Superlative and regression-based consumer price indexes for apparel using U.S. scanner data

by

John S. Greenlees
Robert McClelland

U. S. Bureau of Labor Statistics

July 30, 2010

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 a number of results from an analysis of those data. In particular, we examine price trends and construct a variety of long run price indexes.

Paper prepared for presentation at the conference of the International Association for Research in Income and Wealth, St. Gallen, Switzerland, August 27, 2010. The authors thank Taylor Blackburn, Marisa Gudrais, and Abigail Lackner for excellent research assistance. All views expressed in this paper are those of the authors and do not necessarily reflect the views or policies of the U.S. Bureau of Labor Statistics.

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."

The data also speak to the issue of price stickiness, a question of continuing interest.[1] Bils and Klenow (2004) examine CPI data for the years 1995 through 1997 and estimate that half of the goods in the sample keep their prices for longer than 4.3 months. Girl's tops, a category similar to the Misses' tops studied here, have prices that last 1.8 months on average. Kashyap (1995) examines 12 items (mostly apparel) in mail order catalogs from 1953 to 1987 and estimates that on average prices change every 14.7 months. In contrast, most of the items studied here change prices more than once a month, in the sense that products from the same IDN are sold at multiple prices during the same month at the same store.

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. We take the opportunity to work with transaction-level data to investigate potential solutions. One obvious solution , an index of average prices, displays no similar downward trend. However, the heterogeneity of the items raises questions about the appropriateness of that approach. We also discuss the prominent role of clearance sales at the end of the item's lifetime, and we examine whether accounting for

[1] See, for example, Eichenbaum, Jaimovich, and Rebelo (2008) and Chevalier and Kashyap (2010).

clearance sales is sufficient to solve the problem of downward index bias. Finally, we explore the effectiveness of the RGEKS and hedonic regression approaches.

A Data

The dataset consists of every transaction covering the 46-month period from January 2004 through October 2007 in all of 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. While there are fewer characteristics than available in BLS data, they are the characteristics most important to the chain. Assuming that the firm is interested in increasing its revenues, the characteristics should be those most important in setting prices. In contrast, the characteristics available to the BLS are also designed to aid in locating the item when an agent enters the outlet.

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 about two thirds of the 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.[2]

[2] Examples of research on sales include Lazear (1986) and Pashigian and Bowen (1991).

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. Prices do not appear to be sticky at all, suggesting that firm are able to easily respond to macroeconomic shocks, such as changes in the money supply, by changing the frequency or depth of sales. 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? Chevalier, Kashyap and Rossi (2003) review several models of pricing behavior in which firms lower prices at times of exogenous increases in demand. For example, episodes of high demand might be accompanied by high price elasticity (Bils 1989 shows that fixed search costs could induce this). Firms may also tacitly collude to keep prices high, but cheat during periods of high demand. Finally, it is possible that some prices are kept low as loss leaders. The last two explanations seem unlikely to explain the pricing found in this paper, but further analysis of the first should allow us to examine the applicability of the first. 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.

The seasonal aspect of these sales may be seen in Figure 2.

Figure 3 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).

In this paper we do not explore the issue of store coupons. These coupons may be applied to any item or set of items. While the data indicate whether or not a coupon was used, the exact nature of the coupon must be inferred. Further, it is unclear how to estimate a cost of living index when the consumer has some control over price, and when he or she benefits from a discount that may be applied to any one of a variety of items.

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 4. 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 5 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.[3] 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 6 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 7 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.

[3] See, for example, Guédès (2007).

For figures 8 and 9, we randomly select 120 IDNs and plot the paths of their average prices. Figure 8 arranges the paths from first month, whenever it occurred, through the 20th month. It shows a sharp downward trend in the initial months. While some prices remain unchanged in the second month, many prices have fallen, with concentrations at 80 percent and 60 percent of initial prices. After four months many of the IDNs disappear, either temporarily or permanently. After six months, the prices of many of the remaining IDNs have hit a minimum, and rise in the following month. The prices of many other items continue to fall, however. By the eighth month the prices of most of the remaining goods are less than 40 percent of the prices in the first month. At the twelfth month, many items disappear. Figure 9 plots the same paths, but starts each path at the appropriate date so that the seasonal nature of the price paths becomes clear.

Figures 6 through 10 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. This is demonstrated in Figure 10, which displays the month-to-month index relatives in chained Laspeyres and Paasche indexes. The monthly relatives are almost always less than one. Compounded over 45 months, this would yield implausible drops in price indexes for misses' tops during our study period. Evidently, construction of an accurate price index requires some alternative to the usual matched-model method.

Figure 11 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. Recent work by Nakamura, Nakamura and Nakamura (2010) focuses on the problem of chain drift when using transaction level data to construct indexes. That drift can occur if prices oscillate as they move on and off sale. In the data in this paper, the relentless downward march of prices completely overwhelm the chain drift issue.

The remaining three indexes in Figure 11 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 IDNs. 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 11 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.

E Alternative Indexes

In the previous section we showed that the standard index formulas yield implausible results, due to the characteristic features of apparel pricing. The scanner data we use here exhibit the familiar pattern that the BLS and other statistical agencies have observed in CPI apparel data, namely a steep and persistent decline in price over time for any given item. Under these circumstances, any matched-model index will follow the same continuous decline.

Recent papers by Kevin Fox, Lorraine Ivancic, and Erwin Diewert (2009) and by Jan de Haan and Heymerik van der Grient (2009) have demonstrated that an RGEKS (Rolling Gini-Eltetö-Köves-Szulc) index can have value in mitigating chain drift in high-frequency scanner data such as we analyze here. Chain drift can occur even in superlative indexes when the mix of items sold varies widely from period to period, reducing the usable samples of price changes for individual matched items. The RGEKS model adapts an approach used in multi-lateral indexes by treating data for consecutive time periods as if they were data for countries or areas. This permits the comparison of prices for like items in non-consecutive periods.

We computed unit-value prices for each store-IDN-month combination, and constructed a 13-month RGEKS index based on the Törnqvist formula. Let T_{rs} be the Törnqvist index in period r relative to period s, formed from the unit-value price ratios and revenue shares of the store-IDN combinations observed in both periods. Then for the first 13 periods of our data set the RGEKS index between periods t and $t-1$ is given by

$$RGEKS_{t,t-1} = GEKS_{t,t-1} = \prod_{s=1}^{13} \left[T_{ts}/T_{t-1,s}\right]^{1/13} \quad t = 1, \dots, 13$$

For periods 14 and later, we compute recursively

$$RGEKS_{t,t-1} = \prod_{s=t-12}^{t} \left[T_{ts}/T_{t-1,s}\right]^{1/13}$$

Unfortunately, in our scanner data the problems associated with the apparel product life cycle equal or outweigh the problems arising from product-mix volatility. As a consequence, the RGEKS approach fails to yield plausible index movements. This is demonstrated in Figure 12. The index declines in the great majority of months, ending in October 2007 at a level of 10.5 on a base of January 2004=100.

The fundamental limitation appears to be that we cannot match prices of an identical item (IDN) over a sufficiently long period. The shelf life of a specific IDN is almost always less than a year, and if two IDNs are essentially identical we do not observe that fact. Therefore, we have no way to treat them as the same item in a matched-model index. If IDNs remained in the sample for more than a year, the cyclical movements in their prices might be picked up by the RGEKS technique, but with life cycles of only a few months there is no way for the RGEKS index to reflect an item's price increase when it returns at the beginning of a new season. This contrasts with the usual situation in the CPI, where an analyst can sometimes follow an apparel item for more than a year (even if that item appears in more than one IDN) or, if necessary, make a judgment about the degree of comparability between a disappearing item and its replacement.

We therefore turned to hedonic regression as a means of dealing with the poor performance of our matched-model indexes. Hedonic models have been used for many years in the US CPI; see, for example, the recent article by Craig Brown and Anya Stockburger (2006).

Our scanner data are not ideal for hedonic regression work. Table 1 lists some IDN-level fields that contain potentially useful product characteristics, such as Brand and Type of fabric. The most valuable is the IDN description text field, which contains a variety of information. Unfortunately, all these fields are blank in a large fraction of cases. Moreover, the IDN description field is not in a fixed format, and the same characteristic can be described in multiple ways. Our descriptive variables had to be defined by searches for specified text strings; more importantly, the absence of information on a given characteristic is difficult to interpret. The lack of any reference to sleeve length, for example, could be interpreted as indicating a default length or simply that the sleeve length was not coded for that item.

Despite these missing-value problems, we proceeded to construct a large number of dummy variables for use in hedonic regressions. The categorical information we employed is shown in table 2, along with frequency distributions by numbers of transactions. We defined dummy variables corresponding to each category of the variables in table 2.

Our first hedonic index was derived from a single regression using our entire data set. The explanatory variables included the dummy variables from table 2 and for brand; dummy variables for each store in our sample, and dummy variables for each month from February 2004 through October 2007. The dependent variable was the logarithm of price, and the regression sample comprised 951,108 observations. The results strongly support a relationship between price and the descriptive variables we constructed. The regression R^2 was .29, and the F statistics for the significance of each explanatory variable set – month, brand, sleeve length, item type, fabric, pattern, fashion, and store – were all above 100 and significant at more than the 0.0001 level. The parameter estimates and standard errors are shown in table 3.[4]

Figure 13 compares the regression index results from table 3 with the average price series shown in figure 10. The two indexes are roughly similar in their movements, and neither exhibits a clear long-term trend, in sharp contrast to our matched-model indexes. Notice, however, that the regression index ends the period at almost the same level as in January 2004, while the average price rises by approximately 15 percent. To avoid seasonality differences, we can compare their levels in January 2007, three years after the start of the sample period. Again, in that month the regression index is noticeably lower, by about 8 percentage points. These are relatively small differences when compared to the volatile month-to-month movements of both series, but in absolute terms differences of this magnitude after 3-4 years is not trivial.

To explore this question, we examined the explanatory variables to identify those that account for the apparent quality improvement over the sample period. Again to avoid intra-year variation we compared the months of January 2004 and January 2007. Over this time period the largest impacts of quality change were in the item type and fabric categories. As seen in table 3 the coefficient on Tank Top is -0.407, indicating that, all else held constant, tank tops sold for about 33 percent less than tops for which no type was coded. Between January 2004 and January 2007 the share of tank tops in our sample fell from about 14 percent to about 0.4 percent, indicating an improvement in "quality" of approximately exp[(-.4070)*(-.136)]-1, or 5.7 percent. The share of tops with satin fabric also declined between the two periods, from about 17 percent to zero, and this yielded a measured quality improvement of approximately 4.2 percent. Computing and aggregating the same effects for all the other regressor variables explains the cumulative difference of about eight percentage points between the indexes in figure 13.

Although our regression results and the associated quality trends are plausible, we recognize that they may be an artifact of our data. It is possible that the changes in sample shares for tank tops, satin fabric, and other item characteristics could merely reflect changes in coding procedures. As noted above, the categories of explanatory variables were not defined by the retailer; we defined them based on the types of information shown in the IDN description text field. Between 2004 and 2007 the share of purchases with coded values of fabric and pattern fell, while the corresponding shares for sleeve length, item type, and fashion rose. It is certainly possible that trends in our measured quality variables do not accurately reflect trends in the actual sample characteristics. Nevertheless, taking our table 3 regression results as a guide, we proceed to examine whether operational hedonic regression methods could yield similar index results.

We took two approaches to computing hedonic indexes for misses' tops using only data available during the month for which the index value applies. First, we constructed an index from a series of 45 month-to-month regressions. Each regression employed two calendar months of individual purchase data and

[4] The brand and store coefficients are not shown, so as to preserve confidentiality.

contained all of our quality dummy variables for store, brand, and the characteristics in table 2, plus a time dummy for the second month of the two-month period. The time dummy coefficients from these 45 overlapping monthly regressions were then exponentiated and chained to produce an index series for our sample period.

The second approach was based on rolling 13-month regressions, in the spirit of the rolling RGEKS indexes discussed above. We again estimated overlapping regressions with the same sets of explanatory variables, but each of these 34 regressions contained 13 months of data and 12 time dummy variables for months. The first regression covered January 2004 through January 2005, and our index for those months was derived by exponentiating and chaining the 12 time dummy coefficients. Then, we computed the index change in February 2005 based on the dummy for that month in our second regression, which contained data for the 13 months from February 2004 through February 2005. That procedure was then followed for the remaining 32 months, ending with a regression with data for October 2006 through October 2007.

These approaches would give the same index results as that from the full table 3 regression if the coefficients on the item characteristic variables were stable from period to period. On the other hand, the chained month-to-month and rolling 13-month methods could break down if the coefficient vectors are volatile. In particular, the risk is that whenever new items are introduced at a high initial price, the regression will identify the characteristics of those items as carrying high "quality" premiums. That is, with so many explanatory variables the differences in relative prices for incoming apparel items may all be attributed by the regression to quality differences, with the time dummy coefficient merely reflecting the downward trends in prices of continuing items.

This disappointing result is reflected in the three hedonic indexes displayed in figure 14. The index based on the month-to-month regressions is roughly similar to the matched-model indexes in figure 10, declining from 100 in January 2004 to 4.5 in October 2007. The rolling 13-month regressions produce a much more reasonable pattern, but it is still clearly downward-biased relative to the full regression index from figure 13. The monthly index changes for each of these three indexes are shown in figure 15. That figure demonstrates that each index reflecting the same monthly fluctuations in price change, but the monthly index changes are consistently highest in the full regression index and lowest in the month-to-month regression index.

The largest difference between the estimates of monthly price change between the full and rolling 13-month regression indexes comes in February 2005, where the two models yield about 19 percent and 5 percent index increases, respectively. Again, we can highlight some of the individual regression coefficients to explain this difference. February 2005 was a month in which there was an influx of short-sleeve shirts, with the sample share rising to about 16 percent from about two percent in January. The full regression has a coefficient of -0.108 on short-sleeve shirts, as seen in table 3, so *ceteris paribus* the increased sample share is treated as a quality decrease. By contrast, the rolling 13-month regression for February 2004 through February 2005 has a coefficient of 0.474 on short-sleeve shirts, implying that they have very high relative quality. This coefficient difference by itself accounts for about 40 percent of the total difference in index change estimated by the two models in February 2005. This is an illustration of the effect described in the previous paragraph, where coefficient volatility in the chained regressions can mask the price increases that occur when new items enter the sample. We note that in the rolling 13-month regressions the coefficient on short-sleeve shirts declined throughout the spring and summer and was -0.026 in the regression for September 2004 through September 2005.

Our general conclusion from the results of this section is that only the hedonic regression produces indexes that are free of significant downward drift. Moreover, only the full-period hedonic index based on a regression using all 46 months of data yields a plausible index. None of our alternative monthly indexes is clearly superior to the simple index of weighted-average log-prices.

Conclusion

In many ways the data we employ in this paper provide the ideal basis for a consumer price index. The data set contains almost one million observations over a period of 46 months on prices for misses' tops. We can observe individual transaction prices along with a store identifier, the list price, and, in a large proportion of cases, detailed item characteristics. The great variety of discounts used in apparel pricing are fully reflected here.

Moreover, the data clearly demonstrate the dominant facts of the apparel industry: the size and prevalence of discounts from list price, the timing and importance of clearance sales, 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.

Against these advantages stand the well-known difficulties of developing price indexes for apparel, particularly a fashion item like misses' tops. We computed monthly chained matched-model indexes by applying the traditional Laspeyres and superlative Törnqvist formulas to our data. Both formulas yielded implausible indexes that fell by more than 99 percent over our sample period. Concluding that the problem arose from the high month-to-month turnover in the mix of items sold, we constructed an index using a 13-month Rolling GEKS approach, but that index exhibited almost as great a decline as the monthly-chained indexes. We then turned to regression-based indexes using dummy variables to reflect detailed item characteristics such as brand and fabric. Due to coefficient instability over time, however, both monthly-chained and 13-month rolling regression indexes declined persistently and implausibly over our sample period.

The operational consumer price indexes for apparel indexes published by national statistical agencies rely on careful matching of identical items, usually combined with special procedures to deal with short product life spans. The BLS, for example, uses hedonic regressions to facilitate comparisons of the prices of exiting and entering items. None of the approaches we tested in this paper demonstrated any superiority to those statistical agency procedures, despite our large and detailed data set. Nevertheless, we plan to continue to search for ways to fulfill the promise of these scanner data by obtaining reliable, quality adjusted indexes for apparel.

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

Sleeve Type	Frequency	Percent
Sleeveless	51,966	5.4
Cap	36,780	3.8
Short sleeve	158,214	16.3
Rouche	28,690	3.0
Flutter	8,752	0.9
Ruffle	28,853	3.0
Puff	6,690	0.7
Volume	1,763	0.2
Pleated	2,582	0.3
Elbow	3,609	0.4
Lantern	2,794	0.3
3/4 length	149,419	15.4
Long sleeve	191,093	19.7
Other or Unknown	297,279	30.7
Total	968,484	100.0

Item Type	Frequency	Percent
Blouse	120,210	12.4
Pullover	15,722	1.6
Tank top	18,333	1.9
Camisole	146,259	15.1
Shell	24,881	2.6
Jersey	3,166	0.3
Tunic	20,858	2.2
Dress shirt	1,154	0.1
Turtleneck	3,753	0.4
Tee	114,670	11.8
Baby Doll	3,425	0.4
Knit shirt	19	-
Wrap shirt	30,669	3.2
Stretch shirt	31,562	3.3
Classic	8,825	0.9
Other or Unknown	424,978	43.9
Total	968,484	100.0

Table 2. Continued

Fabric	Frequency	Percent
Silk	14,558	1.5
Satin	7,188	0.7
Lace	98,124	10.1
Mesh	22,708	2.3
Other or Unknown	825,906	85.3
Total	968,484	100.0

Pattern	Frequency	Percent
Solid	65,571	6.8
Print or Pattern	46,304	4.8
Other or Unknown	856,609	88.5
Total	968,484	100.0

Miscellaneous	Frequency	Percent
Basic	104,269	10.8
Fashion	83,182	8.6
Easy Care	71,914	7.4
Other or Unknown	709,119	73.2
Total	968,484	100.0

Table 3. Full Period Regression Coefficients

Variable	Coefficient	Standard Error	t-statistic
Sleeveless	-0.0805	0.0025	-32.8
Cap	-0.0774	0.0028	-28.0
Short sleeve	-0.1080	0.0018	-61.3
Rouche	0.1454	0.0030	49.0
Flutter	-0.0478	0.0056	-8.5
Ruffle	-0.0269	0.0033	-8.2
Puff	0.0951	0.0058	16.4
Volume	0.2850	0.0109	26.1
Pleated	0.1676	0.0162	10.4
Elbow	0.2647	0.0076	34.7
Lantern	0.2744	0.0089	30.8
3/4 length	0.0162	0.0019	8.7
Long sleeve	0.1469	0.0018	82.2
Blouse	0.0349	0.0019	18.6
Pullover	0.0715	0.0040	18.0
Tank top	-0.4073	0.0039	-105.8
Camisole	-0.1977	0.0021	-96.1
Shell	-0.1289	0.0034	-38.4
Jersey	0.1233	0.0109	11.3
Tunic	0.0631	0.0036	17.4
Dress shirt	0.1455	0.0208	7.0
Turtleneck	0.2100	0.0084	25.1
Tee	-0.1771	0.0021	-85.2
Baby Doll	0.1086	0.0078	13.9
Knit shirt	0.4094	0.1044	3.9
Wrap shirt	0.1166	0.0028	41.0
Stretch shirt	0.0714	0.0029	24.8
Classic	-0.0744	0.0051	-14.5
Silk	0.0100	0.0040	2.5
Satin	-0.2342	0.0056	-41.7
Lace	0.0099	0.0019	5.3
Mesh	0.0545	0.0033	16.7
Solid	0.0303	0.0020	15.0
Print or Pattern	-0.0010	0.0024	-0.4
Basic	-0.2196	0.0020	-109.1
Fashion	-0.2804	0.0021	-135.4
Easy Care	-0.0057	0.0022	-2.6

Figure 1. Distribution of Transactions by Percent of List Price

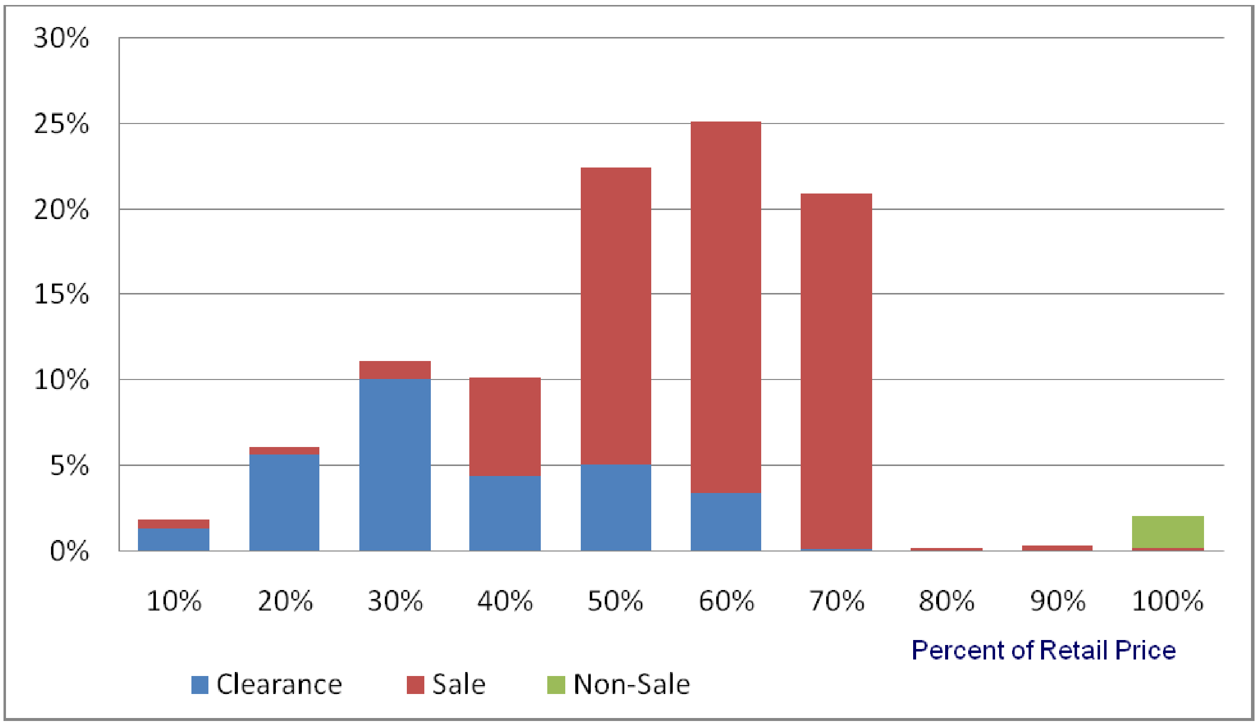


Figure 2: Mean Price as a percent of List price

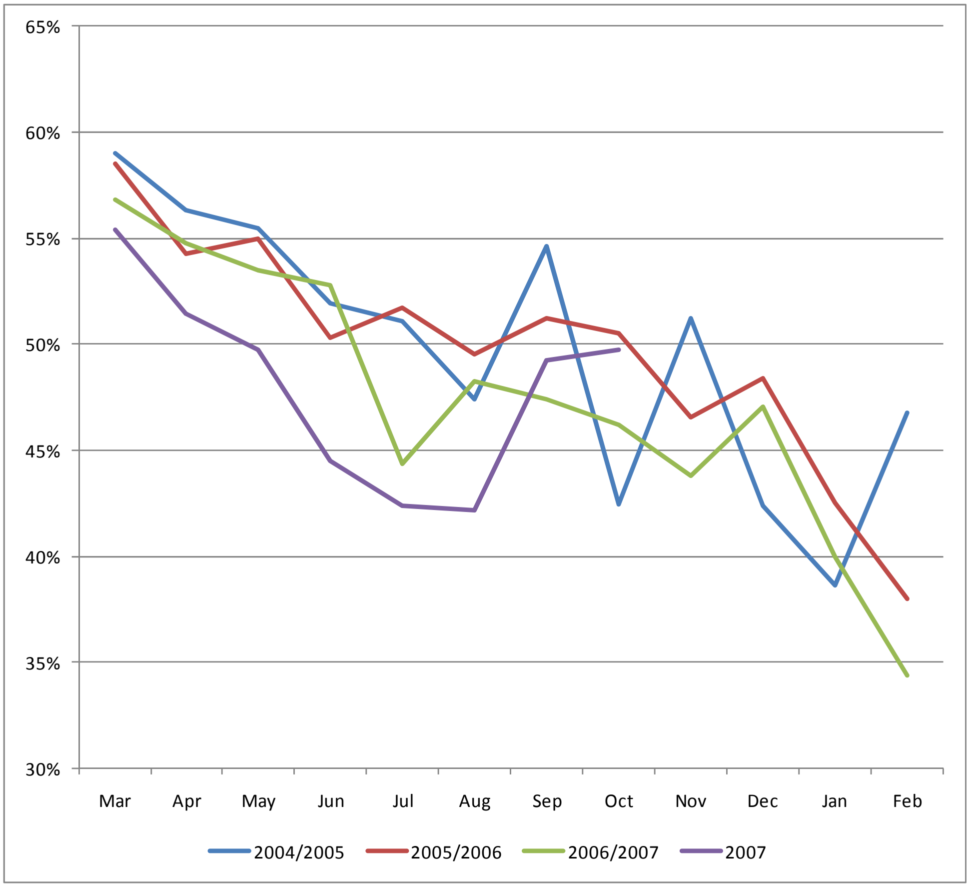


Figure 3. Monthly Transactions and Average Prices
S/S Tee Shirt Item

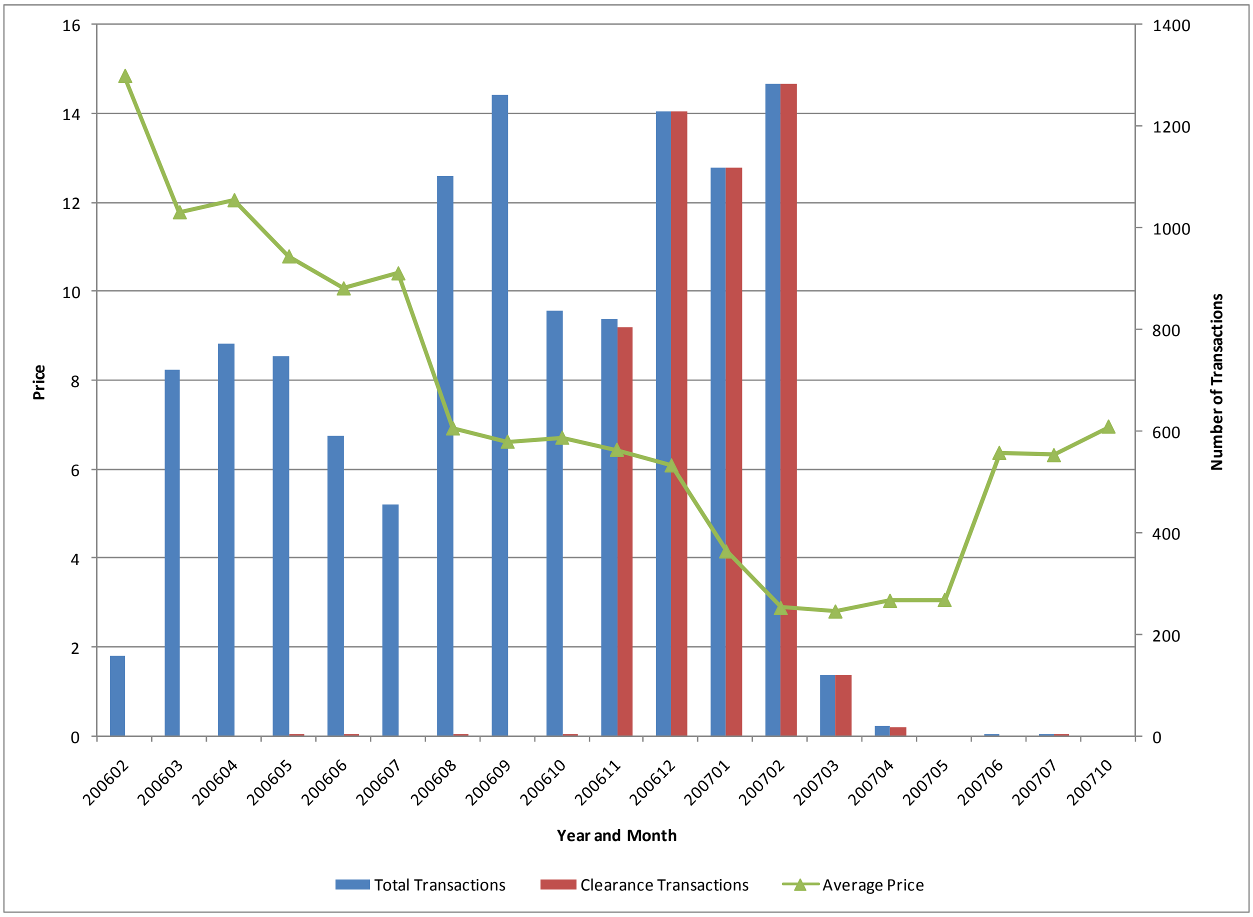


Figure 4. Transactions and Prices by Day of Week

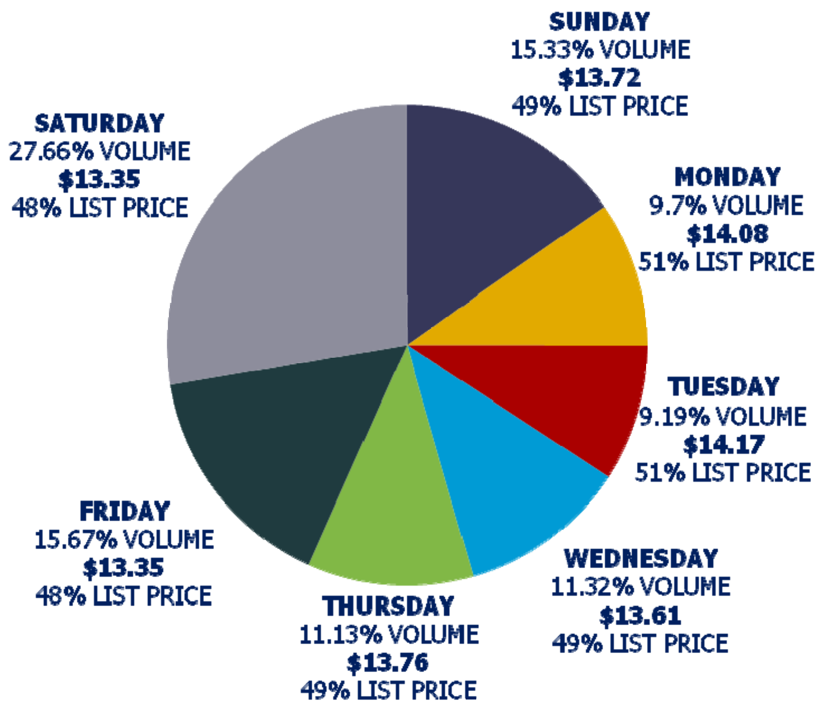


Figure 5. Indexes of Average Prices (200401=1)

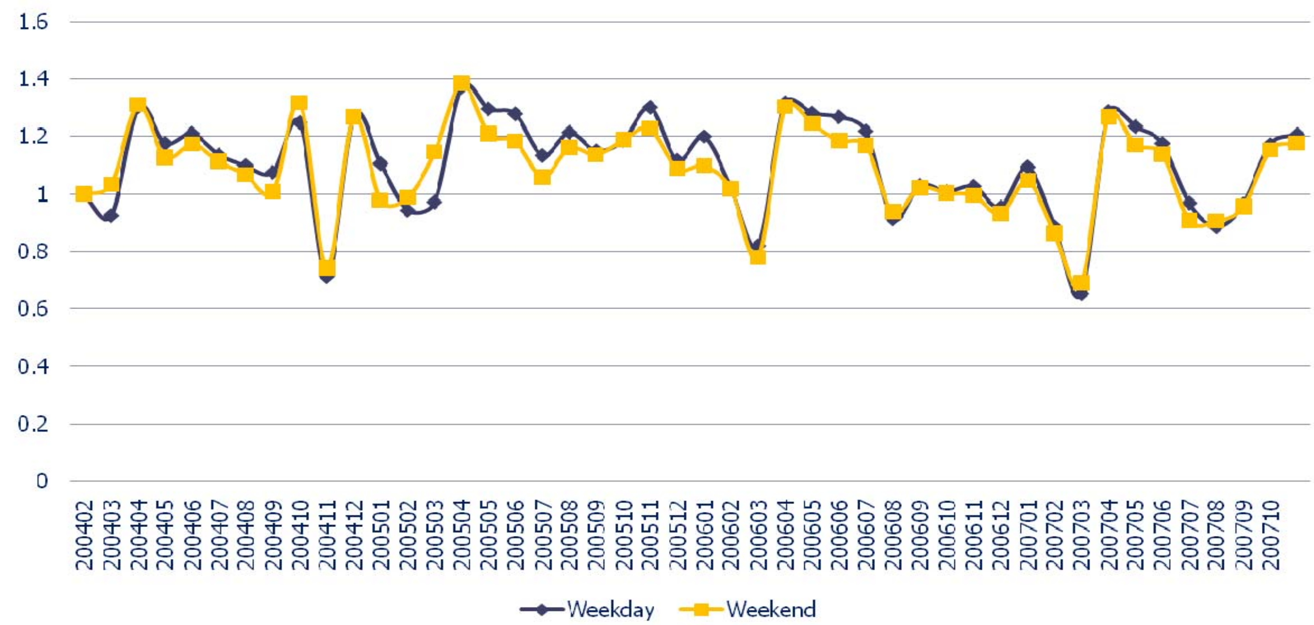


Figure 6. Average Monthly Rates of Price Change

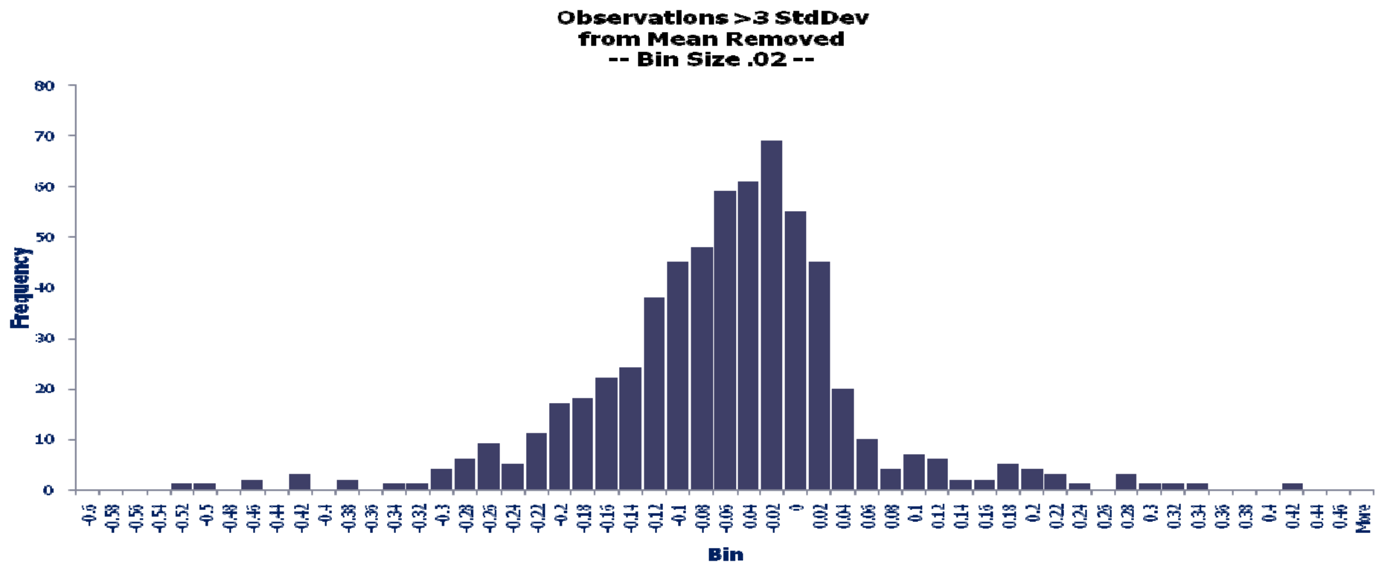


Figure 7. Monthly Matched-Model Rates of Price Change

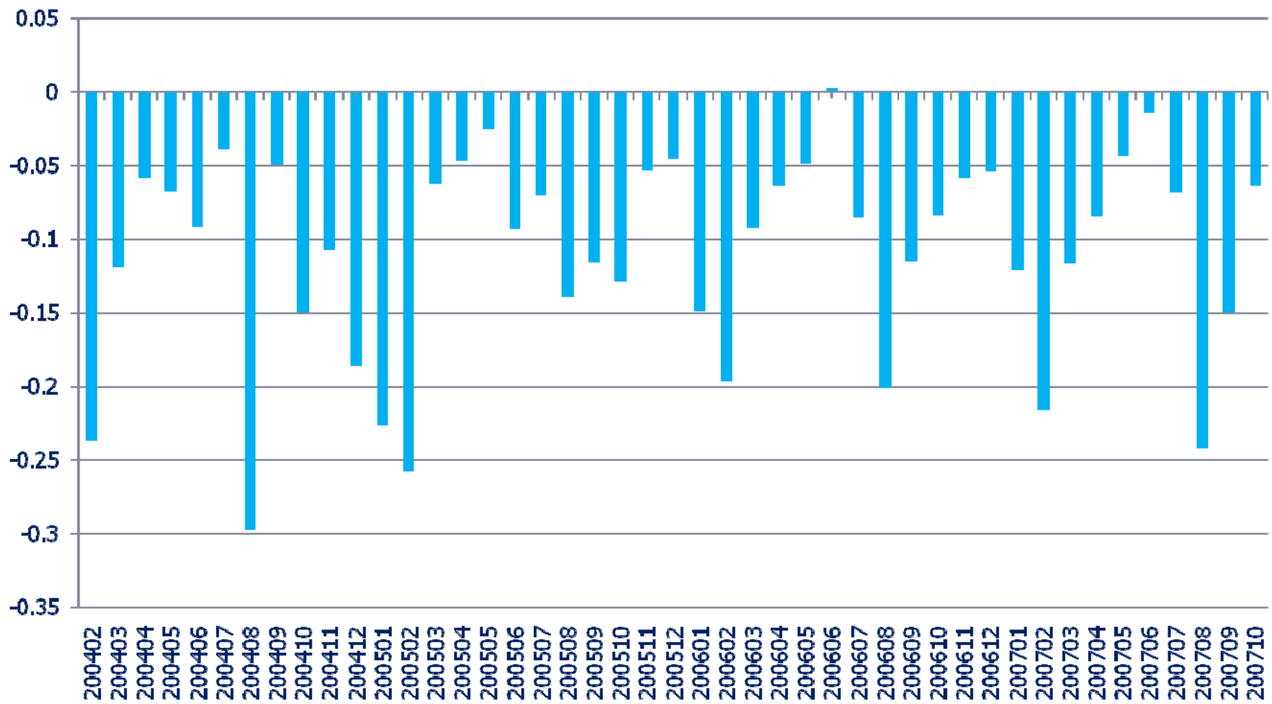


Figure 8. Indexes of Average Price, 120 IDNs, First 20 Months

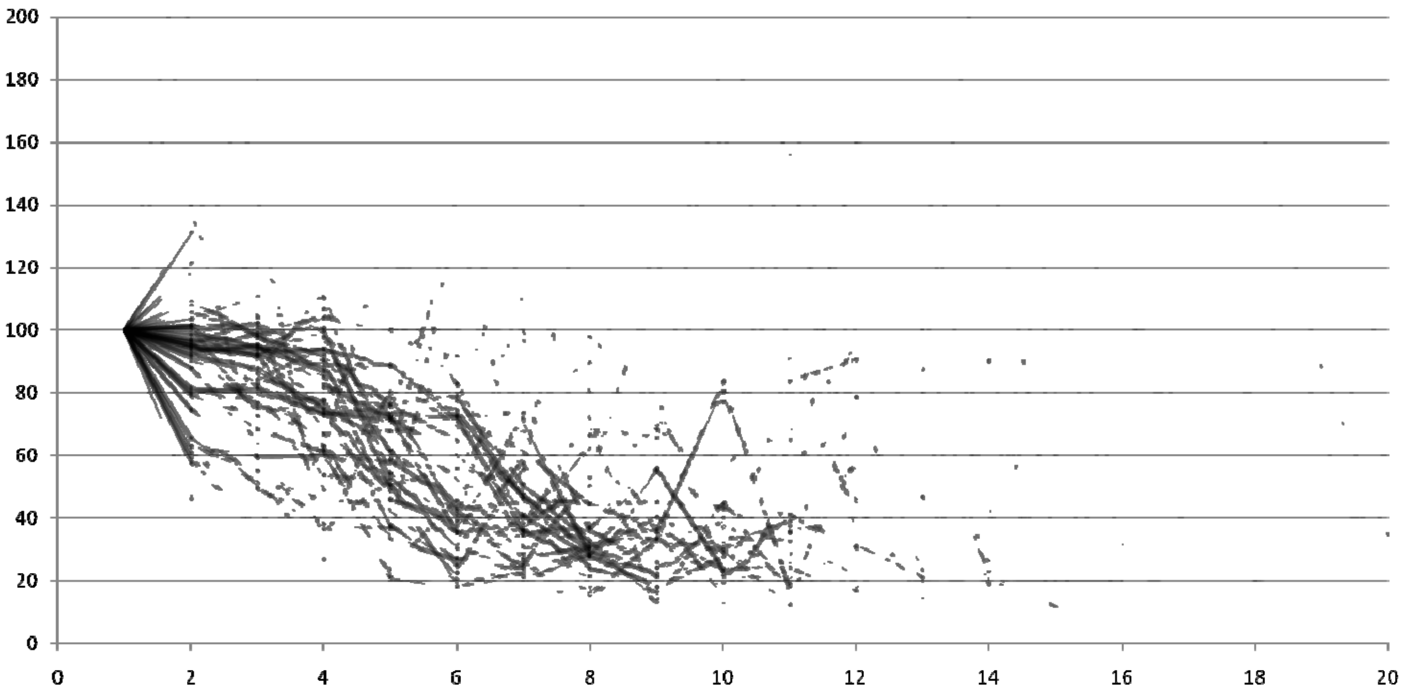


Figure 9. Indexes of Average Price, 120 IDNs, by Sample Month

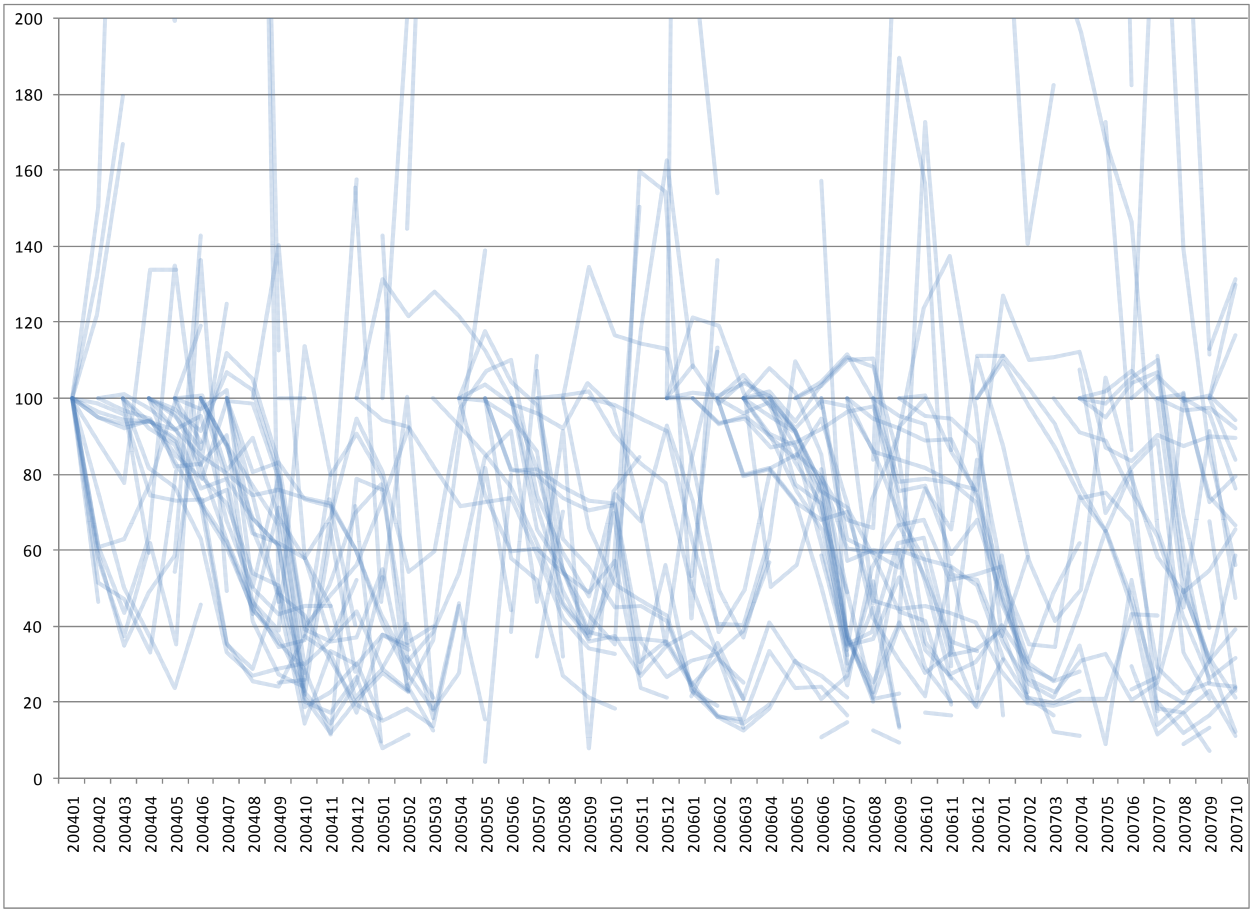


Figure 10. Laspeyres and Paasche Month-Month Indexes

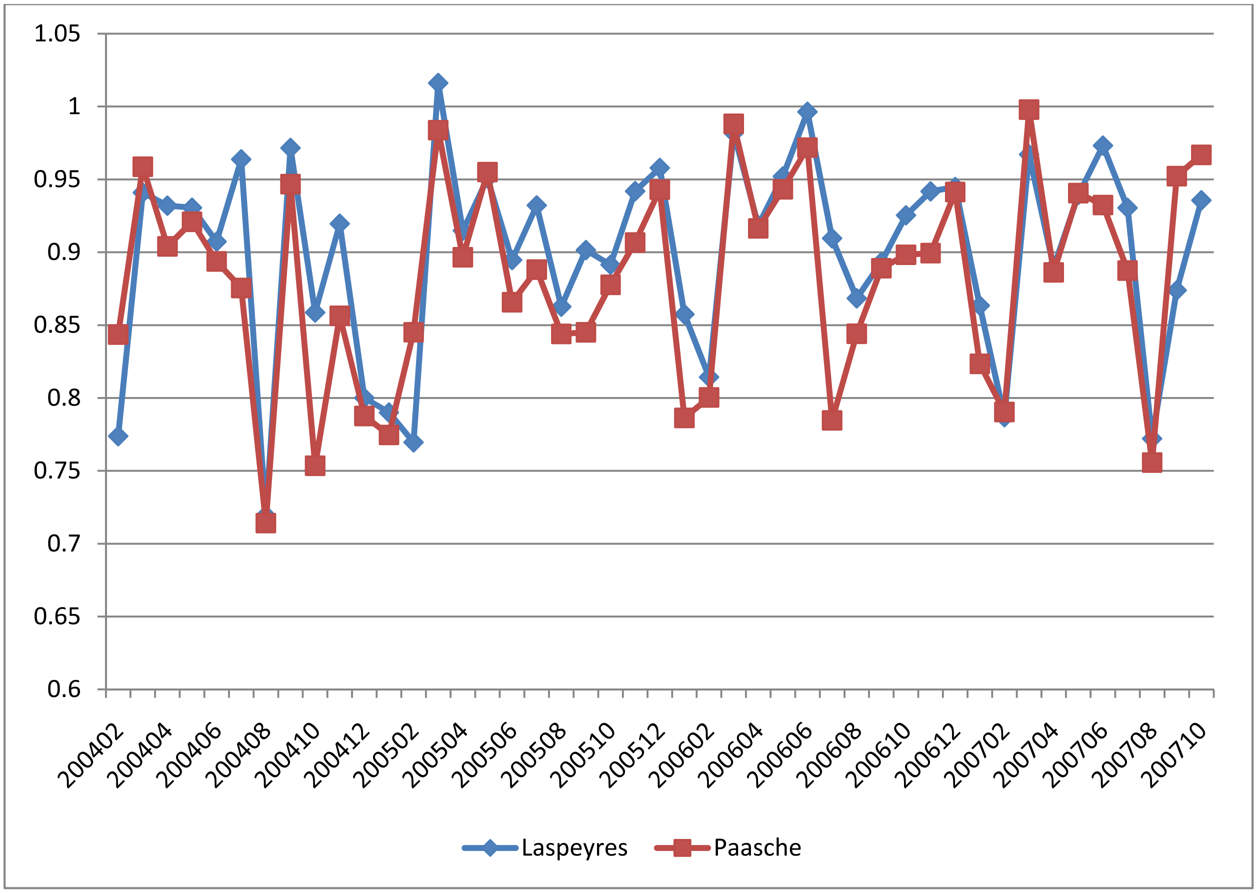


Figure 11. Alternative Price Indexes for Misses' Tops (200401 = 1)

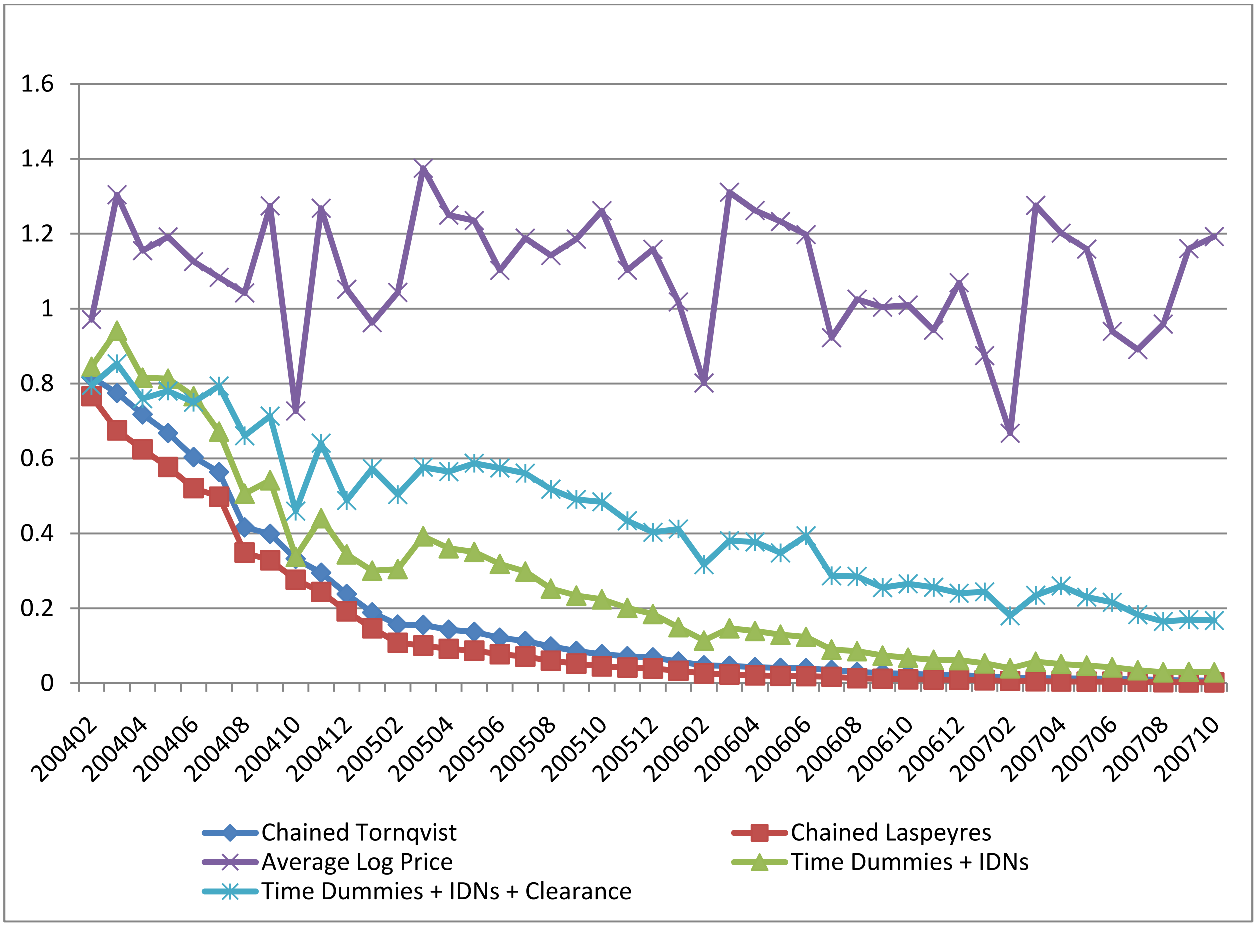


Figure 12. Rolling 13-month GEKS Index (January 2004=100)

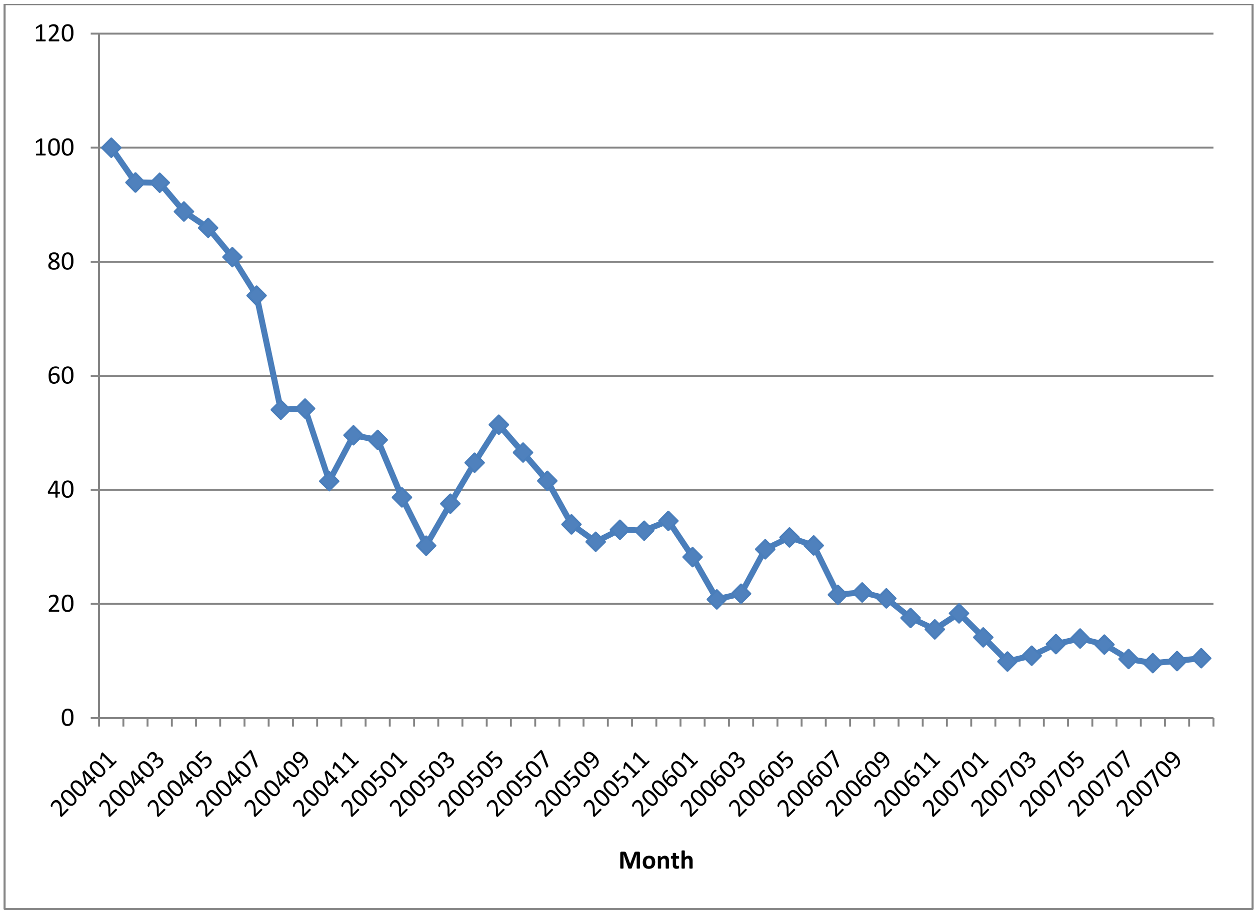


Figure 13. Average Log Price and Full Regression Index (January 2004=100)

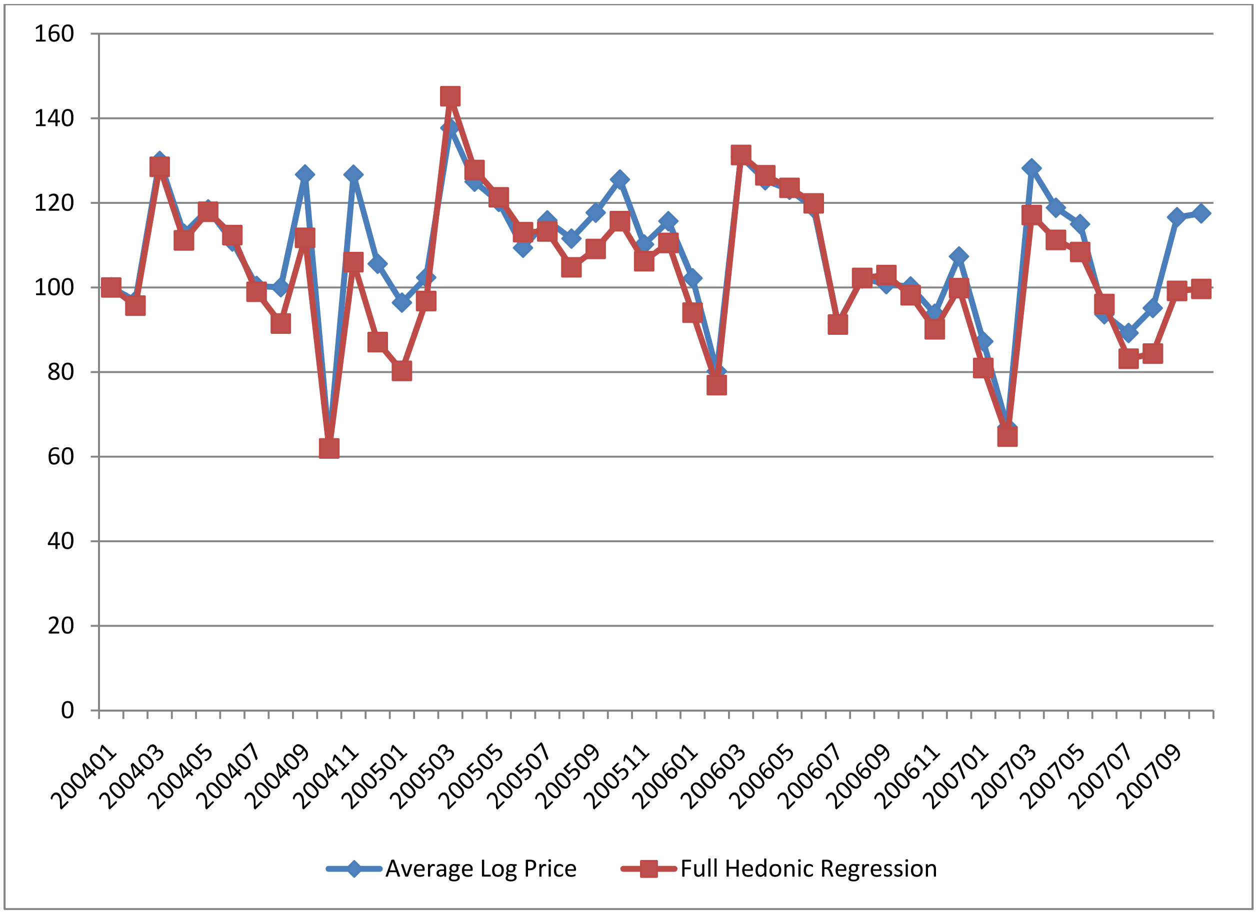


Figure 14. Full Regression Index, Monthly Chained Index, and Rolling 13-month Chained Index, January 2004=100

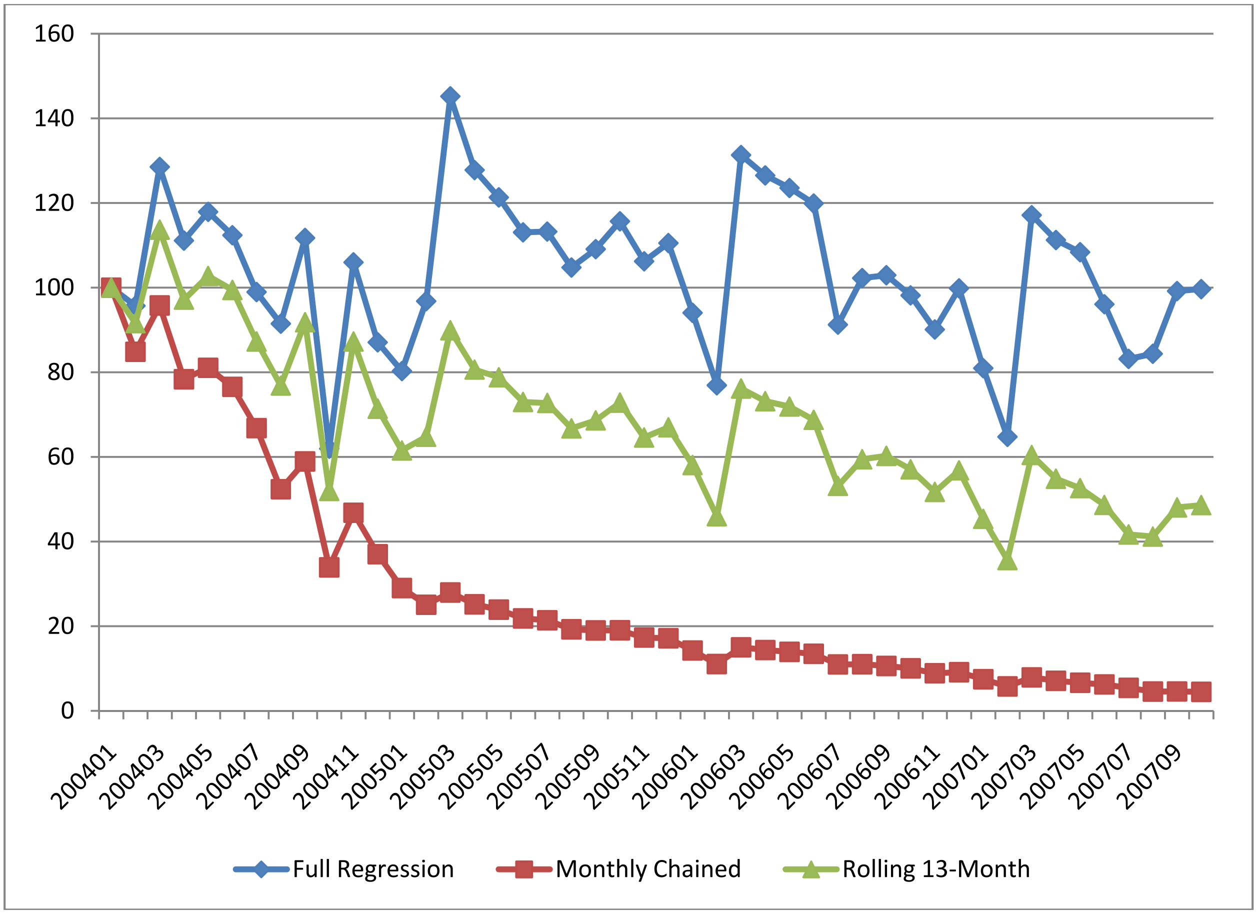
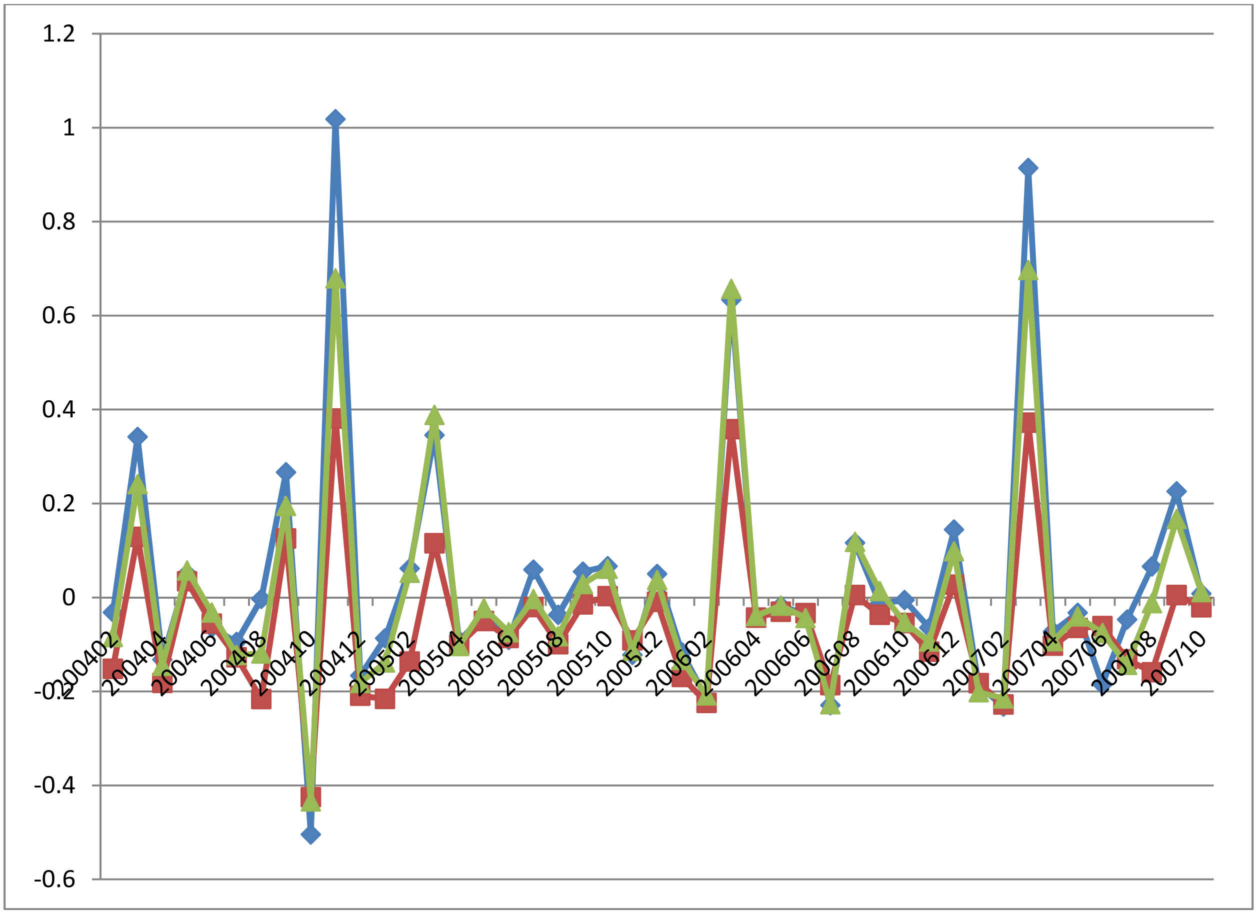


Figure 15. Month-to-month Log Changes, Full Regression Index, Monthly Chained Index, and Rolling 13-month Chained Index



References

Bils, Mark (1989): "Pricing in a Customer Market," *Quarterly Journal of Economics*, pp. 699-718, November.

Bils, Mark, and Peter Klenow (2004): "Some evidence on the importance of sticky prices," *Journal of Political Economy*, v. 112, pp. 947-985, October.

Brown, Craig, and Anya Stockburger (2006): "Item replacement and quality change in apparel price indexes," *Monthly Labor Review*, v. 129, pp. 35-45, December. Available at http://www.bls.gov/opub/mlr/2006/12/art3full.pdf.

Chevalier, Judith A., and Anil K. Kashyap (2010): "Best Prices," manuscript, July.

Chevalier, Judith A., Anil K. Kashyap, and Peter E. Rossi (2003), "Why Don't Prices Rise During Periods of Peak Demand? Evidence from Scanner Data," *American Economic Review*, v. 93, pp. 15-37, March.

de Haan, Jan, and Heymerik van der Grient (2009): "Eliminating Chain Drift in Price Indexes Based on Scanner Data," presented at the Eleventh Meeting of the Ottawa Group, Neuchatel, Switzerland, April. Available at http://www.ottawagroup.org/Ottawa/ottawagroup.nsf/51c9a3d36edfd0dfca256acb00118404/c0b785f3c0f0f765ca25727300107fd9?OpenDocument.

Eichenbaum, Martin, Nir Jaimovich, and Sergio Rebelo (2008): "Reference Prices and Nominal Rigidities," NBER Working Paper 13829, March.

Fox, Kevin, Lorraine Ivancic, and W. Erwin Diewert (2009): "Scanner Data, Time Aggregation and the Construction of Price Indexes," presented at the Annual Meeting of the American Economic Association, January 4. Forthcoming, *Journal of Econometrics*. Available at http://www.aeaweb.org/assa/2009/index.php.

Guédès, Dominique (2007) "Fashion and Consumer Price Index," presented at the Tenth Meeting of the Ottawa Group, Ottawa, Canada, October. Available at http://www.ottawagroup.org/Ottawa/ottawagroup.nsf/51c9a3d36edfd0dfca256acb00118404/c0b785f3c0f0f765ca25727300107fd9?OpenDocument.

Kashyap, Anil (1995): "Sticky Prices: New Evidence from Retail Catalogs," *Quarterly Journal of Economics*, v. 110, pp. 245-74, February.

Lazear, Edward P. (1986): "Retail Pricing and Clearance Sales," *American Economic Review*, v. 76, pp. 14-32, March.

Nakamura, Alice, Emi Nakamura, and Leonard I. Nakamura (2010): "Price Dynamics, Retail Chains and Inflation Measurement," manuscript, March.

Pashigian, B. Peter, and Brian Bowen (1991): "Why are Products Sold on Sale?: Explanations of Pricing Regularities," *Quarterly Journal of Economics*, pp. 1015-1038, November.