sale price, or to a new price which prevails for a longer period of time. We term the non-sale price as the 'regular' price. Since sales are discounts on regular prices, it is expected that over the long run the movement of sale and regular prices would be similar. However, sales can affect the measurement of inflation if sale price movements differ from regular price movements and purchasing at sale prices vis-à-vis regular prices change between periods, perhaps due to macroeconomic conditions.

Some concern has been expressed over whether sale prices are properly accounted for in the current practices of constructing the CPI, and the possibility that an inadequate treatment of sale price movements systematically biases the measurement of inflation. Under-sampling, or improper sampling, of sale prices in relation to expenditure during sale periods as a potential source of bias has been mentioned by many including Feenstra and Shapiro (2003), Triplett (2003), Hosken and Reiffen (2004a, 2004b), Griffith, et al. (2009) and de Haan and van der Grient (2011). For example, de Haan and van der Grient (2011; p. 37) observe the following from scanner data on detergents for a Dutch supermarket chain:

> "The quantity shifts associated with sales are dramatic. Consumers react instantaneously to discounts and purchase large quantities of the good—as a matter of fact, they hardly buy the good when it is not on sale. In this respect it is inappropriate to speak of a regular price during non-sale weeks."

The primary sources of quantity responses to sales are typically thought to be the following: (1) more consumption due to a lower price (Ailawadi and Neslin, 1998), (2) substitution from other items (van Heerde, Gupta and Wittink, 2003) and (3) a stockpiling effect (Hendel and Nevo 2006).[1] In terms of a cost-of-living interpretation of the CPI, stockpiling implies that consumers continue to consume at the purchased sale price (plus the storage cost) even when the price has returned to the regular price. If sale prices are in general under-sampled, there will a tendency for over-estimating the cost of living.[2]

Apart from potential substitution bias due to consumers switching to the sale goods, the bias at the elementary level of price index construction can occur due to the selection of an unrepresentative set of prices. Because regular prices are more prevalent, there is a tendency in the statistical agency procedures to select regular prices. National statistical agencies exert substantial effort to choose representative items and stores (de Haan, Opperdoes and Schut 1999). For example, the U.S. Bureau of Labor Statistics (BLS) conducts a household survey—Telephone Point of Purchase Survey (TPOPS)—to obtain information on the relative amount spent in different outlets for each item strata, and field agents obtain information on the revenue and volume sold at the outlet to ascertain the relative importance of the varieties in an item strata (BLS, 2007). However, this effort does not extend to the sampling of sales and regular prices within the item-store choices. Therefore, even if the item-store is properly chosen according to expenditure shares, the selected price prevailing at the time of price collector's visit to the store, which is either a

[1]Sobel (1984) and Pesendorfer (2002) explain sales as a means for firms and retailers to engage in intertemporal price discrimination where sale prices target consumers who have low reservation values and low waiting costs; they respond to sales by stockpiling and then consuming from the stock until the next sale is offered. Retailers wait to offer the next sale so that the demand accumulates to reach the point where discounting becomes optimal.

[2]Hosken and Reiffen (2004b; p. 143) note the following: "The average of weekly and monthly prices, unweighted by quantities, will overstate the cost of buying a good, especially for those consumers who "stock up" during sales. This in turn implies that if the frequency of sales differs over time and between locations, the true costs to the consumer can differ dramatically, even if the unweighted average price is the same. Hence, inflation measures based on unweighted averages can over- or understate the actual change in prices."

sale or a regular price, may not be representative of the corresponding expenditure share.[3]

While the Boskin Commission (Boskin et al. 1998), Lebow and Rudd (2003) and others have looked extensively into various potential sources of bias for the overall CPI, they did not explicitly explore the implications of the treatment of sales in CPI construction. Hence, this paper fills an overlooked gap in the literature.

2 Approach

A price collector surveying stores to collect the price of an item may find that, on the day of survey, the item was displaying either on a sale price or a regular price. The typical practice of statistical agencies, such as the Bureau of Labor Statistics (BLS), Australian Bureau of Statistics (ABS), Statistics Canada and UK Office of National Statistics (ONS), is to record the listed price at the time of collection where the listed price, taken to be the transaction price, is either a sale price or a regular price. Irrespective of whether the collected price is a sale price or a regular price, the price of the item is accorded the same weight in the index number formula; i.e. the typical statistical agency procedure does not have any mechanism to explicitly weight the price of an item depending on whether the collected price is a sale or a regular price. Suppose, in a given store, three prices corresponding to three items are collected. Out of these three prices, one price corresponds to a sale price while the other two prices correspond to regular prices. This implies that in that particular store, implicitly a one-third weight is given to sale prices and a two-thirds weight to regular prices.[4]

These implicit weights depend on the probability that a price collector while surveying the store finds that the item of interest is listed at a sale or a regular price. The longer the total period of sales of a item in a given year, the higher is the chance that the price collectors collect sale prices and, consequently, the lower is the chance that the price collectors collect regular prices. Since sales are temporary and infrequent (Hosken and

[3]It is not straightforward how this bias can be rectified through weighting of price relatives, even if the weights correspond to expenditure shares. For example, if most purchases of a item-store choice took place at sales prices, but the sampled price—the price prevailing when the price collecter visited the store—was a regular price, then the measure of price change may be biased.

[4]Not all countries include all sale prices in their national CPI. For example, in Greece "[s]pecial offers and discounts are not taken into account. Instead, the reduced prices of general offers and general discounts are collected." Japan "excludes temporary bargain (within a week) prices". Spain includes "price reductions (since January 2002) but excludes special offers". See *OECD Main Economic Indicators: Sources and Definitions—Consumer price indices*, http://stats.oecd.org/mei/ (accessed 10 March 2015).

Reiffen 2004a, Kehoe and Midrigan 2008, Nakamura, et al. 2011), the probability of a sale price being collected is low, particularly compared to the probability that a regular price is collected. This is in contrast to their corresponding expenditure shares, with consumers buying in larger quantities during sales (de Haan and van der Grient 2011, Kehoe and Midrigan 2008).[5] Thus statistical agency procedures tend to under-sample sale prices in comparison to their relevance to consumers as given by their expenditure shares.

In order to understand whether the under-sampling of sale prices biases the measure of price movements, we construct three sets of price relatives corresponding to three different ways of calculating unit values.[6] Beginning with our preferred approach, we calculate the price relatives, $P_i^{(W)}$, for items $i = 1, \ldots, N$, as a ratio of unit values, $(p_i^0)^{(W)}$ and $(p_i^1)^{(W)}$ for periods 0 and 1 respectively, as follows:

$$P_i^{(W)} = \frac{(p_i^1)^{(W)}}{(p_i^0)^{(W)}} = \frac{p_{r,i}^1 \cdot w_{r,i}^1 + p_{s,i}^1 \cdot w_{s,i}^1}{p_{r,i}^0 \cdot w_{r,i}^0 + p_{s,i}^0 \cdot w_{s,i}^0}, \tag{1}$$

where $(p_i^t)^{(W)} \equiv p_{r,i}^t \cdot w_{r,i}^t + p_{s,i}^t \cdot w_{s,i}^t = \sum_{j=1}^{J^t} p_{r,j,i}^t w_{r,j,i}^t + \sum_{k=1}^{K^t} p_{s,k,i}^t w_{s,k,i}^t$, for $t = 0, 1,$. The $p_{r,j,i}^t$ are the regular prices of item i in period t for transactions $j = 1, \ldots, J^t$. Similarly the $p_{s,k,i}^t$ are the sale prices of item i in period t for transactions $k = 1, \ldots, K^t$. $w_{r,j,i}^t = v_{r,j,i}^t / (\sum_{j=1}^{J^t} v_{r,j,i}^t + \sum_{k=1}^{K^t} v_{s,k,i}^t)$ is the quantity share of (j, i) in period t where $v_{r,j,i}^t$ and $v_{s,j,i}^t$ are the quantity of (j, i) sold at regular and sale prices at period t, respectively. Similarly, $w_{s,k,i}^t = v_{s,k,i}^t / (\sum_{j=1}^{J^t} v_{r,j,i}^t + \sum_{k=1}^{K^t} v_{s,k,i}^t)$ refers to the quantity share of (k, i) in period t.

Having sale prices in the calculation of unit values clearly lowers the unit values in each period, but the important question for our purpose is whether this inclusion systematically affects the price relatives, p_i^1/p_i^0, i.e. the average price change for item $i = 1, \ldots, N$. Sale prices affect the price relatives if (i) the sale price movements differ from the regular price movements and (ii) the quantity shares during sales changes between periods.[7]

Our second set of price relatives, $P_i^{(R)}$, is calculated from unit values $(p_i^0)^{(R)}$ and

[5] For example, using a US scanner data set, Kehoe and Midrigan (2008) report that 35.4% of quantity was sold in sales periods, even though the fraction of sales week was only 20.3%.

[6] See e.g. de Haan (2004), Silver (2011) and Ivancic and Fox (2013) for more on unit values.

[7] An implication of including sale prices is that they can make the price relatives, and hence price indexes, very volatile. Evidence shows that of $p_{r,i}^1/p_{r,i}^0$ and $p_{s,i}^1/p_{s,i}^0$, the former is more stable (Hosken and Reiffen 2004a; Nakamura et al. 2011). Some of these volatile price movements may take place in opposite directions and therefore, when included in an index number formula may cancel each other out. However, Ivancic, Diewert and Fox (2011) showed that even when "superlative" indexes (Diewert, 1976) are calculated, in many cases sale prices may produce erratic measures of inflation.

$(p_i^1)^{(R)}$ that use only regular prices as follows:

$$P_i^{(R)} = \frac{(p_i^1)^{(R)}}{(p_i^0)^{(R)}} = \frac{p_{r,i}^1 \cdot g_{r,i}^1}{p_{r,i}^0 \cdot g_{r,i}^0}, \tag{2}$$

where $(p_i^t)^{(R)} \equiv p_{r,i}^t \cdot g_{r,i}^t = \sum_{j=1}^{J^t} p_{r,j,i}^t / J^t$ for $t = 0, 1$. $p_{r,j,i}^t$ refers to the same regular price of item i for transactions $j = 1, \ldots, J^t$ as in equation (1). Note that each regular price transaction receives the same weight, $1/J$, in the construction of the unit values.

For the third method, the quantity shares in (1) are replaced with the proportion of the period an item is sold at each price. The corresponding price relative, $P_i^{(F)}$ is as follows:

$$P_i^{(F)} = \frac{(p_i^1)^{(F)}}{(p_i^0)^{(F)}} = \frac{p_{r,i}^1 \cdot f_{r,i}^1 + p_{s,i}^1 \cdot f_{s,i}^1}{p_{r,i}^0 \cdot f_{r,i}^0 + p_{s,i}^0 \cdot f_{s,i}^0}, \tag{3}$$

where $(p_i^t)^{(F)} \equiv p_{r,i}^t \cdot f_{r,i}^t + p_{s,i}^t \cdot f_{s,i}^t = \sum_{j=1}^{J^t} p_{r,j,i}^t/(J^t + K^t) + \sum_{k=1}^{K^t} p_{s,k,i}^t/(J^t + K^t)$ for $t = 0, 1$. Suppose, we are interested in constructing monthly unit values, i.e, period t refers to a particular month and that there are typically four weekly prices in a given month.[8] Suppose that out of these prices, three are regular prices and the remaining one is a sale price. Hence, $J^t = 3$ and $K^t = 1$, each transaction gets a weight of $1/(J^t + K^t) = 0.25$, the regular prices jointly get a weight of $J^t/(J^t + K^t) = 0.75$ and the sale price is accorded a weight of $K^t/(J^t + K^t) = 0.25$, i.e. it gets weighted by the sale frequency. Hence, we refer to $P_i^{(F)}$ as the frequency weighted price relative of item i.[9]

We have defined our three different price relatives in (1), (2) and (3) from three different ways of calculating unit values in each period. Note that $(p_i^t)^{(W)} < (p_i^t)^{(F)} < (p_i^t)^{(R)}$ for $t = 0, 1$. However, this inequality in the unit values does not necessarily imply that their corresponding price relatives also differ in a systematic manner. The price relatives $P_i^{(R)}$ and $P_i^{(F)}$ would differ from our preferred price relative $P_i^{(W)}$ if (i) there are changes in the magnitude of sale price dips, leading to differential movements of regular and sale prices and (ii) the deviation between the relative frequency of sales and the corresponding quantity share changes between the comparison periods.

[8] The evidence from the literature shows that retail prices are usually set at most once a week, implying there will be a maximum of 52 different prices of a item in a given year, out of which some are sale prices while others are regular prices (Dutta et al. 2002, Chevalier et al. 2003, Kehoe and Midrigan 2008 and Eichenbaum et al. 2011).

[9] In practice, agencies collect prices during a particular week of a month rather than every week of a month as implied in equation (3). If the occurrence of sales does not differ systematically across weeks of a month then the implicit weight accorded to the sale prices while surveying a particular week of a month would be the same as is in equation (3). Indeed, this is what we find in our empirical results.

Suppose the magnitude of sale price dip increases in the current period and the sale prices fall at a faster rate than the regular prices between the comparison periods. This differential price movement would be accorded different weights in equations (1) and (3) resulting in a discrepancy between $P_i^{(F)}$ and $P_i^{(W)}$. In particular, since frequency weights for the sale prices would be smaller than the quantity share weights, $P_i^{(F)}$ would provide an estimate of price movements smaller than $P_i^{(W)}$. The impact would however be larger for $P_i^{(R)}$ specified in equation (2) because $P_i^{(R)}$, which accords zero weight to sale prices, would not capture any differential price movements between regular and sale prices.[10]

The change in the responsiveness of quantity purchased to sales between the comparison periods would also lead to deviation between $P_i^{(F)}$ and $P_i^{(W)}$. Suppose that $w_s^1/f_s^1 > w_s^0/f_s^0$, i.e. the quantity share to sales frequency ratio is higher in the current period compared to the base period. This implies that the extent to which the sale prices are under-weighted in $P_i^{(F)}$ increases in the current period, leading $P_i^{(F)}$ to over-estimate price change. If, on the other hand, the under-weighting of sale prices decreases in the second period, $P_i^{(F)}$ would provide an estimate of price movements smaller than $P_i^{(W)}$. That is, the dynamics of p_s^t/p_r^t and f_s^t/w_s^t determine whether the measure of price movements provided by $P_i^{(F)}$ systematically differs from that provided by $P_i^{(W)}$. We study these two indicators in section 3.

In the *first stage* of constructing the price indexes, we construct indexes using three alternative formulae based on each price relative $P_i^{(V)}$, where $V \in [W, R, F]$ corresponds to equations (1), (2) and (3), respectively. These elementary indexes are constructed separately for each product and each city. Hence, nine elementary indexes are constructed for each product-city pair. In the *second stage*, we aggregate up the elementary indexes across cities to obtain indexes separately for each product which in turn, in the final *third stage*, are aggregated to obtain overall indexes for all our products and cities.

The Jevons price index, a symmetrically weighted geometric mean index, is used by many leading statistical agencies at the elementary level of aggregation when appropriate weights for item price relatives are unavailable. The Jevons index between periods 0 and 1, $P_J^{0,1(V)}$, can be written as follows:

$$P_J^{0,1(V)} = \prod_{i=1}^{I^{0,1}} \left[\frac{(p_i^1)^{(V)}}{(p_i^0)^{(V)}} \right]^{1/I^{0,1}}, \tag{4}$$

[10]See Fox and Syed (2015) for a detailed derivation of these results.

for items $i = 1, \ldots, I^{0,1}$ and $V \in [W, R, F]$. Here, i refers to an item which has a distinct product code sold in a distinct outlet. In other words, each item within a product category sold in a distinct outlet is treated as a separate item. These are also the item-outlet pairs which are matched in period 0 and 1, giving a total of $I^{0,1}$ items.[11]

A price index with a similar geometric form that can be used when expenditure share weights are available is the Törnqvist index given in equation (5), $P_T^{0,1}$, where we drop the superscript V for notational convenience though we construct three separate indexes for $V \in [W, R, F]$:[12]

$$P_T^{0,1} = \prod_{i=1}^{I^{0,1}} \left(\frac{p_i^1}{p_i^0} \right)^{0.5(\mathcal{S}_i^0 + \mathcal{S}_i^1)}. \tag{5}$$

As before, i refers to a particular item-outlet pair which are matched between periods 0 and 1. $\mathcal{S}_i^t$ is the expenditure share of i in period $t = 0, 1$ and is calculated as $\sum_{n=1}^{Nt} p_{i,n}^t v_{i,n}^t / \sum_{i=1}^{I^{0,1}} \sum_{n=1}^{Nt} p_{i,n}^t v_{i,n}^t$ for $t = 0, 1$, where $p_{i,n}^t$ and $v_{i,n}^t$ are the price and quantity of item i sold in week n in period $t = 0, 1$. In the case where $P_i^{(R)}$ is the price relative, the expenditure shares are obtained from the quantities sold only at regular prices.

As the "chaining" of indexes is usually favoured when there are new and disappearing goods, chained versions of (4) and (5) are considered, where e.g the chained Törnqvist index going from period 0 to period M is as follows:

$$P_T^{0,M} = P_T^{0,1} \times P_T^{1,2} \times \ldots \times P_T^{m-1,m} \times \ldots \times P_T^{M-2,M-1} \times P_T^{M-1,M}, \tag{6}$$

where items are matched between adjacent periods.

While there are well-documented advantages from chaining, problems with "chain drift" can emerge with highly volatile data, as is typical with high-frequency scanner data; chaining can result in price change estimates that are so explosive that they lack credibility. Ivancic, Diewert and Fox (2011) proposed a solution to this, which they labelled the Rolling Window GEKS (RWGEKS) index. This uses the multilateral GEKS index, updated using a rolling window of a prespecified length. For monthly indexes, they proposed that a

[11] As the Jevons index assigns equal weights to the price relatives, this can be thought of as providing a "purer" view of the impact of the alternative methods of construction of the price relatives compared to the other indexes considered. Of the class of elementary indexes, the Jevons formula has been shown to have relatively attractive properties (Diewert, 2010). Although it is not considered here, the Dutot index is also commonly used by statistical agencies at the elementary level. See Silver and Heravi (2007) for a comparison of the Jevons and Dutot indexes using scanner data.

[12] The Törnqvist index is a member of the "superlative" family of indexes, which have been shown to have attractive properties from the economic approach to index numbers (Diewert, 1976).

natural choice for the length of a window is thirteen months as it allows strongly seasonal commodities to be compared. This yields the Rolling Year GEKS (RYGEKS) index. While Ivancic, Diewert and Fox (2011) used the GEKS index, which is a geometric mean of all bilateral Fisher index comparisons, we use the multilateral index of Caves, Christensen and Diewert (1982) (CCD), which is a geometric mean of all bilateral Törnqvist index comparisons. This approach is consistent with de Haan and van der Grient (2011), and in using the Törnqvist index it is closer to the practice of the Bureau of Labor Statistics in CPI compilation (BLS, 2007). We call this the Rolling Year CCD (RYCCD) index which has the following form, going from period 0 to period T, where $T > 12$, and using the Törnqvist index formula as in (5):[13]

$$P_{RYCCD}^{0,T} \equiv \prod_{t=0}^{12} \left[P_T^{0,t} \times P_T^{t,12}\right]^{1/13} \prod_{t=13}^{T} \prod_{T-12}^{T} \left[P_T^{T-1,t} \times P_T^{t,T}\right]^{1/13}. \tag{7}$$

In this case, to maximize the items included, matching is between each of the comparison periods in each index constructed.[14]

In the *second stage* of the construction of indexes, we aggregate the elementary indexes defined in equations (4), (5) and (7) using expenditure share weights to obtain indexes separately for each product. We define $P_{Z,x,c}^{m-1,m(V)}$ as the elementary index measuring the price changes between periods $m-1$ and m for product category x in city c, that uses the price relative $V \in [W, R, F]$ and the index number formula $Z \in [J, T, RYCCD]$. Let $exp_{x,c}^t \equiv \sum_{i=1}^{I^{m-1,m}} \sum_{n=1}^{N^t} p_{i,n,x,c}^t v_{i,n,x,c}^t$ be the total expenditure on all items in product category x in city c for $t = m-1, m$, and $exp_x^t \equiv \sum_{c=1}^{C} exp_{x,c}^t$ be the total expenditure on all items in product category x aggregated over all cities for $t = m-1, m$. Then we calculate the index for product category x between periods $m-1$ and m, and for each

[13] In unreported results, we found that using either the Fisher or the Törnqvist index made little difference, and the resulting RYGEKS and RYCCD indexes approximate each other to a very high degree.

[14] In addition to the above 9 elementary indexes for each product-city pair, we calculated two other sets of Törnqvist indexes. In the first set, in calculating the unit values, an item with a distinct product code sold in different outlets is treated as the same item (as opposed to distinct items). Hence, the unit values defined in equation (1), (2) and (3) and the corresponding expenditure share weights are calculated by aggregating the transactions across weeks and different outlets. In the second set, we consider the transactions of only week 2 of each month, while treating each item sold in distinct outlets as a different item. Since there is no aggregation required in this case to obtain unit values, the price relatives in (1) and (3) become the same. The main thrust of the results shown by these two additional sets of indexes is the same as is found from the indexes in equations (4), (5) and (7).

$V \in [W, R, F]$ and each $Z \in [J, T, RYCCD]$ as follows:

$$P_{Z,x}^{m-1,m(V)} = \prod_{c=1}^{C} \left[\frac{P_{Z,x,c}^{0,m(V)}}{P_{Z,x,c}^{0,m-1(V)}} \right]^{0.5(\mathcal{S}_{x,c}^{m-1}+\mathcal{S}_{x,c}^{m})}, \tag{8}$$

where $\mathcal{S}_{x,c}^{t} = exp_{x,c}^{t}/exp_{x}^{t}$ is the expenditure share of city c for product x for $t = m-1, m$.[15] The indexes in equation (8) constructed for two consecutive periods are chained as in (6) in order to obtain an index measuring the price changes between period 0 and M for each product category x.[16]

In the *third stage* of our index construction, we aggregate all the $P_{Z,x}^{m-1,m(V)}$ indexes of equation (8) to obtain price indexes measuring the overall price movement of all products and cities included in the analysis:

$$P_{Z}^{m-1,m(V)} = \prod_{x=1}^{X} \left[\frac{P_{Z,x}^{0,m(V)}}{P_{Z,x}^{0,m-1(V)}} \right]^{0.5(S_{x}^{m-1}+S_{x}^{m})}, \tag{9}$$

where $S_x^t = exp_x^t / \sum_{x=1}^{X} exp_x^t$ is the expenditure share of product x across all cities for t=$m-1, m$. The indexes in equation (9) are chained in a similar way as in (6) to obtain a cumulative index measuring price changes between period 0 and M.[17]

3 Data and Results

We use the IRI Academic Data Set for the period 2001-2011, which provides weekly prices and quantities for each item sold separately in each store in different cities in the US (Bronnenberg, Kruger and Mela, 2008).[18] We use data for six major cities: Chicago, Houston, Los Angeles, New York, Philadelphia and Washington, DC. The ten products selected for this study are beer and ale, carbonated beverages, coffee, cold cereal, frozen dinner and

[15]In the special case where m=1, i.e. the prices are compared between period 0 and 1, the denominator of the equation (8) takes the value 1.

[16]In the second stage, we have also constructed indexes for each city which are obtained by aggregating the elementary indexes across all products; for results, see Fox and Syed (2015).

[17]These aggregated indexes are shown in Figure 2 of Section 3 for all $V \in [W, R, F]$ and $Z \in [J, T, RYCCD]$.

[18]In constructing our monthly indexes, starting from the beginning of a year, we define the first four weeks as the first month, the second four weeks as the second month and the next five weeks as the third month. The same procedure is followed to define the other months of the year. This implies that the 3rd, 6th, 9th and 12th month of a year consist of five weeks, while the other months consist of four weeks of data.

entrees, household cleaning products, laundry detergents, margarine and butter, peanut butter and soup. Many of these products match closely with the item definitions used by BLS price collectors at stores during sample collection for the CPI (BLS, 2007). From Table 1, this sample of ten products used in our analysis has around 220 million observations. The most important product category is carbonated beverages, accounting for a 26.8% share of expenditure, followed by beer & ale and cold cereal, accounting for 16.1% and 15.8% of expenditure, respectively.

Although scanner data sets provide detailed information on prices and quantities, they typically do not flag whether the transaction took place at a regular or a sale price.[19] We apply a new "sales spotter" algorithm that attributes a price change to sale price if the price change adheres to certain rules reflecting the basic feature of sale prices.[20] The application of these rules depends on four parameters: (1) the maximum number of periods the spotter is set to search backwards in time for an observed price (M); (2) the maximum duration of reduced prices to be treated as sale prices (K); (3) minimum percentage drop in price (E); and (4) minimum percentage recovery to consider the end of a sale (F). Through calibration on the data on a retail chain in Chicago in the US, the Dominicks Finer Foods, which flags more than 7.5 million sales, we have chosen the values of the parameters.[21] These are: $M = 13$ weeks, $E = 2\%$, $K = 6$ weeks and $F = 25\%$. M and E are set by observing of the empirical distributions of the relevant variables, and K and F are set using optimisation rules where the objective is to identify the maximum number of flagged sales subject to the constraint that the difference in the mean duration between the flagged and identified sales is minimised. See Syed (2015) for further details and Table 1 for some descriptive features of the identified sales in our data.[22]

[19]The IRI data provides an indicator taking the value of 1 if the total price reduction (TPR) is 5% or greater, 0 otherwise. This simple rule, on the one hand, is likely to miss some sale prices and, on the other hand, incorrectly identify non-sale price reductions as sale prices.

[20]A number of recent studies investigating persistence of retail prices with and without temporary price changes have developed alternative algorithms, or "filters", in order to create price series that reflects the most frequently occurring or representative price in a given period. While the details of the filters vary between the studies (and to some extent depend on the purpose of the study), the approaches of Eichenbaum et al. (2011), Chahrour (2011), and Kehoe and Midrigan (2008), can be described as creating a hypothetical price series from modal prices and regarding the other observed prices within a given window as temporary prices. Alternatively, Hosken and Reiffen (2004a) and Nakamura and Steinsson (2008) consider the price movements as temporary when they take place due to sales.

[21]The Dominick's data set is made available for research by Kilts Center for Marketing, Booth School of Business, University of Chicago (http://research.chicagobooth.edu/marketing/databases/dominicks/index.aspx). Chevalier et al. (2003) use the Dominick's sales flag to study the pricing behaviour of retailers.

[22]Sensitivity to this parameterisation was explored, particularly with respect to K. For example, for

Table 1 shows that the sale prices are substantially lower than the regular prices (22.7%), where the highest sale price dip is found for cold cereals (28.4%) and the lowest for beer & ale (12.4%) over the period 2001-2011. Table 2 shows that the sale frequency share is systematically much lower than the corresponding quantity share.[23] On average, items are sold at sale prices around 22.1% of the transaction weeks, while the quantity share during these sales weeks is 39.3%, around 1.8 times higher than the sale frequency share. The largest difference is seen with cold cereal where the quantity share is 2.2 times the corresponding share of sale frequency and the lowest difference is seen in beer and ale where the quantity share is 1.5 times the corresponding percentage of the period with sale prices.[24] This implies that statistical agencies over-estimate the unit values, which implicitly use frequency weighting; compared to the use of quantity shares, more weight is given to regular prices and less weight is given to discounted low prices.

As discussed in section 2, if the unit values in both periods are overestimated by the same magnitude then it would not have any effect on the measured price change. The ways the degree of this overestimation may change are when the magnitude of sale price dip changes over time and the deviation between the share of sale frequency and the corresponding quantity share differs between the periods. We find that the magnitude of the sale price dip and sale frequency share-quantity share ratio remain fairly stable in our sample period. Table 2 shows the estimates of the growth rate of the magnitude of the sale price dip and sale frequency share-quantity share ratio over the sample period. In most cases, the estimated coefficients are not significant at the 5% level, indicating that there is no deterministic trend of these two variables over the period 2001-2011.[25] With respect to price index construction, it implies that while unit values are overestimated in

$K = 4$ and $K = 6$, the results on price indexes obtained from the two sets of identified sales are qualitatively similar. Therefore, only the results corresponding to $K = 6$ are discussed.

[23]The sale frequency is calculated as the ratio of the number of sale weeks to the total number of transaction weeks. For a product-city pair, a weighted average of [total number of sale transaction weeks (all items across all stores)]/[total number of transaction weeks(all items across all stores)] was used to form an average over the six cities, where the weight corresponds to the share of total transaction weeks in each city. Quantity share of each product is constructed in a similar manner.

[24]This difference persists across sub-periods of comparison.

[25]The growth rate is estimated by regressing the natural log of the magnitude of sales on a constant and yearly time trend for each product. The time trends correspond to a particular month of year, thus providing us with 12 different estimated coefficients of the time trends. The average growth rate is the simple mean of the estimated coefficients of the time multiplied by 100. The average standard deviation is a combination of within-and between-standard deviations of the estimates adjusted for the degrees of freedom (see Rubin 1987). The annual growth rate of the sale frequency-quantity shares ratio is obtained in a similar manner.

each period if frequency weighting is used, there is little evidence that the degree of this overestimation changes between comparison periods.[26]

We now see how these observations follow through to price indexes. In the *first stage of aggregation*, we construct (chained) Jevons, Törnqvist indexes, and RYCCD indexes as described in equations (4), (5) and (7) of Section 2, using the three different approaches to calculating the unit values (and hence price relatives) from (1), (2) and (3); i.e. weighting by quantity shares, excluding sale prices, and weighting by frequencies of sales and regular prices. These indexes are constructed monthly over the period 2001 to 2011, for each product category and city, treating each item within a product category sold in a distinct outlet as a separate item. In the *second stage of aggregation* we aggregate across cities using expenditure share weights as in equation (8) to obtain aggregate indexes for each product category. In the *third stage of aggregation*, we then aggregate across products using expenditure share weights as in (9) to obtain indexes of overall price movement.

Table 3 presents results from the second stage of aggregation, showing average annual deviations of price indexes that use only regular prices and sale frequency weights from our preferred indexes that uses quantity share weighting. Completely excluding sale prices, i.e. using only regular prices, causes an upward deviation on average over all categories for the sample period, with the Jevons index being almost 5 percentage points per year higher each year on average compared to the quantity share weighted index. The Törnqvist index is only 0.56 points higher if sales are excluded, but there are large deviations for some product categories, such as household cleaners (2.64 points) and coffee (2.28 points). By comparison, the deviations are relatively small for all product categories in the case of the RYCCD index, with an overall average of 0.61 points if sales are excluded. Thus, the use of the RYCCD index at the elementary level then seems, in general, to result in relatively small deviations from quantity share weighted indexes, suggesting that the use of this index could mitigate the effects of severe under-sampling of sale prices.

The use of frequency weights results in lower deviations than if the sale prices are excluded. There is notably more variation across indexes and products, especially in terms of the signs of the deviations, with around half being negative. Hence, there does not appear to be a systematic bias from the use of frequency weights relative to using quantity

[26]The findings are similar when trends are estimated from quadratic and cubic fits. As an indicative summary of the findings, we only produce yearly growth rates obtained from fitting a linear trend for the whole sample period in this paper.

share weights in constructing the price relatives. This result is consistent with our earlier finding that there is no tendency for the quantity-to-frequency weights to change over time.

In Table 4, still at the second stage of aggregation, for each product category we consider the implications on the indexes of using the Jevons index at the elementary level, as is common in statistical agency practice, as compared with the superlative Törnqvist index and the RYCCD index. For each elementary index we consider our three alternative weighting schemes for constructing unit values. The results show that on average over the product categories, using the Jevons index and excluding sales leads to estimates of price change around 3 percentage points higher than if either the Törnqvist index or RYCCD index were used. With all prices included, using either frequent or quantity share weights results in deviations that are negative for all product categories except carbonated beverages, and substantially smaller in magnitude on average. In addition, there is little difference on average if frequency or quantity shares are used. In summary, using the Jevons index at the elementary level when sales are severely under-sampled results in significantly higher indexes over all product categories than if either the Törnqvist or RYCCD indexes are used, but lower indexes otherwise. Thus, ensuring that sales are appropriately captured in sampling appears more important than which of our index formulae is used at the elementary level.

Figure 1 plots the Törnqvist indexes for each product category using the three different approaches to calculating price relatives from (1), (2) and (3). While there are varying patterns of price paths for these products over the sample, consistently the exclusion of sale prices leads to noticeable (generally upward) deviations from our preferred approach which uses all prices and the corresponding quantity share weights. In contrast, the under-weighting from using frequency weights seems to result in little difference.

Figure 2 plots results from the third stage of aggregation as in equation (9), which constructs indexes of overall price movement over all product categories and cities. It is clear that placing zero weight on sales (i.e. excluding them in constructing the price relative as in (2)), results in indexes with an upward bias. However, consistent with the results reported in Table 3, there appears to be no clear systematic relationship between the results from using frequency weighting and quantity share weighting in constructing price relatives, regardless of whether Jevons, Törnqvist or RYCCD indexes are used. Thus, it is clear that the inclusion of sale prices dominates the choice of quantity or frequency weights in the price relatives.

Finally, as statistical agencies often collect price information from a particular week in a month in constructing indexes, Figure 3 plots the results from the third stage of aggregation using quantity share weights but making different assumptions on which week's data are available, including using data from all weeks. The figure shows that chain drift can have a large directional impact when indexes are constructed from a particular week's data using Jevons or Törnqvist indexes, yet it appears that the RYCCD index is correcting for this directional bias; that is, monthly RYCCD indexes constructed from transactions of a particular week provide a closer approximation to the corresponding index constructed from the data from all weeks. These results are of particular relevance for statistical agencies that mostly use data from a particular week in each month, providing another justification for using the RYCCD approach. Also, these results have implications for constructing real time indexes using incomplete data, again suggesting that the RYCCD approach is a preferred approach.

4 Conclusion

We have used a large scanner data set from US supermarkets to examine the impact of price discounts on the measurement of inflation. While there has been much recent attention to the issue of price dynamics at the micro level, the impact of these dynamics on inflation measurement has been relatively overlooked. In filling this gap in the literature, we have found that statistical agency practice systematically under-weights sale prices and this can result in biased inflation measurement. Specifically, we have found that national statistical agencies that exclude or severely under-sample sales prices in the measurement of price changes potentially introduce an upward bias in their inflation measures. This source of bias may be more prevalent than one might immediately suppose, with many countries seeming to have different approaches to the treatment of sales and similar price discounts in their national CPIs.[27]

The extreme case of zero weight on sales prices has been empirically found to be

[27] For statistical agencies that include sales, in our analysis we are implicitly assuming that the price sampling methodology is accurate in appropriately capturing sale prices. The extent to which sale prices are inadvertently omitted may also be a source of bias. If the sampling methodology does not appropriately choose representative items and outlets, that may affect the selection of sale and regular prices.

problematic, but the same is not true of the use of frequency weights, which tend to under-weight sale prices. These weights correspond most closely to those implicitly used by the statistical agencies that include sale prices in their inflation measures. Over ten product categories and five cities, we have found little systematic difference between the use of frequency weights and the preferred quantity share weights, which capture the changes in purchases due to price discounts. This is a perhaps somewhat surprising, yet reassuring result for the accuracy of inflation measures. Effectively, we have found that if the sale prices are included even though they are under-weighted, as long as the degree by which this under-weighting takes place remains the same, the measured inflation will be close to the true price change.[28]

We have also found that if statistical agency practice is to (mainly) use data from a particular week in a month, Jevons and Törnqvist indexes can have chain drift with a large directional impact. The RYCCD index appears to mitigate this problem, also suggesting that it is a preferable index for constructing real time indexes with incomplete data.

While this paper has presented a range of results using a large data set and a variety of methods, more analysis, including over a wider range of products, countries and alternative types of discounts (e.g. quantity discounts, as in Fox and Melser 2014), may reveal further insights into the relationship between consumer purchasing behaviour and the measurement of inflation. This type of research with a measurement focus seems overdue, especially given the extent of related analysis on price dynamics in the marketing and macroeconomic literatures, and the importance of accurate inflation measurement to public policy.

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[28]There are a number of other interesting results which are worthy of pursuit in future research. In particular, why the chained Jevons index has a downward trend while the others have an upward trend, and why there is not more chained drift in the Törnqvist index relative to the RYCCD index.

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Table 1: Data description and some facts on Sales

Products†	No. of Obser.‡ (ml.)	Exp. Share by Prods (%)	Exp. Share at Sales (%)	Average Sales Price Dip* (%)	Average Sales Duration (weeks)
Beer & Ale	17.77	16.07	32.99	12.40	2.92
Carb. Bever.	42.96	26.81	46.38	21.60	2.29
Coffee	16.71	6.23	33.10	21.66	2.78
Cold Cereal	30.78	15.82	33.57	28.38	2.43
FZ Din. & Ent.	40.41	12.30	40.71	27.42	2.54
House. Clean.	10.33	2.24	23.09	21.04	2.52
Laundry Deter.	13.54	8.17	38.52	25.79	2.52
Marg. & Butter	7.36	2.76	24.62	21.92	2.35
Peanut Butter	5.48	1.94	25.34	19.47	2.68
Soup	34.46	7.67	28.47	28.05	2.60
All Items**	219.79	100.00	37.13	22.71	2.53

† Data description corresponds to 6 cities: Chicago, Houston, Los Angeles, New York, Philadelphia and Washington, DC.
‡ Total number of observations used for calculating price indexes.
* Calculated as the fall in price in the first week of sale compared to the immediately preceding regular price.
** The figures for "No. of Obser." and "Exp. Share by Prods" are summations while others are expenditure share weighted averages across products.

Table 2: Frequency and size of Sales, volume sold during Sales and their changes during 2001–2011

Products†	Sale Weeks and Volume Sold		Changes in the Magnit. of Sales		Ratio of Sale Freq. to Quant. Share	
	Sale Freq.‡ (%)	Quant. Share‡ (%)	Growth Rate* (%/yr)	Std. Error	Growth Rate* (%/yr)	Std. Error
Beer & Ale	15.36	23.07	-1.80**	0.92	3.50**	1.20
Carb. Bever.	26.79	45.53	-0.21	1.32	1.69	1.28
Coffee	20.73	37.17	-0.70	1.13	2.81	1.93
Cold Cereal	19.42	43.20	0.05	1.10	1.77	1.35
FZ Din. & Ent.	30.10	48.22	-2.32**	1.02	1.29	1.40
House. Clean.	17.29	28.07	2.12	1.72	-0.30	1.79
Laundry Deter.	21.95	44.90	0.12	0.99	2.28	1.39
Marg. & Butter	18.83	30.57	2.21	1.75	3.44**	1.52
Peanut Butter	16.99	33.07	0.04	2.09	1.85	1.72
Soup	17.47	32.70	0.08	1.56	3.49**	1.47
All Items§	22.08	39.32	-0.54	1.20	2.21	1.39

† The figures of each product correspond to 6 cities: Chicago, Houston, Los Angeles, New York, Philadelphia and Washington, DC.
‡ See footnote 22 for explanation of how these are calculated.
* See footnote 24 for the method used to obtain the growth estimates.
** Denotes statistical significance at the 5% level.
§ The figures are expenditure share weighted averages across products.

Table 3: Average annual deviation of the regular price index and sale frequency weighted index from the quantity share weighted index for 2001–2011 (in percentage points)

Products†	Jevons Index		Törnqvist Index		RYCCD Index	
	Regular Price Deviation*	Frequency Weight Deviation**	Regular Price Deviation	Frequency Weight Deviation	Regular Price Deviation	Frequency Weight Deviation
Beer & Ale	1.78	0.01	-0.24	-0.04	0.23	-0.04
Carb. Bever.	4.46	-0.13	-1.14	0.09	0.71	0.25
Coffee	6.19	0.08	2.28	0.12	1.08	0.36
Cold Cereal	5.67	-0.21	1.55	-0.31	0.66	0.08
FZ Din. & Ent.	6.43	-0.14	1.13	-0.28	0.25	-0.27
House. Clean.	5.00	0.07	2.64	0.29	0.89	0.17
Laundry Deter.	7.64	-0.11	2.55	-0.18	1.00	0.06
Marg. & Butter	3.29	-0.09	1.13	-0.05	0.40	0.01
Peanut Butter	3.22	-0.06	0.85	-0.02	0.09	-0.12
Soup	5.22	0.07	0.80	-0.29	0.86	-0.01
All Items‡	4.84	-0.08	0.56	-0.09	0.61	0.07

† For each product, the indexes are calculated separately for each city. These indexes are aggregated across cities using the Törnqvist index formula.
* Regular Price Deviation is the difference between the cumulative index for 2001–11 obtained from the unit values calculated from only the regular prices and the quantity share weighted unit values of the regular and sale prices. This difference is divided by 11 in order to obtain the annual deviation.
** Frequency Weight Deviation is the similar deviation between the frequency share weighted and quantity share weighted indexes.
‡ The figures are expenditure share weighted averages across products.

Table 4: Average annual deviation between Jevons index, and Törnqvist and RYCCD indexes for 2001–2011 (in percentage points)

Products	Jevons vs. Törnqvist Index†			Jevons vs. RYCCD Index		
	Reg. Prices: Freq. Share Weights	All Prices: Freq. Share Weights	All Prices: Quant. Share Weights	Reg. Prices: Freq. Share Weights	All Prices: Freq. Share Weights	All Prices: Quant. Share Weights
Beer & Ale	0.74	-1.23	-1.28	0.89	-0.61	-0.66
Carb. Bever.	5.71	-0.10	0.12	4.13	0.02	0.39
Coffee	2.16	-1.79	-1.74	1.79	-3.61	-3.32
Cold Cereal	2.47	-1.55	-1.65	3.60	-1.70	-1.41
FZ Din. & Ent.	3.31	-1.86	-2.00	3.74	-2.31	-2.44
House. Clean.	1.06	-1.53	-1.31	1.29	-2.92	-2.82
Laundry Deter.	4.19	-0.84	-0.91	4.30	-2.50	-2.34
Marg. & Butter	1.16	-1.05	-1.00	0.89	-2.10	-2.01
Peanut Butter	1.49	-0.92	-0.88	1.10	-1.97	-2.03
Soup	2.51	-1.55	-1.91	1.81	-2.47	-2.55
All Items‡	3.20	-1.08	-1.09	2.96	-1.43	-1.27

† The cumulative difference between Jevons and Törnqvist indexes during 2001–2011 is divided by 11 in order to obtain the average annual deviation. The deviation between Jevons and RYCCD indexes is obtained in a similar way.
‡ The figures are expenditure share weighted averages across products.

Figure 1: Törnqvist indexes constructed from different unit values, 2001–2011

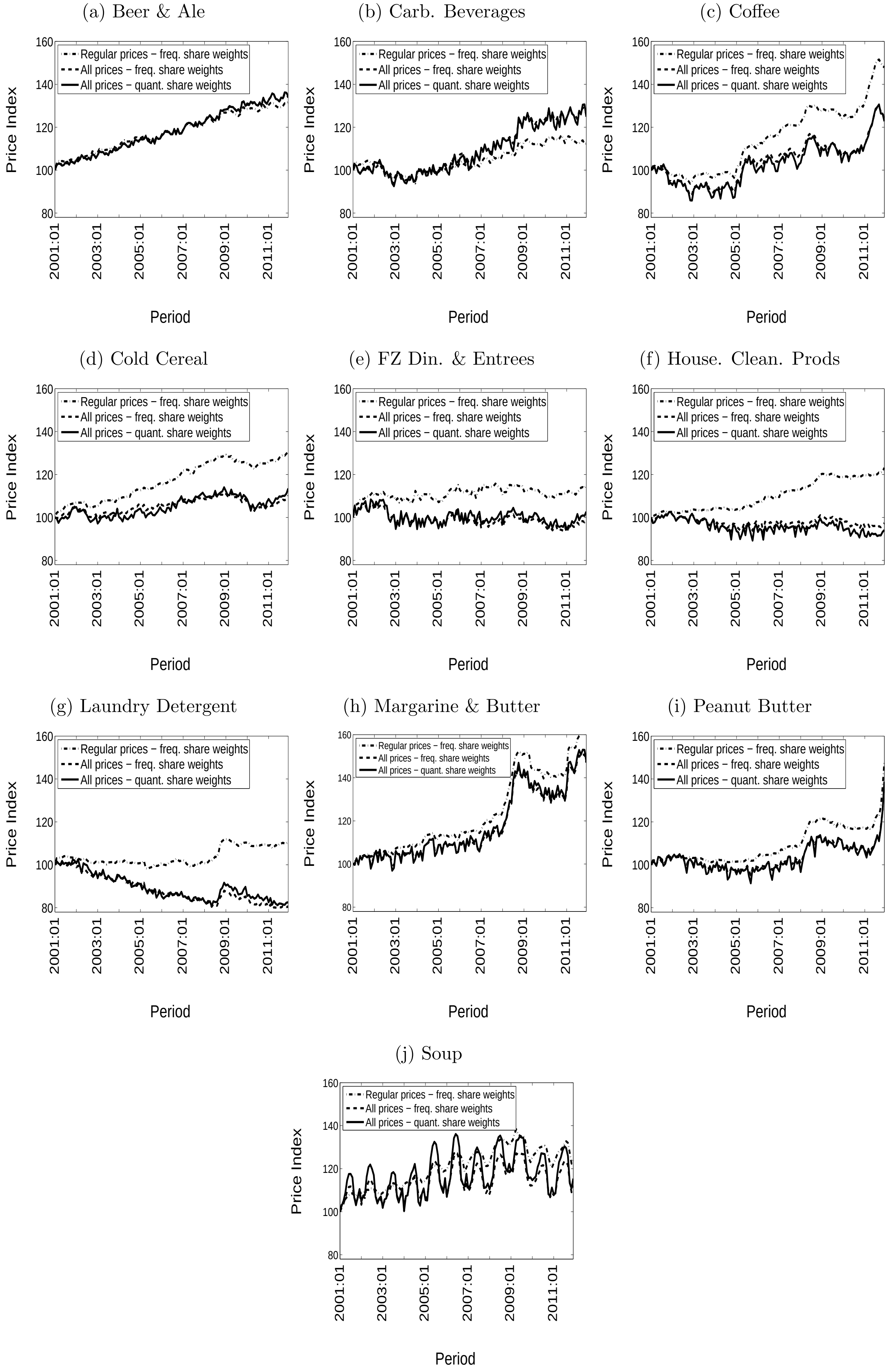


Figure 2: Aggregate indexes across all 6 cities and 10 products, 2001-2011

(a) Jevons Index (b) Törnqvist Index (c) RYCCD Index

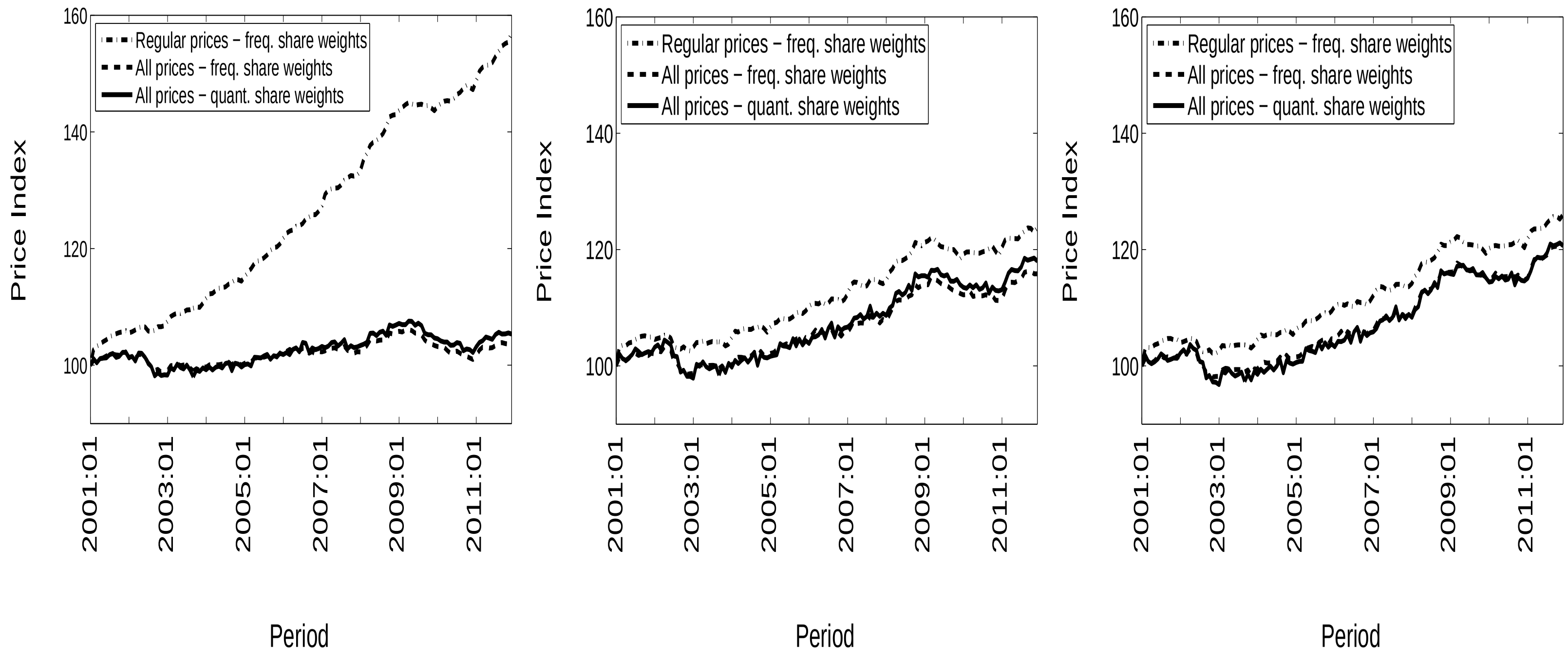
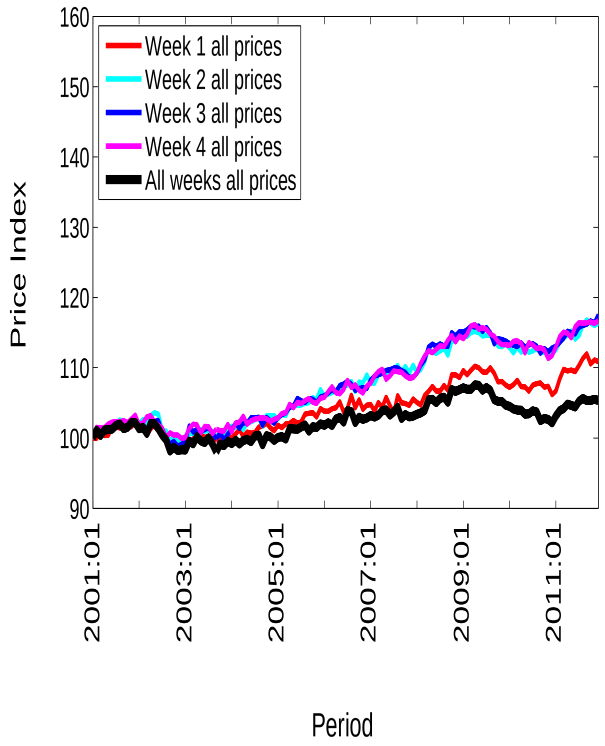
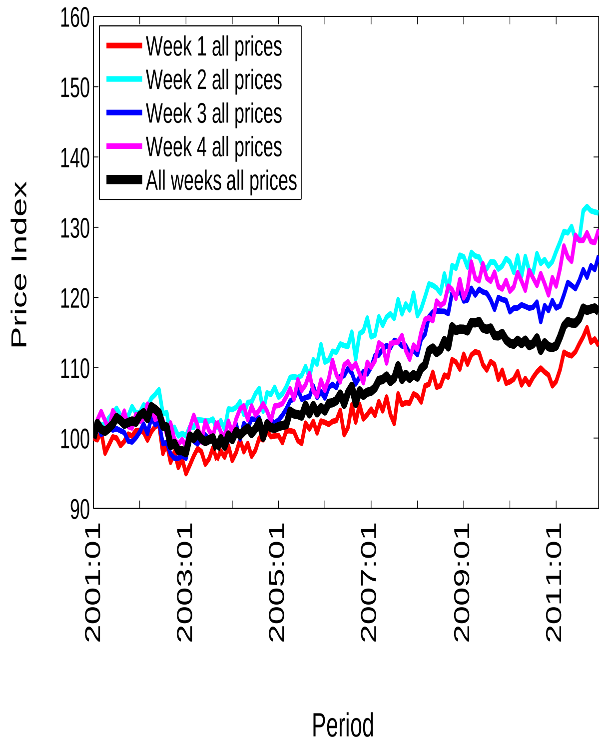


Figure 3: Aggregate monthly indexes constructed using different and all weeks of data across all 6 cities and 10 products, 2001-2011

(a) Jevons Index



(b) Törnqvist Index



(c) RYCCD Index