Apparel Price Indexes Using Scanner Data: Initial Results

by

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Abstract

Consumer price indexes rely, to a greater or lesser extent, on data that are either aggregated or comprise a representative selection of a much larger set of observations. In this paper we describe a dataset that contains every transaction for a single apparel good – Misses' tops – of a large retail chain in a major U.S. metropolitan area. The dataset contains a wide array of variables, and we describe here the results from an initial analysis of those data.

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Introduction

Consumer price indexes rely, to a greater or lesser extent, on data that are either aggregated or comprise a representative selection of a much larger set of observations. In this paper we describe a dataset that contains every transaction for a single apparel good – Misses' tops – of a large retail chain in a major U.S. metropolitan area. The dataset contains a wide array of variables, and we describe here the results from an initial analysis of those data.

To begin, we examine the distribution and frequency of sale prices and clearance sales. Field agents for the U.S. Bureau of Labor Statistics (BLS) note whether or not an item is on sale when its price is collected, but the relatively small number of price quotes collected each month reveals little about the distribution of sale prices or the frequency with which items are on sale. This is potentially important if changing the frequency of sales is used as a method for raising or lowering prices. In addition, the use of clearance sales may be particularly problematic for measuring price changes of items with high rates of turnover. In that case, exiting goods sold on clearance will have particularly low prices, and creating a long run index by simple chaining of short run indexes will rapidly drop the price index towards zero.

These data also allow us to study the potential difference between the price trends of items sold on weekdays versus those sold on weekends. As noted by the Boskin Commission, "The BLS does not collect prices on weekends and holidays when certain items and types of outlets disproportionately run sales. There appears to have been a sizeable increase in the fraction of purchases made on weekends and holidays, perhaps reflecting the increased prevalence of two-earner families. We know of no systematic study of this issue and urge the BLS to conduct the research necessary to examine it thoroughly, perhaps with scanner data."

Finally, we examine price trends and construct a variety of long run indexes. The consistent downward trend of the prices of individual items suggests that long run indexes formed by chaining together month to month indexes will be subject to severe downward bias. Confirming this expectation, using our data simple chained indexes decline by more than 90 percent between January 2004 and October 2007. In contrast, an index of average prices displays no similar downward trend. We discuss the prominent role of clearance sales at the end of the item's lifetime, and we examine whether accounting for clearance sales is sufficient to solve the problem of downward index bias.

A Data

The dataset consists of every transaction covering the 46-month period from January 2004 through October 2007 in all the chain's outlets in a major metropolitan market in the United States. Several edits to the dataset were necessary. First, any transaction with a zero price was eliminated. In addition, we eliminated a small number of transactions that were bottoms rather than tops and a small number of transactions with very odd list prices. Each item is assigned an identification number (IDN). Of 697 IDNs, 139 were excluded because they involved exactly one sale, and two were eliminated because they were used for 'miscellaneous' items. This leaves 556 IDNs representing 968,484 transactions.

Table 1 lists the information available for each transaction. Some variables, such as Type of fabric, List price, and IDN description, differ rarely or not at all across transactions for a given IDN. A few of the fields are blank a large proportion of the time and are therefore of limited value. The most important transaction-level variables for our purposes are the Date of transaction, Size of item sold, Coupon used, Price paid by customer, and Type of discount—that is, whether the discount is temporary (Sale) or permanent (Clearance). If the customer purchased several items at once, these are coded as separate transaction records. Note, however, that the price for a given transaction may have been affected by other transactions, such as during a "Buy one item, get a second item at 50 percent off" sale.

The IDN descriptors also provide the opportunity to construct variables to represent the characteristics of the item. A few categorical variables are shown in table 2, along with their frequency distributions by numbers of transactions. For the most part, these variables have to be defined by searches through text fields, and it is often impossible to know whether the absence of wording specifying sleeve length, for example, should be interpreted as indicating a default length or simply that the sleeve length was not coded. We hope to learn more about these questions in the future.

The distribution of transactions by item is very skewed. The four most common items of the 556 each account for more than 10,000 transactions and together comprise almost seven percent of all transactions. At the other end of the scale, 94 items, each with less than 100 transactions, comprise less than 0.2 percent of our sample. The distribution by store is also skewed, with 16 of the 22 stores accounting for over 99 percent of the transactions in our sample.

B Sale, Clearance and Discount Prices

Sale prices and clearance prices (temporary and permanent discounts, respectively) obviously are important determinants of the purchasing decision. The prominence with which sales are announced, both in advertisements and in the store, suggests the same. If the retailer faces an elastic demand for apparel, lowering the price will increase revenues, which might create an incentive to hold sales fairly frequently.

Nevertheless, it is surprising to find that over 98 percent of transactions occur at sale or clearance prices. Only 1.75 percent of transactions, representing 3.59 percent of revenue, take place at the full retail list price. This brings into question the entire concept of a fixed or stable price. It also begs the question of consumer choice: are items continuously on sale, or do consumers only purchase them on the occasions when they are on sale? Further analysis should allow us to distinguish the role of consumer choice.

Among the non-retail price transactions, 69.89 percent, representing 79.82 percent of discount revenues, were at sale prices. Among those transactions involving sale prices, 20.84 percent or about one-fifth also used coupons. The remaining 30.11 percent of discount transactions (20.18 percent of discount revenues) were items on clearance. Of those, 14.39 percent of the transactions also used coupons.

The distribution of prices as a percent of list price is represented in Figure 1. For example, just over 10 percent of transactions took place at prices between 30 and 40 percent of the retail price. Of these, slightly under half were clearance transactions. Most notable is the absence of small discounts. Very few purchases reduce prices to 90 percent or 80 percent of list. Instead, typical sale prices are between 30 percent and 50 percent below list price. Clearance discounts are larger still, with a mode between 70 and 80 percent off list price. Overall, the median discount is almost exactly 50 percent of list price. While firms may change prices by changing the depth of the sale, this chain clearly does not change the frequency of sales to change prices.

Figure 2 displays the monthly pattern of prices, sales, and transactions for one of the most common IDNs, a particular type of short-sleeved tee shirt. That item was sold in 16 stores, beginning in February 2006, in a total of 11,251 transactions. The list price for this IDN was $20, but the figure shows that the average monthly transaction price was just under $15 ($14.84) in the first month and then declined almost monotonically to under $3 ($2.82) in March 2007. A particularly sharp drop in average price, from $10.41 to $6.93, occurred in August 2006, accompanied by a more than doubling of transactions between July and August. The figure also shows that there were a negligible number of clearance transactions until November 2006, after which essentially all transactions were at clearance prices. After March 2007 the average price drifts upward, but on a base of almost no transactions (31 over the last seven months of our sample period).

C Weekday and weekend prices

Prices are collected for the U.S. Consumer Price Index (CPI) throughout the month, but almost exclusively during weekdays. This occurs in part because managers often are too busy during the weekend to talk to field agents sent out by the BLS. As noted above, this has the potential to bias price indexes for apparel.

The potential becomes apparent in Figure 3. Approximately 43 percent of our misses' tops transactions take place on Saturday and Sunday, and nearly 60 percent of transactions occur on Friday through Sunday. In contrast, only 1.5 percent of all quotes collected for the CPI are on Saturday and Sunday, and only 14 percent are collected on Friday through Sunday. Average prices tend to be slightly lower on the weekend as well. The figure shows that Friday and Saturday have the lowest average price, $13.35, and the lowest average percent of retail price, 48 percent. That does not necessarily indicate a problem, however. As long as prices are changing at the same rate on both weekends and weekdays, price indexes constructed from weekday quotes should not be biased.

To examine this, in Figure 4 we plot over time simple indexes of the average price on weekdays and the average price on weekends, with both average prices set equal to 100 in January 2004. The two indexes do not entirely coincide: differences occur in several different periods, including the end of 2004, the middle of 2005 and the middle of 2006. Nevertheless, the two indexes are remarkably close. This provides evidence that relying on prices during the weekday does not bias price indexes.

D Price Trends

By reputation, the prices of apparel items are highest when they enter and lowest when they exit. Considerable research has been conducted on methods for comparing the price of an item when it exits to the price of a replacement item. If no account is made of the difference – if price changes for the new item without accounting for difference between the old and new item – CPIs will have a downward bias. Here we describe two types of long run indexes, those formed by chaining short run indexes and those formed by using average prices in each time period.

Figure 5 provides a histogram of the long run price trends for the IDNs in our sample. The horizontal axis represents the average percent decline in prices per month. While there are some items that have an upward trend, it is clear that on average the price trend is negative. The distribution has a mode of about -3 percent and a median of about -6 percent. Figure 6 plots the month-to-month change in price, calculated by comparing only prices of IDNs that appear in both months. With the exception of June, 2006, these prices of "matched models" declined significantly in every single month. Some months, such as August 2004, show particularly sharp price declines of 20 percent or more. Figures 7 and 8 display the predominantly downward-sloping price paths of 120 randomly chosen IDNs over 20-month and 46-month periods, respectively.

Figures 5 through 8 thus confirm our expectation that misses' tops, like other items of apparel, trend downward in price over time. They also highlight a fundamental problem in constructing price indexes for apparel. Statistical agencies typically construct price indexes by selecting a sample of items and comparing prices of identical items from month to month. As noted above, however, the median monthly matched-model price change in our sample is a negative 6 percent. Compounded over 45 months, this would yield an implausible 94-percent drop in the price index for misses' tops during our study period. Evidently, construction of an accurate price index requires some alternative to the usual matched-model method.

Figure 9 displays the results of various alternative approaches to solving this problem. The first two are matched-model indexes using prices and transactions aggregated to the IDN level. One of these uses a Chained Laspeyres formula with each IDN's average price change weighted by the IDN's share of transaction value in the previous month, while the other employs a Chained Törnqvist formula based on both the current-month and previous-month shares of transaction value. The difference in formula has little effect. Both these indexes fall by more than 80 percent in the first year and end at an index value of less than 1 on a base of 100.

The remaining three indexes in Figure 9 are derived from regressions on the whole set of transaction microdata. Each regression has a set of 47 dummy variables corresponding to months after January 2004. The dependent variable in each case is the logarithm of price. The top line in the figure is the index from a regression with only the time dummies as explanatory variables. Constructed in this way, the index is just a measure of the geometric-mean transaction price in each period. That index displays fairly consistent seasonal patterns, such as troughs in February and peaks in March, but remains roughly

level in the long run. For example, the index falls by 8.9 percent between August 2004 and August 2007, or about 2.8 percent per year.

The average-price index behaves in a much more reasonable manner than the chained matched-model indexes, but has the potentially critical flaw that it fails to account for any changes in average item characteristics or "quality" over time. (The BLS does not publish a CPI for this category. In the CPI publication scheme, the lowest-level index that includes misses' tops is Women's Suits and Separates.) One way to hold quality constant is to include the item identifiers as explanatory regression variables. When we add a dummy variable for each IDN to the regression, however, the resulting index exhibits a decline almost as steep as those of the matched-model indexes. In effect, including the IDN dummies means that the effect of time will be estimated from changes in price within IDN's. That index's final level in October 2007 is 3.0.

It might be expected that the downward drift would be mitigated by adding to the month and IDN dummies one more dummy variable to indicate clearance sale transaction. In that regression, the lower prices for clearance transactions is attributed to the fact of the clearance sale rather than to the passage of time. Figure 8 shows that the clearance dummy does, in fact, mitigate the trend, but it does not nearly eliminate it. The associated index still falls by about 43 percent in the first year and to a level of 17.0 at the end of the 46-month period.

Conclusion

The BLS acquired these scanner data with the goal of determining whether such data could be used in the production of the CPI. The results reported here still leave that question unanswered. In further analysis we plan to estimate additional regression-based indexes for misses' tops using item-characteristic variables such as those shown in Table 2, thereby directly addressing the problem of adjusting for possible trends in quality. We also will explore the use of the GEKS and RGEKS approaches[1] as potential ways of dealing with the seasonality of item availability and price.

Our exploratory analyses have thus far given us no reason to think that these scanner data are seriously flawed in any particular way. Moreover, the data clearly demonstrate some of the dominant facts of the apparel industry: the size and prevalence of discounts from list price, the large share of weekend purchases, the significant rate of product turnover, and the consistent downward trend of prices within a given item's lifecycle. The data also are rich enough to enable us to reject the hypothesis, at least for this product category, that weekday price collection causes a bias in the CPI.

[1] See, for example, Kevin Fox, Lorraine Ivancic, and W. Erwin Diewert, "Scanner Data, Time Aggregation and the Construction of Price Indexes," presented at the Annual Meeting of the American Economic Association, January 4, 2009. Available at http://www.aeaweb.org/assa/2009/index.php.

Table 1. Variables on Data File

ID Number
Outlet ID
Date of transaction
Earliest date the product is available
The planned date for the IDN to be out of stock
Coupon used
Type of Coupon
Brand
Type of fabric
Item type/style
IDN description (typically style and brand info)
Size of item sold
Size range of IDN
Number of days the item was available
Price paid by customer
Amount of employee discount
Type of discount
Amount of discount
List price

Table 2. Examples of Item Characteristics

Frequency	Percent	Brand
716,957	73.52%	BRAND A
87,816	9.00%	BRAND B
75,436	7.74%	BRAND C
46,356	4.75%	BRAND D
	95.01%	TOTAL

Frequency	Percent	Type of Top
104,727	10.74%	BLOUSE
146,507	15.02%	CAMI
98,966	10.15%	TEE
20,777	2.13%	TUNIC
18,139	1.86%	TANK
294,867	30.23%	SHIRT
5,950	0.61%	HALTER
	<70.74%	TOTAL

Frequency	Percent	Type of Sleeves
149,592	15.34%	3/4 SLEEVE
191,450	19.63%	LONG SLEEVE
143,678	14.73%	SHORT SLEEVE
60,085	6.16%	SLEEVELESS
	<55.86%	TOTAL

Figure 1. Distribution of Transactions by Percent of List Price

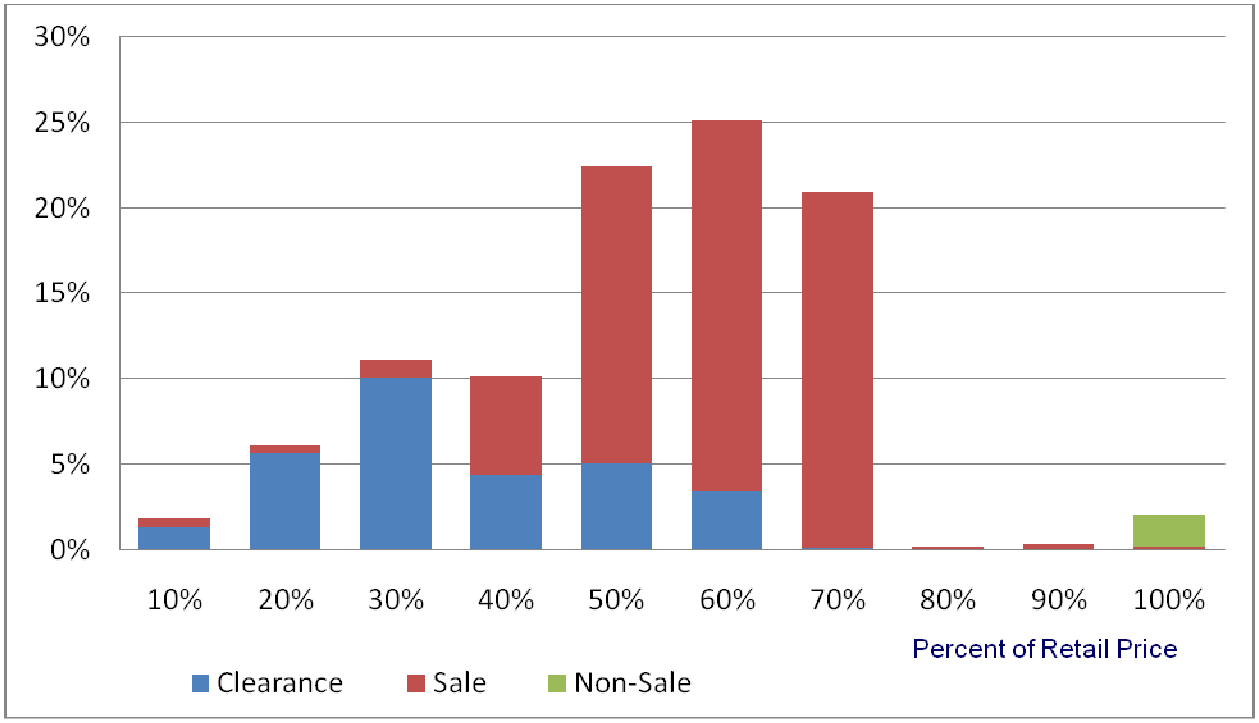

Figure 2. Monthly Transactions and Average Prices
S/S Tee Shirt Item

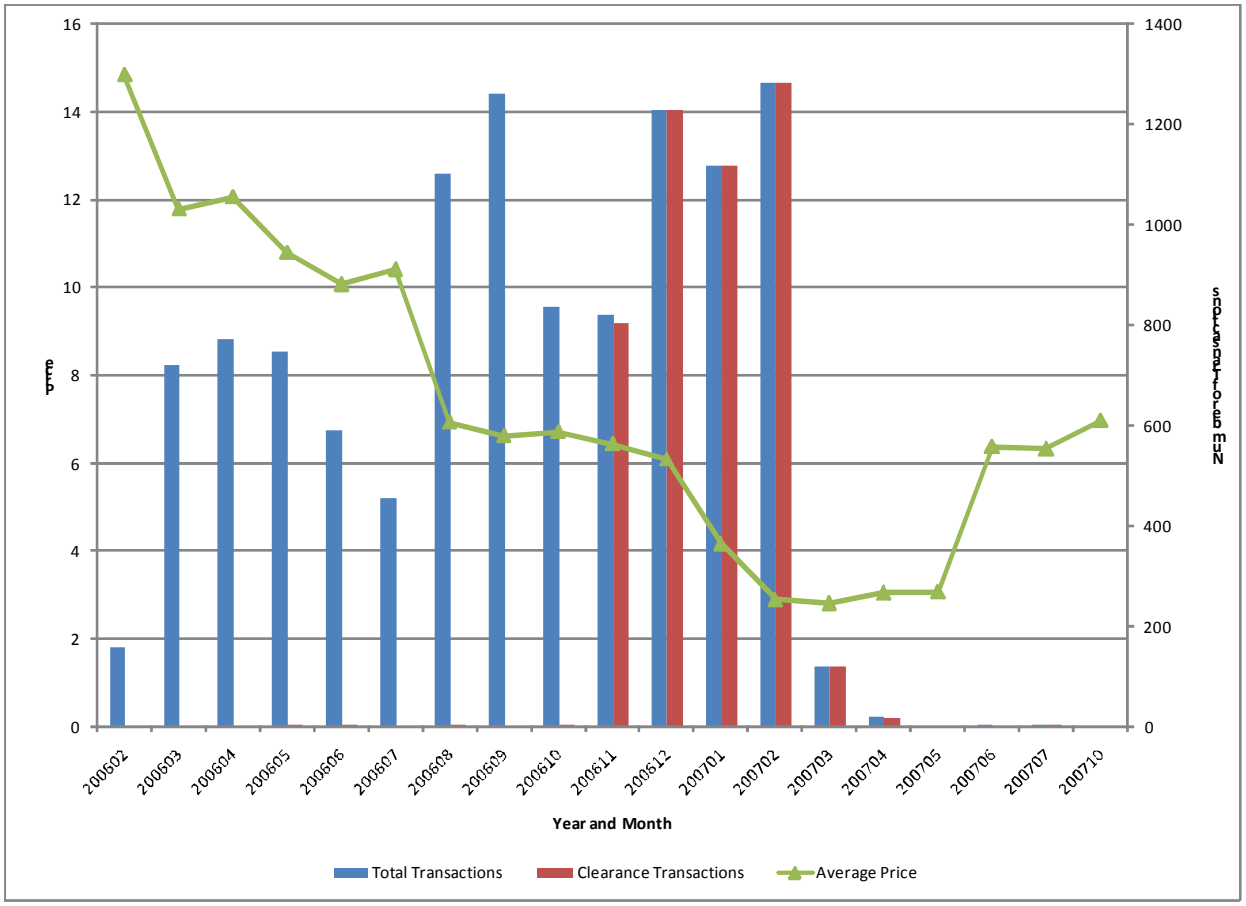

Figure 3. Transactions and Prices by Day of Week

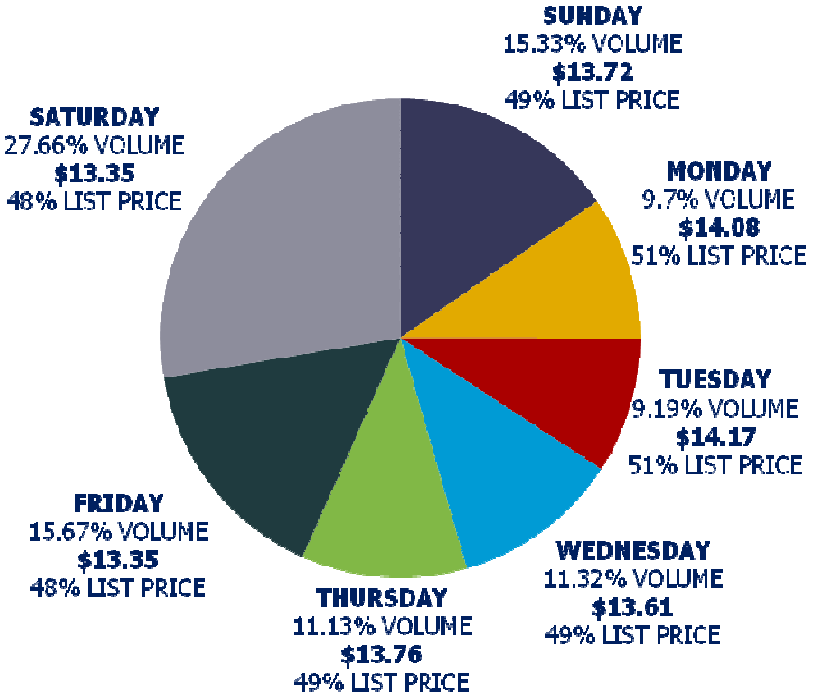

Figure 4. Indexes of Average Prices (200401=1)

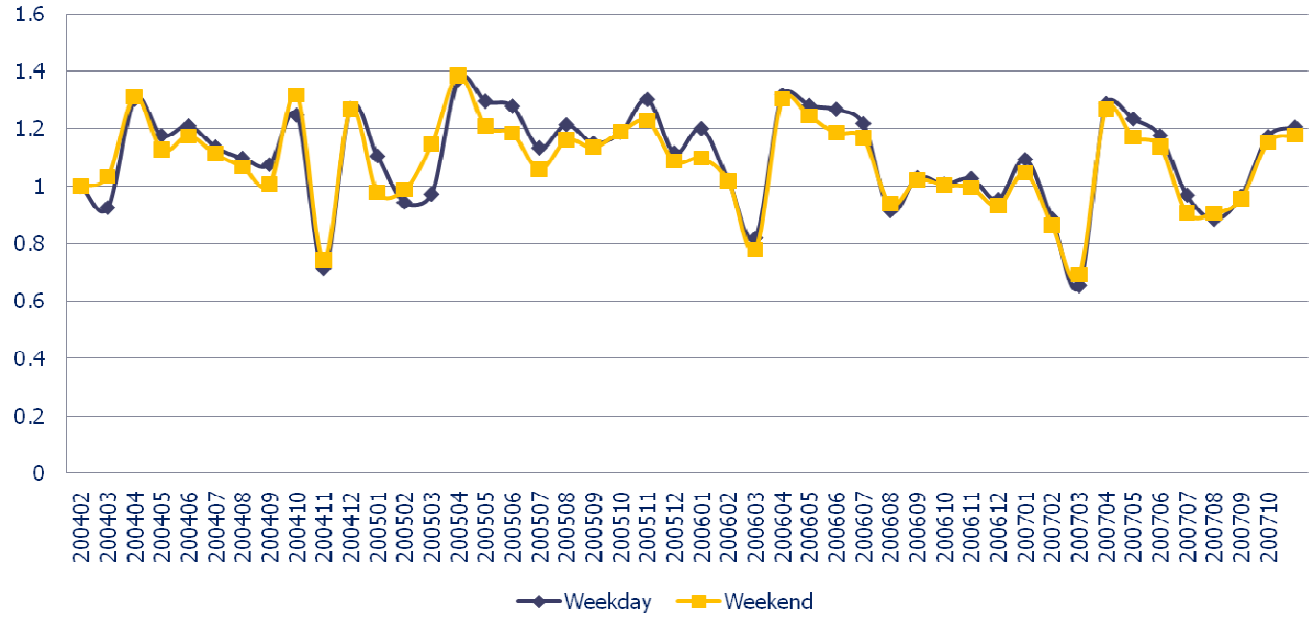

Figure 5. Average Monthly Rates of Price Change

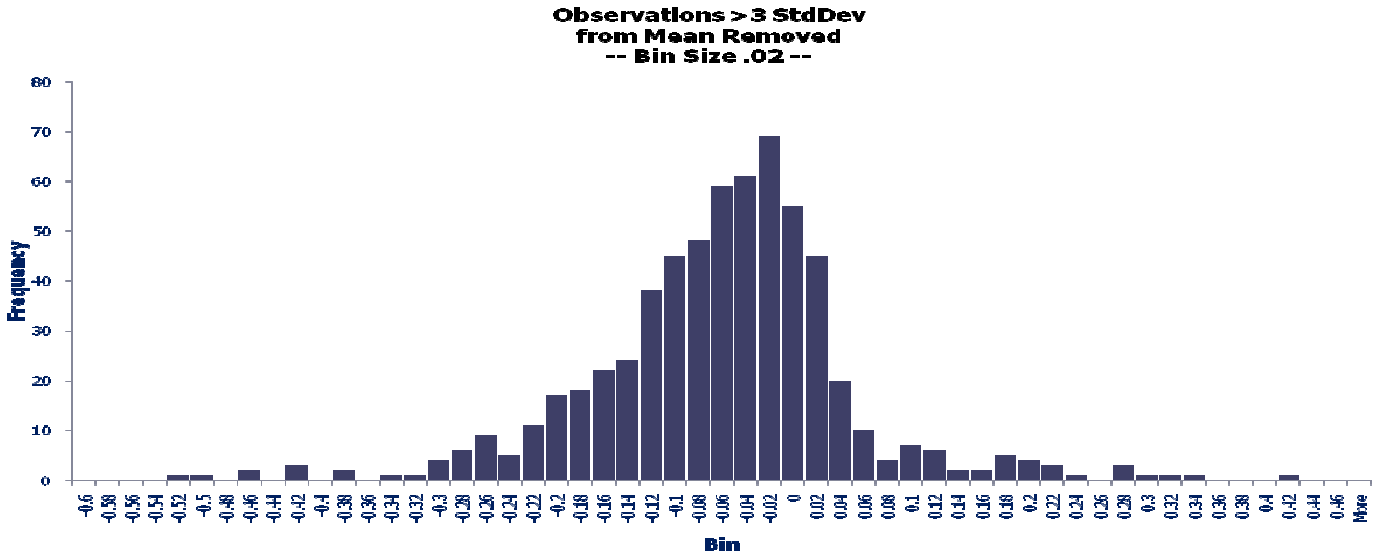

Figure 6. Monthly Matched-Model Rates of Price Change

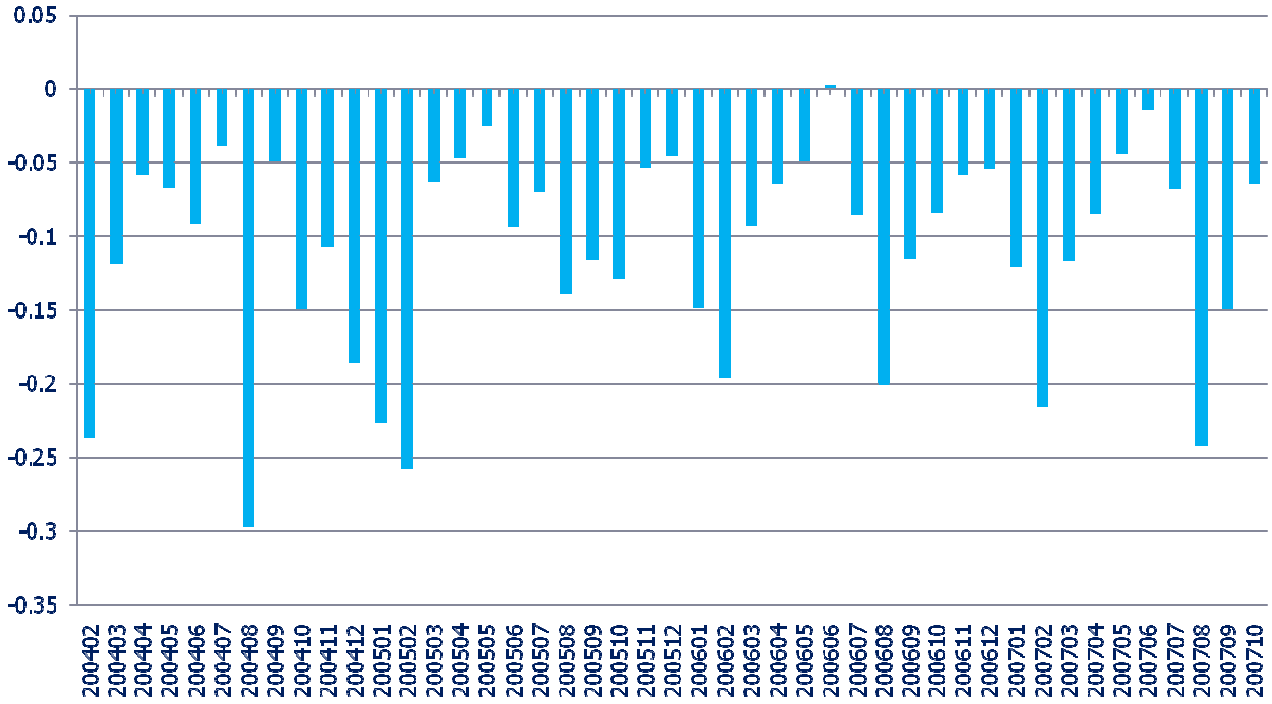

Figure 7. Indexes of Average Price, 120 IDNs, First 20 Months

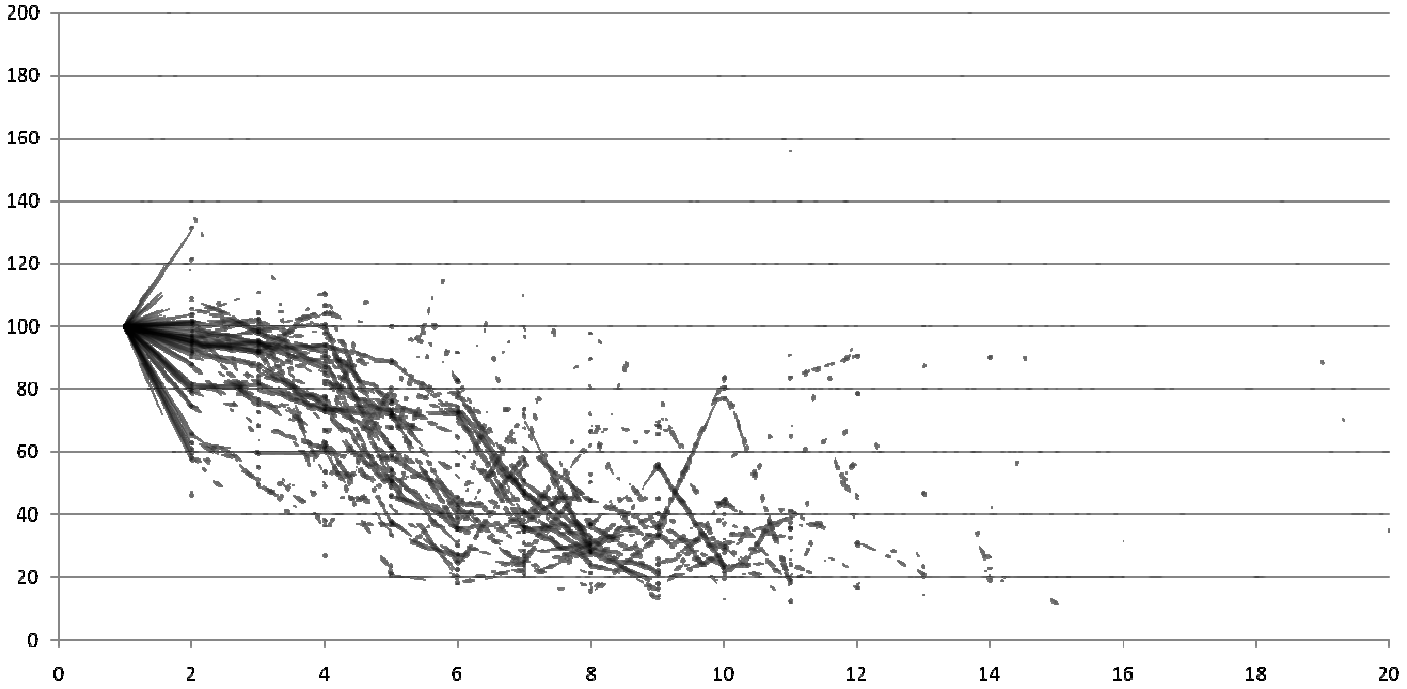

Figure 8. Indexes of Average Price, 120 IDNs, by Sample Month

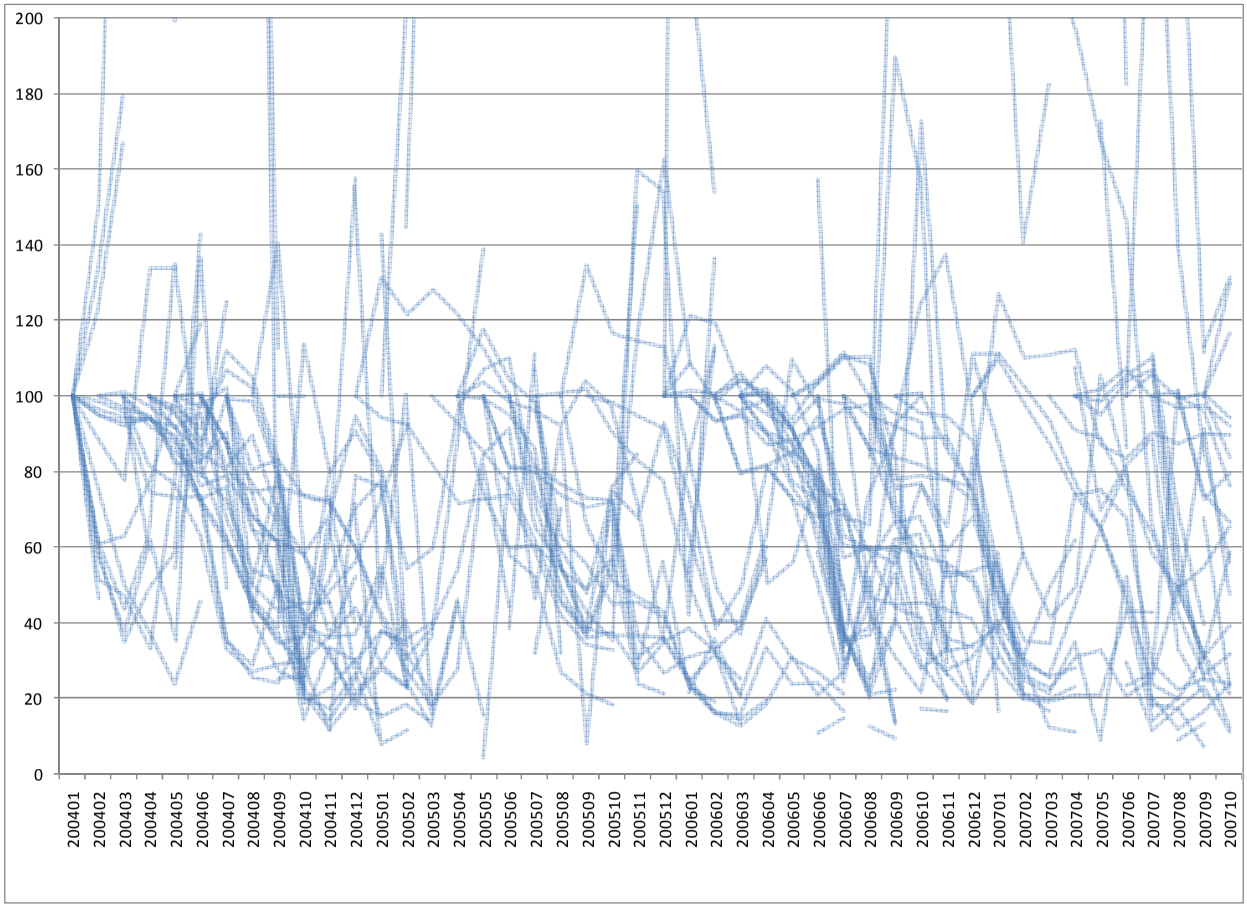

Figure 9. Alternative Price Indexes for Misses' Tops (200401=1)