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Australian School of Business Research Paper No. 2014 ECON 05

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Last updated: 11/02/14 CRICOS Code: 00098G

Price Discounts and the Measurement of Inflation

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January 2014

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

JEL Classification: C43, E31

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1 Introduction

Price discounts are a frequent and prevalent part of the consumer shopping experience. It is clear that consumers in general are very responsive to sales, yet the methods used by national statistical agencies for constructing key inflation measures, such as the Consumer Price Index (CPI), typically under-weight sale prices. There is little information on how this 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; Klenow and Kryvtsov 2008; Nakamura and Steinsson 2008, 2013; Eichenbaum, Jaimovich and Revelo 2011; Bils, Klenow and Malin 2012; Dhyne et al. 2006). 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, there can be changes in the behavior of sale prices vis-à-vis regular prices. For example, it may happen that the average price dips and the spread around the average price dips change over time. Another way sales can affect the measurement of inflation is if there is a systematic movement away from purchasing at regular prices to sale prices, 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 2006a, 2006b; van Heerde, Leeflang and Wittink 2004).[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. 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."

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 put in substantial effort to choose representative items and stores (de Haan, Opperdoes and Schut 1999). For example, the 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 sale or a regular price, may not be representative of the corresponding expenditure share. This bias cannot be rectified through weighting of price relatives, even if the weights correspond to expenditure shares. [2]

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

[2]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.

While the Boskin Commission (Boskin et al. 1998) 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 Unit Values and Price Relatives

A price collector surveying stores to collect the price of a 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 a item depending on whether the collected price is 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.[3]

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. This implies that 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 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. The question is, given the low frequency of sales, whether the statistical agency procedures are under-sampling the sale prices and sale price movements compared to the corresponding expenditure undertaken during the sale period.

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; 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

[3]Not all agencies include all sale prices. For example, de Haan and van der Grient (2011) report that Statistics Norway deliberately drop off the sale prices, and Nakamura et al. (2011) report that Germany, Italy and Spain do not include sale prices during seasonal sale periods in the CPI sample.

sales week was only 20.3%.[4]

We calculate the monthly unit values, p_i^t, for each item $i = 1, \ldots, N$ aggregated over sale and regular prices for each period $t = 1, \ldots, T$. The price relative of item i comparing prices of period 0 and 1 is then as follows:

$$\frac{p_i^1}{p_i^0} = \frac{p_{r,i}^1 g_{r,i}^1 + p_{s,i}^1 g_{s,i}^1}{p_{r,i}^0 g_{r,i}^0 + p_{s,i}^0 g_{s,i}^0}, \tag{1}$$

where $g_{r,i}^t$ and $g_{s,i}^t$ are the share of item i's quantity sold at regular ($p_{r,i}^t$) and sale ($p_{s,i}^t$) prices to the total quantity sold, respectively. The inclusion of sale prices in the calculation of unit values will clearly lower the unit values in each period, but the important question is whether the inclusion of sale prices systematically affects the price relatives, p_i^1/p_i^0, the average price change for item $i = 1, \ldots, N$. Sale prices will affect the price relatives if (1) the sale price movements differ from the regular price movements and (2) the quantity share during sales changes between periods.

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). In some cases regular price changes only around once a year (Nakamura and Steinsson 2008). This implies that the introduction of sale prices can make the price relatives, and hence price indexes, very volatile.[5]

We construct three different sets of price relatives: (i) unit values are calculated using the share of quantity sold at each price (the preferred approach); (ii) only regular prices are used; and (iii) the percentage of sample periods a price prevailed in the market is used as the weight for the price in the construction of the unit value. The second two approaches are motivated by the actual practice of different national statistical agencies. Some statistical agencies drop sales price on the ground that they are temporary. Other statistical collect sales prices if the price prevailing during the collection is the sale price and, therefore, the implicit weight the sale prices are accorded depends on the fraction of periods sales are on. We now define each set of price relatives in turn, beginning with P_i^W, our preferred price relatives, for items $i = 1, \ldots, N$:

$$P_i^{(W)} = \frac{(p_i^1)^{(W)}}{(p_i^0)^{(W)}} = \frac{p_{r,i}^1 \cdot w_{r,i}^1 + p_{s,i}^1 \cdot w_{s,i}^1}{p_{r,i}^0 \cdot w_{r,i}^0 + p_{s,i}^0 \cdot w_{s,i}^0}, \tag{2}$$

where, for $t = 0, 1$, $p_{r,i}^t \cdot w_{r,i}^t = \sum_{j=1}^{J} p_{r,j,i}^t w_{r,j,i}^t$ and $p_{s,i}^t \cdot w_{s,i}^t = \sum_{k=1}^{K} p_{s,k,i}^t w_{s,k,i}^t$. The $p_{r,j,i}^t$ are the regular

[4] The weekly information on unit values and total volume sold in scanner data sets are typically obtained by aggregating prices and quantities over the days in a week for which a store sales circular is active. This implies that the averaging in order to obtain weekly data does not affect the frequency and magnitude of price changes of individual items. This has been regarded by various authors including Dutta et al. (2002), Chevalier et al. (2003), Kehoe and Midrigan (2008) and Eichenbaum et al. (2011) as an important advantage of using scanner data sets for studying price dynamics.

[5] 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 and unrealistic measures of inflation.

prices of item i in period t for transactions $j = 1, \ldots, J$, similarly the $p^t_{s,k,i}$ are the sale prices of item i in period t for transactions $k = 1, \ldots, K$, $w^t_{r,j,i} = v^t_{r,j,i}/(\sum_{j=1}^J v^t_{r,j,i} + \sum_{k=1}^K v^t_{s,j,i})$, is the quantity share of (j, i) in period t where $v^t_{r,j,i}$ and $v^t_{s,j,i}$ are the quantity of (j, i) sold at regular and sale prices at period t, respectively. Similarly, $w^t_{s,k,i} = v^t_{s,k,i}/(\sum_{j=1}^J v^t_{r,j,i} + \sum_{k=1}^K v^t_{s,k,i})$ refers to the quantity share of (k, i) in period t.

Price relatives obtained from only regular prices, $P_i^{(R)}$, are then as follows:

$$P_i^{(R)} = \frac{(p_i^1)^{(R)}}{(p_i^0)^{(R)}} = \frac{p^1_{r,i} \cdot q^1_{r,i}}{p^0_{r,i} \cdot q^0_{r,i}} \tag{3}$$

where, $p^t_{r,i} \cdot q^t_{r,i} = \sum_{j=1}^J p^t_{r,j,i} q^t_{r,j,i}$. $p^t_{r,j,i}$ refers to the same regular price as in equation (2), and $q^t_{r,j,i} = w^t_{r,j,i}/\sum_{j=1}^J w^t_{r,j,i}$ is the quantity share of (j, i) in period t when only regular prices are included in the calculation of unit values.

In the third method, the quantity shares in (2) are replaced with the proportion of the period an item is sold at each price:

$$P_i^{(F)} = \frac{(p_i^1)^{(F)}}{(p_i^0)^{(F)}} = \frac{p^1_{r,i} \cdot f^1_{r,i} + p^1_{s,i} \cdot f^1_{s,i}}{p^0_{r,i} \cdot f^0_{r,i} + p^0_{s,i} \cdot f^0_{s,i}}, \tag{4}$$

where $p^t_{r,i} \cdot f^t_{r,i} = \sum_{j=1}^J p^t_{r,j,i}/(J + K)$ and $p^t_{s,i} \cdot w^t_{s,i} = \sum_{k=1}^K p^t_{s,k,i}/(J + K)$. This means that each transaction receives the same weight in the construction of the unit values. Suppose, we are interested in constructing monthly unit values, i.e, period t refers to a particular month. Then, drawing on the empirical literature on price changes, there are typically four weekly prices in a given month, and suppose that out of these prices, three are regular prices and the remaining one is a sale price. Hence, $J = 3$ and $K = 1$, each transaction gets a weight of $(1/J + K =)$ 0.25, the regular prices jointly get a weight of $K/(J + K) = 0.75$ and the sale price is accorded a weight of $J/(J + K) = 0.25$, i.e. it gets weight by the sale frequency. Hence, we refer to this approach as using frequency weights.

We have defined our three different price relatives in (2), (3) and (4) 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 $t = 0, 1$. The question is whether there is any systematic difference, not only in the unit values themselves, but also in the ratio of the unit values, the price relatives. We compare equation (3) and (4) with the preferred price relative (2), for a fixed item i, dropping the item subscript for notation simplicity.

Let $p^0_s = (1 - a^0)p^0_r$ and $p^1_s = (1 - a^1)p^1_r$, where $0 < a^0, a^1 < 1$. a^0 and a^1 refer to the price dips due to sales in period 0 and 1, respectively. If a^0 and a^1 differ then the movement of regular prices differs from the movement of sale prices; otherwise, $p^1_r/p^0_r = p^1_s/p^0_s$.

For $w^0_s = b^0 f^0_s$ and $w^1_s = b^1 f^1_s$, then b^0 and b^1 provide a measure of deviation between the frequency and quantity shares of sale prices in periods 0 and 1, respectively. Since proportionately larger quantities are bought during the sale period, $b^0, b^1 > 1$. If b^0 and b^1 differ, then it means that this deviation changed between period 0 and 1; otherwise, $w_r^1/w_r^0 = f_r^1/f_s^0$. The difference between b^0 and b^1 will turn out to be most important in our derivation of potential bias in inflation measurement.

Comparing $P_i^{(F)}$ with the preferred price relative $P_i^{(W)}$, setting $w_r^t = 1 - w_s^t$ and $f_r^t = 1 - f_s^t$, we obtain a measure of bias:

$$\Pi^{(F)} = \frac{P^{(F)}}{P^{(W)}} = \frac{(p^1)^{(F)}}{(p^1)^{(W)}} \times \frac{(p^0)^{(W)}}{(p^0)^{(F)}} = \frac{1 - a^1 f_s^1}{1 - a^1 b^1 f_s^1} \times \frac{1 - a^0 b^0 f_s^0}{1 - a^0 f_s^0}. \tag{5}$$

If we set $f_s^0 = f_s^1 = f_s$ and $b^0 = b^1 = b$, so that the frequency shares and the corresponding quantity shares do not change between period 0 and 1, we obtain the following:

$$\Pi^{(F)} = \frac{1 - a^1 f_s}{1 - a^1 b f_s} \times \frac{1 - a^0 b f_s}{1 - a^0 f_s}.$$

Note that both a^0 and a^1 appear in the numerator and denominator of the equation. This implies that even if a^0 and a^1 differ (i.e. the movement of sale prices differ from the movement of regular prices between periods 0 and 1), the effect in equation (5) may be small. The other parameters, b^0 and b^1, on the other hand, do not appear in both the numerator and denominator in the equation. Therefore, their difference is likely to have a relatively larger effect on the bias.

Suppose that $b^0 = \alpha b^1$ where $\alpha \neq 1$, so that α provides a measure of the change in the deviation between sale frequency and quantity share. If $\alpha > 1$, then the deviation is larger in period 0 compared to period 1. With $f_s^0 = f_s^1 = f_s$, this implies that the quantity share at the sale prices in the second period has fallen, i.e. the extent to which the sale prices are under-weighted has fallen. If we set $a^0 = a^1 = a$, then equation (5) becomes:

$$\Pi^{(F)} = \frac{1 - a\alpha b^1 f_s}{1 - a b^1 f_s}.$$

In the above equation, $0 < 1 - ab^1 f_s < 1$. If $\alpha > 1$, the numerator is smaller than the denominator and, as a result, $\Pi^{(F)} < 1$, i.e. $P^{(F)}$ provides an estimate of price movements smaller than $P^{(W)}$. On the other hand, if $\alpha < 1$, then $\Pi^{(F)} > 1$, i.e. $P^{(F)}$ provides an upwardly biased measure of price change. Suppose that the quantity share corresponding to sale prices is 0.40 (i.e. $b^1 f_s = 0.40$) and the average dip of sale prices is 0.20 of the regular prices.[6] Further, suppose that $\alpha = 0.9$, i.e. the deviation between the sale frequency and the quantity share increases by around 10% from period 0 to 1. In this case, $\Pi^{(F)} = 1.0087$, i.e. $P^{(F)}$ provides an upward bias measure of price change by 0.87 percentage point. By

[6]These are around the averages we find in our data.

differentiating $\Pi^{(F)}$ with respect to α:

$$\frac{\delta\Pi^{(F)}}{\delta\alpha} = \frac{-ab^1 f_s}{(1 - ab^1 f_s)} < 0.$$

Hence, if α, from a value below 1, goes up, the bias goes down. The bias reaches 0 when $\alpha = 1$. Any further increase in α results in a downwardly biased measure of price change. The important point to note is that if the deviation between the proportion of sale frequency and the quantity share remains the same between the comparison periods (i.e. $\alpha = 1$), the price relative $P^{(F)}$ provides an accurate measure of price change.

Comparing $P_i^{(R)}$ with the preferred price relative $P_i^{(W)}$, we obtain the following measure of bias:

$$\Pi^{(R)} = \frac{P^{(R)}}{P^{(W)}} = \frac{q_r^1}{q_r^0} \times \frac{1 - a^0 w_s^0}{1 - a^1 w_s^1}.$$

If $a^1 > a^0$, i.e. the price dip is higher in period 1, then the denominator of the term after the product becomes smaller than the numerator and, hence, $\Pi^{(R)}$ becomes larger; if sale prices fall at a faster rate that the regular prices, $\Pi^{(R)}$, not capturing this differential movement, will produce a larger bias. Suppose that $a^0 = \beta a^1$, meaning that if β is greater than 1, then price dip was lower in period 0 compared to period 1. By differentiating $\Pi^{(R)}$ with respect to β, we obtain the following:

$$\frac{\delta\Pi^{(R)}}{\delta\beta} = \frac{q_r^1}{q_r^0} \times \left[\frac{-a^1 w_s^0}{1 - a^1 w_s^1}\right] < 0.$$

If $\beta < 1$ and then if it changes towards 1, the upward bias in $\Pi^{(R)}$ would become smaller. The implication is that the differential movement between sale and regular prices, while it may not matter in $P^{(F)}$, it does matter in generating bias in $P^{(R)}$, which excludes sale prices by construction.

3 Index Number Formulae

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, $P_J^{0,1}$, can be written as follows:

$$P_J^{0,1} = \prod_{i=1}^{N} \left(\frac{p_i^1}{p_i^0}\right)^{1/N}, \tag{6}$$

for items $i = 1, \ldots, N$. Thus, every price relative gets equal weight in the index. Of the class of elementary indexes, the Jevons formula has been shown to have relatively attractive properties (Diewert, 2010).[7] A price index with a similar geometric form that can be used if expenditure share weights are available is the Törnqvist index, $P_T^{0,1}$:

$$P_T^{0,1} = \prod_{i=1}^{N} \left(\frac{p_i^1}{p_i^0} \right)^{0.5(\mathcal{S}_i^0 + \mathcal{S}_i^1)}, \tag{7}$$

where $\mathcal{S}_i^t$ is the expenditure share of item i in period $t = 0, 1$. 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).

Chained indexes are usually favoured when there are new and disappearing goods, as chaining allows for updating of the items covered by the index. Hence, chained versions of (6) and (7) will be considered, where e.g the chained Törnqvist index going from period 0 to period 2 is $P_T^{0,2} = P_T^{0,1} \times P_T^{1,2}$, with items matched between adjacent periods.

While there are 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 unrealistic indicies that show incredible price changes. Ivancic, Diewert and Fox (2011) proposed a solution to this, which they label the Rolling Window GEKS (RWGEKS) index, which uses the multilateral GEKS index, updated using a rolling window of a prespecified length. For monthly indexes, they proposed that a natural choice for the length of a window is thirteen months as it allows strongly seasonal commodities to be compared. This led to the Rolling Year GEKS (RYGEKS) index, which has the following form, going from period 0 to period T, where $T > 12$, and using the Törnqvist index formula as in (7):

$$P_{RYGEKS}^{0,T} \equiv \prod_{t=0}^{12} \left[P_T^{0,t} \times P_T^{t,12} \right]^{1/13} \prod_{t=13}^{T} \prod_{T-12}^{T} \left[P_T^{T-1,t} \times P_T^{t,T} \right]^{1/13}. \tag{8}$$

In this case, to maximize the items included, matching is between each of the comparison periods in each index constructed. While Ivancic, Diewert and Fox (2011) used the Fisher index in their application of this method, we follow de Haan and van der Grient (2011) in using the Törnqvist index as its use is closer to the practice of the Bureau of Labor Statistics in CPI compilation (BLS, 2007).[8]

[7]The Jevons index is considered as through assigning equal weights to the price relatives it can be considered as providing a "purer" view of the impact of the alternative methods of construction of the price relatives compared to the other indexes considered. 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.

[8]More correctly, this version of the RYGEKS index should probably be termed the Rolling Year CCD index, after the approach of Caves, Christensen and Diewert (1982), who replaced the Fisher index with the Törnqvist index in the standard GEKS formula. To avoid introducing terminological confusion in the literature, we stick with "RYGEKS". In unreported results, we found that using either the Fisher or the Törnqvist index made little difference, and the resulting different versions of RYGEKS approximate each other to a very high degree.

4 Data and Results

We use the IRI Academic Data Set for the period 2001-2006, which provides weekly prices and quantities for each item sold separately in each store (Bronnenberg, Kruger and Mela, 2008). We use data for the five largest cities in 2012, according to the US Bureau of Census: Chicago, Houston, Los Angeles, New York and Philadelphia. The ten products selected for this study are beer/ale, carbonated beverages, coffee, cold cereal, frozen dinner/entrees, household cleaning products, laundry detergents, margarine/butter, peanut butter and soup. Many of these products match closely with the item definition used by BLS price collectors at stores during sample collection for the CPI (BLS, 2007). As can be seen from Table 1, this sample of ten products has more than 100 million observations and 8,000 varieties of items. The most important product category is carbonated beverages, accounting for a 28.8% share of expenditure, followed by cold cereal and beer, accounting for 17.0% and 16.5% of expenditure.

Although scanner data sets, such as ours provide detailed information on prices and quantities, these data sets typically do not flag whether the transaction took place at a regular or a sale price. An exception to this is the data on Dominick's Finer Foods, a retail chain in Chicago in the US.[9] Although sales are only partially flagged, there are more than 7 million flagged sales in the data. We develop an algorithm that is able to identify these flagged sales, and apply it to our data set.[10]

The goal of this algorithm is to identify the maximum number of sales while at the same time minimising the incorrect attribution of non-sale price reductions as sale prices. This task is not straightforward.[11] While the majority of sale prices are of regular type in the sense that price reduction is high, duration of the reduced price is low and the price returns to its original price after the sale is over (U-shaped sales), there are also a large number of sales where price dips are very low (around 10% of Dominick's flagged sales have price dips of 4% or less), duration is high (around 5% have a duration of five weeks or more) and prices do not return to their original pre-sale prices (around 30% of flagged sales have lower return prices). The problem lies in identifying the latter types of sales because in many cases these sales are indistinguishable from non-sale price changes. In addition, complications

[9] The Dominick's data set is made available for research by James M. Kilts Center, Graduate School of Business, University of Chicago (http://research.chicagobooth.edu/marketing/databases/dominicks/index.aspx). The papers that use the Dominick's sales flag to study retail pricing behaviour include Chevalier et al. (2003) and Chen et al. (2008).

[10] The IRI data provides an indicator taking the value of 1 if the total price reduction (TPR) is 5% or greater, 0 otherwise. The following discussion would indicate that 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.

[11] In recent years, a number of studies investigating persistence of retail prices with and without temporary price changes have developed 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 (which 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.

may arise in identifying sale pries due to large number of missing prices, price variations within a single sale and frequent price spikes.

Our "sales spotter" algorithm, as it moves forward over time, detects price changes. Whether the spotter attributes the price change to sale price depend on whether the price change adheres to certain rules reflecting the basic feature of sale prices. The application of these rules depends on four parameters: (1) M, the maximum number of periods the spotter is set to search backwards in time for an observed (non-missing) price; (2) K, the maximum duration of reduced prices to be treated as sale prices; (3) E, minimum percentage drop in price; and (4) F, minimum percentage recovery to consider the end of a sale. The values of the parameters are set to maximise the identification of the flagged sales in the Dominick's data and at the same time minimising the attribution of non-flagged price reductions as sale prices. In the case of M and E, the values are set at 13 weeks and 2%, respectively, through simple observations of the empirical distributions of relevant variables. In the case of K and F, the values are set at 4 weeks and 0.70, respectively. These are obtained through the setting of 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. Our sales spotter has some advantages over previous sales identification approaches: the spotter directly targets temporary price reductions taking place only due to sales, guards against incorrectly identifying non-sale price reductions as sale prices, is more flexible as it introduces new parameters (such as F) and most importantly, sets the values of the parameters from the features of more than 7 million flagged sales. See Syed (2014) for further details. Using the above parameters, 88.4% of the flagged sales are identified.[12] We then apply this parameterisation of the algorithm to our data set in order to identify sales.[13]

From Table 1, the average price dip from sales is 18.9% and the average duration of these sales is less than two weeks. The largest average price dip is for carbonated beverages (23.6%) and the lowest is for household cleaning products (12.1%). The average duration of sales for each product is between one and two-and-a-half weeks.

Table 2 shows that the frequency of sales are systematically much lower than their corresponding quantity shares. On average, items are sold on sale prices around 18.2% of the transaction weeks, while the quantity share during these sales week is 35.2%, almost two times higher. Over the 2001-2006 period, the largest difference is seen with cold cereal where the quantity share is 2.4 times the

[12]The remaining sales are not identified because of various reasons including that some sales are initial prices, have very low price dips and large duration and due to additional complications arising out of missing prices. Among the four parameters, the identification is most sensitive to K. If K is increased from 4 to 6 weeks, the number of identified sales increases by around 4 percentage points, out of which around one-half are flagged sales.

[13]Sensitivity to this parameterisation was explored, particularly with respect to K. For example, for $K = 4$ 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 $K = 4$ are discussed.

corresponding frequency of sales. The lowest difference, on the other hand, is seen in household cleaning products, where the quantity share is 1.7 times of the corresponding percentage of the period with sale prices. This difference persists across sub-periods of comparison; on average, the ratio is 2.2, 1.93, 1.80 for 2001-02, 2003-04 and 2005-06, respectively.[14] 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 sale 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. One way the degree of this overestimation may change is when the deviation between the frequency of sales and the corresponding quantity share differs between the periods. Table 2 shows that both the frequency of sales and the quantity share change over periods, but their ratio remains fairly stable implying they change in the same direction and by around the same magnitude.

The issue of whether the ratio of quantity share to frequency of sales changes systematically over periods is addressed more formally in Table 3, which presents average growth rates for the different product categories and periods. There are more negative growth rates than positive growth rates, although most of the estimated coefficients are not statistically significant at the 5% level. This indicates that the quantity response to sales remains fairly stable over the sample period. With respect to price index construction, it implies that while unit values are overestimated in each period if frequency weighting is used, there is little evidence that the degree of this overestimation changes between comparison periods.

Table 4 provides estimates of the difference in the percentage change in regular prices and the percentage change in the sale prices over the two year comparison periods. Most of the estimates are found to be statistically significant. For example, a large difference is seen for cold cereal in 2001-2002; the average change in the regular prices between 2001 and 2002 is 9.8 percentage points higher than the average change in the sale prices during the same period. This implies that if sale prices are not taken into account in the calculation of price movements, the measurement of price change will likely be biased.

The key results so far can be summarised as follows. (1) There is a systematic under-weighting of sale prices through the use of sale frequencies rather than quantities shares. This is as is expected from the consumers' stockpiling behaviour and as is evidenced from the deviation between the percentage of period items are sold on sales and the percentage of total quantity sold during these sale periods. The unit values in each period are therefore overestimated. (2) For the purpose of constructing index

[14]Results over two year periods are presented for compactness. Annual results are available from the authors on request.

numbers, the more important issue is the changes between the two comparison periods. Evidence shows that there is little reason to believe that the consumers' stockpiling behaviour changes between periods. Though the unit values themselves are mismeasured, the extent to which they are biased remains the same between the comparison periods. (3) The sale prices are, as expected, substantially lower than the regular prices. Again the important question is whether the regular prices move differently to sale prices. The evidence shows that regular and sale prices move at different rates (though not in any particular direction). This means that the average price dips due to sales change over time. This implies that if sale prices are excluded from price indexes, the measurement of inflation will be biased. (4) However, 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.

We now see how these observations follow through to price indexes. We construct the Jevons, Törnqvist indexes, and RYGEKS indexes as described in Section 3, using the three different approaches to calculating price relatives from (2), (3) and (4); 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 72 month period, from 2001 to 2006. Each of these indexes are constructed separately for each product and each city, and aggregated further to obtain indexes for each product category. The results in Table 5 for each category are obtained by aggregating across the five cities. In order to obtain the aggregated RYGEKS indexes, the aggregated Törnqvist indexes are fed into equation (8).

The results from Table 5 show that completely excluding sale prices causes an upward bias in all categories over 2001-06, with the Jevons index being almost 5 percentage points per year higher each year on average compared to the quantity share weighted index (Reg-Price Dev.). The Törnqvist index is 2.3 points higher if sales are excluded, and just over 1 percentage point for the RYGEKS index. The use of the RYGEKS then more than halves the upward bias of the Törnqvist index, demonstrating another possible advantage of the method; at the aggregate level it can reduce the bias arising from excluded sales prices, although there is some variation across the sub-periods and product categories.

The use of frequency weights (Freq-Weight Dev.) results in lower biases than if the sale prices are excluded, but are generally positive, being 0.2 percentage points higher per year on average over the period 2001-06 using the RYGEKS index. There is notably more variation across indexes and products, especially in terms of the signs of the biases, with a substantial number of negatives. Hence, there does not appear to be a systematic bias from the use of frequency weights relative to using quantity 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.

Figures 1 and 2 plot the Törnqvist indexes for carbonated beverages and cold cereal, respectively, for each of the five cities individually, using each of (2), (3) and (4) for the price relatives. Note that, for ease of viewing the results for each city, the y-axis scale is different across panels.[15] While there are some differences across cities and product categories, it is clear that placing zero weight on sales (i.e. excluding them in constructing the price relative as in (3)), results in indexes with an upward bias. However, consistent with the results reported in Table 5, there is no clear systematic relationship between the results from using frequency weighting and quantity share weighting in constructing price relatives.

Aggregate results across all five cities and ten products for all three index formula, using the three methods for constructing price relatives, are plotted in Figure 3. The symmetrically weighted geometric mean Jevons index shows the most dramatic deviations depending on whether or not sale prices are included, with the choice of either set of (positive) weights in the price relatives being almost irrelevant. This observation is carried over to the other two panels which plot the Törnqvist and RYGEKS indexes, where it is clear that the inclusion of sale prices dominates the choice of quantity or frequency weights in the price relatives.

5 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 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; de Haan and van der Grient (2011) report that Statistics Norway deliberately exclude sale prices, and Nakamura et al. (2011) report that Germany, Italy and Spain do not include sale prices during seasonal sale periods in the CPI sample.[16]

While the extreme case of zero weight on sales prices has been empirically found to be problematic, 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

[15] Carbonated beverages and cold cereal were chosen for plotting as from Table 1 they have the two highest expenditure shares. Törnqvist indexes are plotted as they approximate most closely the formula used by the BLS in CPI compilation.

[16] 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.

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.

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 2013), 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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Table 1: Data description and some facts on Sales

Products†	No. of Obser. (in m.)	No. of Items	Expend. Share (in %)	Average Sales Price Dip (in %)‡	Average Sales Duration (in weeks)
Beer/Ale	9.35	1222	16.45	15.50	2.20
Carb. Bever.	22.41	1482	28.80	23.56	1.49
Coffee	7.55	1007	5.55	14.11	2.45
Cold Cereal	15.74	1287	17.01	19.59	1.69
FZ Din./Ent.	17.44	1535	10.66	21.06	1.78
House. Clean.	3.01	319	1.34	12.10	2.09
Laundry Deter.	6.82	795	8.83	16.84	1.88
Marger/Butter	3.92	166	2.78	12.59	2.13
Peanut Butter	2.70	130	1.92	16.71	2.31
Soup	14.02	875	6.67	13.33	2.05
All Items*	102.95	8818	100.00	18.91	1.84

† Data description corresponds to 5 cities: Chicago, Houston, Los Angeles, New York and Philadelphia.
‡ 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.", "No. of Items" and "Expense Share" are summations while others are expenditure share weighted averages across products.

Table 2: Percentage of sale weeks and the corresponding share of volume sold

Products†	2001-2002		2003-2004		2005-2006		2001-2006	
	Sale Freq.‡	Quant. Share*	Sale Freq.	Quant. Share	Sale Freq.	Quant. Share	Sale Freq.	Quant. Share
Beer/Ale	10.16	19.01	12.28	21.13	13.67	20.35	11.88	20.13
Carb. Bever.	19.48	39.12	22.86	41.71	24.77	42.13	22.22	40.83
Coffee	11.59	27.58	18.29	37.98	20.03	38.37	16.45	34.07
Cold Cereal	12.80	34.09	16.76	40.28	18.65	40.28	15.94	37.87
FZ Din./Ent.	20.52	38.01	27.94	44.97	29.10	44.82	25.56	42.29
House. Clean.	10.33	17.73	17.15	28.02	17.66	31.15	14.77	25.02
Laundry Deter.	12.73	33.05	18.62	42.43	21.40	43.59	17.34	39.15
Marger/Butter	13.34	27.11	17.79	31.31	18.71	29.85	16.36	29.18
Peanut Butter	10.52	24.49	15.63	32.74	17.30	34.31	14.21	30.16
Soup	10.92	27.63	17.52	35.50	17.44	35.08	15.07	32.27
All Items*	14.92	32.16	19.27	37.18	20.82	37.17	18.16	35.24

† The figures of each product correspond to 5 cities: Chicago, Houston, Los Angeles, New York and Philadelphia.
‡ 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 five cities, where the weight corresponds to the share of total transaction weeks in each city. Note that since it is more likely that missing transaction weeks correspond to the regular price periods, the sales frequency is expected to be over estimated.
* Quantity share was constructed in a similar manner.
** The figures are weighted averages where weights are sales frequency and quantity shares across products.

Table 3: Estimates of monthly growth rate in the quantity-to-frequency weights (in %)

Products	2001-2002		2003-2004		2005-2006		2001-2006	
	Growth Rate†	Std. Error	Growth Rate	Std. Error	Growth Rate	Std. Error	Growth Rate	Std. Error
Beer/Ale	-1.10	2.00	-0.25	1.05	-1.37	2.61	-0.42	0.50
Carb. Bever.	-0.62	0.61	-0.36	0.42	-0.32	0.48	-0.39*	0.14
Coffee	-1.60	0.94	0.18	1.01	-0.01	0.51	-0.46	0.34
Cold Cereal	-0.44	1.34	-0.47	0.75	-0.43	0.31	-0.48*	0.24
FZ Din./Ent.	-0.51	0.84	-0.20	0.38	-0.47	0.61	-0.37	0.33
House. Clean.	-0.39	1.89	-0.48	1.58	0.64	2.15	0.04	0.34
Laundry Deter.	-0.98	0.95	0.03	0.91	-0.52	0.68	-0.48	0.35
Marger/Butter	-0.62	0.91	-0.36	1.24	-0.30	0.88	-0.44	0.31
Peanut Butter	-0.48	0.75	-0.31	1.26	-0.73	1.26	-0.24	0.24
Soup	-1.46	1.20	0.39	0.67	-0.55	0.85	-0.50*	0.20
All Items‡	-0.79	1.09	-0.23	0.72	-0.54	0.92	-0.42	0.28

† The natural log of the quantity share-to-frequency of sales is regressed on a constant and monthly time trend separately for each product and each city. The growth rate is the estimated coefficient of the time trend multiplied by 100. The average estimate of each product is obtained using the methodology of Rubin (1987). For each product, the estimated growth rate is is the simple average of the estimated coefficients for the 5 cities, and the average standard deviation is a combination of within- and between-standard deviations of the estimates adjusted for the degrees of freedom.

‡ The figures are quantity share weighted averages across products.

* Denotes statistical significance at the 5% level.

Table 4: Estimates of the difference in the movements of sale and regular prices (in %)

Products	2001-2002		2003-2004		2005-2006		All Years‡	
	Coef. of Differ.†	Std. Error	Coef. of Differ.	Std. Error	Coef. of Differ.	Std. Error	Coef of Differ.	Std. Error
Beer/Ale	-0.18	0.05	-0.92	0.06	-1.22	0.08	-0.45	0.06
Carb. Bever.	4.04	0.09	1.69	0.09	1.07	0.08	2.12	0.09
Coffee	2.82	0.14	1.00	0.13	-0.57	0.16	0.24	0.14
Cold Cereal	9.81	0.09	-0.78	0.09	-0.41	0.10	1.22	0.09
FZ Din./Ent.	3.62	0.09	0.82	0.08	4.33	0.10	1.23	0.09
House. Clean.	-2.73	0.23	-2.53	0.24	-7.02	0.26	-2.42	0.24
Laundry Deter.	0.56	0.14	-0.88	0.14	-4.19	0.13	-0.77	0.14
Marger/Butter	0.19	0.19	-2.59	0.19	3.71	0.21	-0.22	0.19
Peanut Butter	2.05	0.17	1.44	0.17	2.67	0.18	-0.34	0.17
Soup	6.85	0.12	-2.33	0.12	-1.68	0.13	-0.29	0.12
All Items‡	3.67	0.11	0.01	0.10	0.05	0.11	0.71	0.10

† The following regression is run separately for each product and each period: $ln(price) = \beta * item\ dummies + \phi * chain\ dummies + \delta * time\ dummy + \gamma * sales\ dummy + \lambda * (time * sales)\ dummy + \epsilon$
The regression is run separately for each two year period, where the time dummy takes the value of 0 in the first year and 1 in the second year. The sales dummy takes the value of 0 during the regular price period and 1 during the sale price period. The reported Coefficient of Difference is the estimated λ coefficient providing a measure of $(\triangle p_{r,t}/p_{r,t}) - (\triangle p_{s,t}/p_{s,t})$ multiplied by 100, i.e. the average percentage difference in the movement of regular and sale prices between the two comparison years.

‡ The figures are the quantity share weighted averages across periods and products.

Table 5: Annual deviation of the regular price index and sale frequency weighted index from the quantity share weighted index (in percentage points)

Products†	2001-2002		2003-2004		2005-2006		2001-2006	
	Reg-Price Dev.*	Freq-Weight Dev.**	Reg-Price Dev.	Freq-Weight Dev.	Reg-Price Dev.	Freq-Weight Dev.	Reg-Price Dev.	Freq-Weight Dev.
Jevons Index:								
Beer/Ale	1.34	-0.03	1.18	-0.07	1.80	-0.02	1.64	-0.04
Carb. Bever.	3.65	0.25	2.87	-0.46	4.46	-0.45	4.16	-0.22
Coffee	5.57	0.55	3.78	0.14	5.06	0.07	5.09	0.20
Cold Cereal	4.50	0.46	4.64	0.05	7.08	-0.01	6.11	0.13
FZ Din./Ent.	7.27	0.18	4.12	-0.32	6.81	-0.73	6.96	0.04
House. Clean.	3.34	0.11	4.31	-0.15	6.14	0.21	4.88	0.21
Laundry Deter.	7.49	0.51	6.57	0.04	9.38	0.42	8.33	0.33
Marger/Butter	2.93	0.59	2.93	0.72	2.82	-0.27	2.61	0.06
Peanut Butter	2.38	0.05	1.05	-0.19	1.64	-0.32	2.23	-0.02
Soup	3.70	0.12	4.47	0.16	5.22	-0.23	5.37	0.26
All Items‡	4.23	0.29	3.60	-0.01	5.04	-0.13	4.77	0.11
Törnqvist Index:								
Beer/Ale	0.67	0.13	-0.52	-0.44	0.12	-0.23	0.26	-0.09
Carb. Bever.	4.23	0.89	-0.27	-0.48	4.04	-0.58	2.81	-0.04
Coffee	4.15	1.58	2.86	0.66	2.87	1.23	2.65	0.68
Cold Cereal	3.42	0.47	0.11	-0.28	2.83	-0.76	3.22	-0.23
FZ Din./Ent.	4.86	-0.54	-0.39	-0.58	0.94	-1.14	3.34	-0.18
House. Clean.	1.41	-0.26	1.32	0.05	1.58	-0.16	2.22	0.20
Laundry Deter.	3.88	-0.86	3.32	-0.70	3.88	-0.06	4.68	-0.11
Marger/Butter	1.57	-0.05	1.68	0.09	2.24	-0.01	1.27	-0.34
Peanut Butter	0.43	0.10	-0.76	-0.53	-0.69	-0.64	0.42	-0.07
Soup	2.16	-0.36	1.33	-0.18	-1.94	-2.24	2.00	-0.53
All Items‡	2.71	0.14	0.88	-0.23	1.58	-0.45	2.28	-0.06
RYGEKS Index								
Beer/Ale	0.51	0.22	-0.58	-0.36	-0.02	-0.28	0.12	-0.05
Carb. Bever.	3.21	1.06	-1.03	-0.54	1.66	-0.27	1.17	0.09
Coffee	3.60	1.52	2.29	1.04	1.34	1.46	1.52	0.84
Cold Cereal	2.45	0.92	-1.35	-0.20	1.26	0.74	1.58	0.53
FZ Din./Ent.	1.76	0.80	-1.59	-0.69	-0.96	-0.95	1.01	-0.18
House. Clean.	0.54	-0.16	0.11	-0.17	0.01	-0.28	0.91	0.14
Laundry Deter.	2.02	0.18	0.38	-0.58	1.07	0.34	1.81	0.38
Marger/Butter	1.21	0.19	1.52	0.40	1.44	0.30	0.76	-0.02
Peanut Butter	0.41	-0.11	-1.24	-0.30	-1.31	-0.48	0.18	0.05
Soup	1.66	-0.01	0.56	0.45	-2.54	-1.07	1.08	0.25
All Items‡	1.78	0.33	-0.08	-0.09	0.21	-0.05	1.02	0.20

† The indexes are calculated separately for each product and each city. The Jevons index for a product is obtained by taking the geometric mean of the city indexes for this product. The Törnqvist Index is obtained by taking the quantity share weighted geometric mean where weights are one-half of the sum of the corresponding quantity shares. The RYGEKS Index in this table is based on similar aggregated Törnqvist Indexes for each product.

* Reg-Price Dev. is the difference between the cumulative index obtained from the unit values calculated from only the regular prices and the quantity share weighted unit values of the regular and sale prices. In order to obtain the annual deviation, this difference is divided by 2 in the two year comparison periods and 6 in the six year comparison period. For example, the figure of 1.34 means that the regular price index is 1.34 percentage points higher than the quantity share weighted target index.

** Freq-Weight Dev. is the similar deviation between the frequency share weighted and quantity share weighted indexes.

‡ The figures are symmetric weighted geometric means across products for Jevons indexes and quantity share weighted geometric means for Törnqvist and RYGEKS indexes.

Figure 1: Törnqvist Indexes for Carbonated Beverages

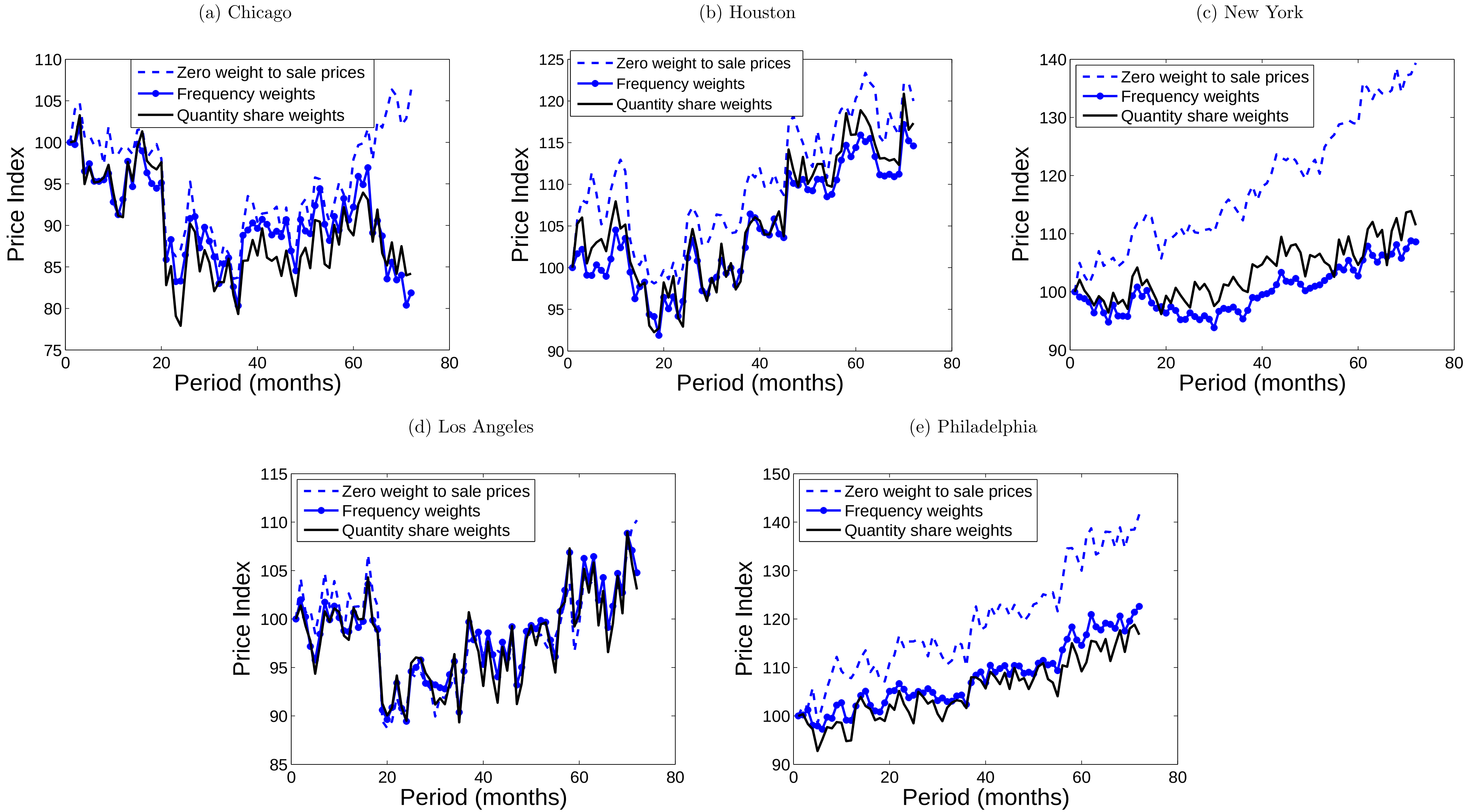
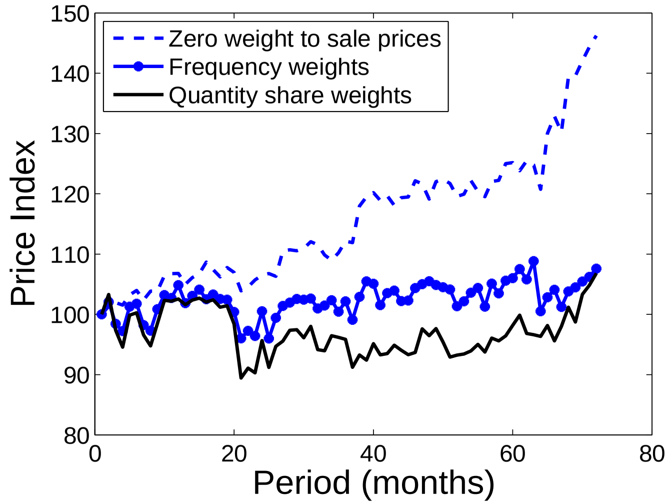
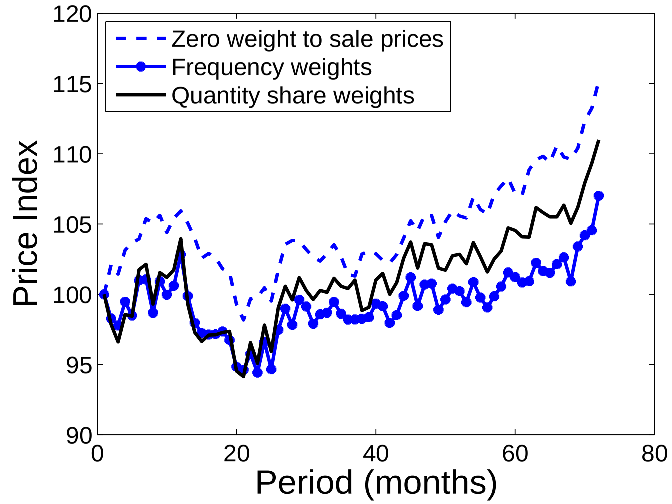


Figure 2: Törnqvist Indexes for Cold Cereal

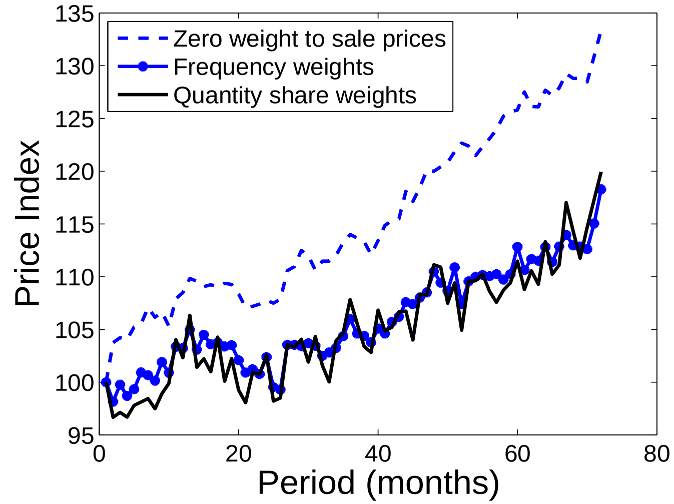
(a) Chicago



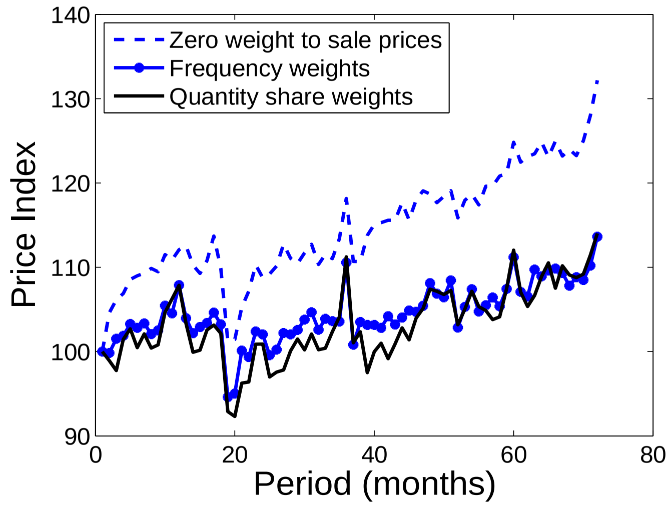
(b) Houston



(c) New York



(d) Los Angeles



(e) Philadelphia

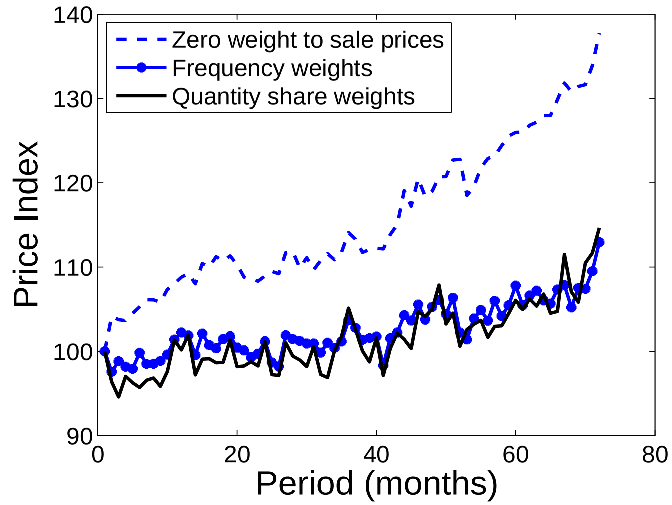


Figure 3: Aggregate indexes across all 5 cities and 10 products

(a) Jevons Index

(b) Törnqvist Index

(c) RYGEKS Index