

## **Can health care claims data improve the estimation of the Medical CPI?**

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## **Can health care claims data improve the estimation of the Medical CPI?**

### **Abstract**

The Committee on National Statistics (CNSTAT) recommends that the U.S. Bureau of Labor and Statistics (BLS) should change Medical Consumer Price Index (MCPI) from an index that is based on input prices for a sample of providers to an index based on prices for a sample of diseases. Additionally, CNSTAT suggests that instead of collecting price quotes directly from providers, the MCPI should use the reimbursement information on retrospective claims data bases. This study uses a retrospective claims database to construct medical price indexes for three PSUs in the Northeast that match the BLS's priced PSUs: Philadelphia-A102, Boston-A103, and New York-A109. We find that drug prices in the claims database are significantly lower than drug prices that BLS collected from 1999 to 2002. We also construct several experimental medical price indexes using the claims database from 1998 to 2002. One index is constructed using the current methodology of the MCPI. A second index is constructed that is disease based. The difference between disease-based index and the BLS MCPI is decomposed into three potential sources: difference in construction methods, difference in sample sizes, and difference in price distribution between the claims database and the BLS sample. In a month-by-month comparison, we did not find statistically significant differences between disease-based indexes and the BLS MCPI. The cumulative effect of the different methods will be tested.

## **Can health care claims data improve the estimation of the Medical CPI?**

### **1. Introduction**

There are three major concerns with the production of the current MCPI. First, the conceptual basis for price indexes in healthcare has been the object of several recent studies that include recommendations to change the index so that it better reflects the price of treating the distribution of diseases that affect American households. In recent years, the BLS has been pricing a fixed bundle of discrete inputs for the MCPI, such as a day in the hospital, a visit to a gastroenterologist, or a serum laboratory test. This measurement overlooks substitution possibilities among medical inputs for treating a particular condition. More specifically, pricing a fixed bundle of inputs does not allow the substitution across various strata, thus overstating the impact of price increases. To better accommodate such substitution effects, recent advisory panel recommendations to the BLS encouraged the pricing of treatment episodes for selected diseases, independent of the actual treatment components.

Second, the current methodology requires price quotes from healthcare providers, which are increasingly difficult to obtain. Some providers are more willing than others to provide requested data, and this can generate undesirable selection effects regardless of the method or formula that is used to generate the MCPI. Because of increasing concerns about medical privacy, it may become more difficult to persuade providers to disclose billing information that can be perceived as compromising the privacy of their patients.

Third, the BLS can only sample a limited number of prices for each type of medical service for a particular geographic area (Primary Sampling Unit or PSU), and this limitation can induce finite sample bias in the MCPI.

A number of studies have looked at the changing price of treatment for specific illnesses. Berndt et al. (), Shapiro, Shapiro, and Wilcox (2001) and Cutler et al. (1998, 1999) have successfully examined the changing price of treatment of depression, cataract surgery and acute myocardial infarction. These studies look at the kinds of treatments patients receive to help them recover from illness. The ultimate demand is for recovery. As the technology available to health care providers improves, the inputs used in an episode of care will change. By measuring the total cost of the restructured episode, these authors were able to track the price of care.

Based largely on this evidence, the Committee on National Statistics (CNSTAT) recommended<sup>5</sup> that the Medical Consumer Price Index (MCPI) should be changed from an index that is constructed with prices that are sampled from providers to an index that derives prices for the total treatment costs of randomly sampled diagnoses. Additionally, CNSTAT suggested that instead of collecting price quotes directly from providers, the MCPI should use the reimbursement information on retrospective claims data bases. Pricing based on diseases and treatment episodes allows for medical care substitution across medical inputs in the treatment of patients. Claims-based pricing also eliminates respondent burden and may have the advantages of larger sample size and greater data validity (since it does not rely on subjective response).

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<sup>5</sup> At What Price? Conceptualizing and Measuring Cost-of-Living and Price Indexes. The National Academy of Science, 2002.

One disadvantage of claims-based pricing is the time lag associated with claims processing. Indexes created using fully adjudicated claims could experience potentially long and variable lags as the larger, more complex medical claims are resolved for payment. Claim lag for outpatient prescriptions drugs are virtually non-existent and simple outpatient and even simple inpatient claims are resolved quickly. Claims for costly hospital stays can take four months or longer to be resolved. These lags pose challenges for the MCPI which is published within a month of data collection.

This paper uses medical insurance claims data to investigate both issues: 1) obtaining transaction prices for representative medical treatments to the impact of third party reimbursement on measured trends in health care inputs (ultimately prescription drugs, physician, and hospital services) and 2) capturing the ability to substitute inputs in the treatment of diseases. In Section 2 we describe the data that are employed. Section 3 focuses on a comparison of the current BLS drug prices and drug prices in a claims database, and describes how similar indexes based on medical claims data are constructed using the BLS method. Section 4 provides the analysis of episodes of care. Section 5 compares the BLS MCPI and the episode-based index, and decomposes the difference between these two indexes into three potential sources: difference in construction method, difference in sample sizes, and difference in price distribution. Section 6 summarizes the current state of our ongoing research.

## **2. Data**

Data for this study come from the Medstat MarketScan Research Databases. These databases are a convenience sample reflecting the combined healthcare service use of individuals covered by Medstat employer clients nationwide. Personally identifiable health information is sent to Medstat to help its clients manage the cost and quality of healthcare they purchase on behalf of their employees. MarketScan is the pooled, and de-identified data from these client databases. Two MarketScan Databases are used in this MPCCI study: 1) the Commercial Claims and Encounters (CC&E) Database and, and 2) the Medicare Supplemental and COB (Medicare) Database.

The Commercial Claims and Encounters Database contain the healthcare experience of approximately 4 million employees and their dependents in 2002. These individuals' healthcare is provided under a variety of fee-for-service (FFS), fully capitated, and partially capitated health plans, including preferred provider organizations, point of service plans, indemnity plans, and health maintenance organizations. The database consists of inpatient admissions, inpatient services, outpatient services (including physician, laboratory, and all other covered services delivered to patients outside of hospitals and other settings where the patient would spend the night), and outpatient pharmaceutical claims (prescription drugs delivered in inpatient settings are unfortunately not separately tracked in the databases).

The 2002 Medicare Supplemental and COB Database contains the healthcare experience of almost 900,000 individuals with Medicare supplemental insurance paid for by employers. Both the Medicare-covered portion of payment (represented as Coordination of Benefits Amount, or COB) and the employer-paid portion are included in this database. The database also consists of inpatient admissions, inpatient services, outpatient services, and outpatient

pharmaceutical claims. For both the replication and episode analyses, we combine the under 65 population of CC&E with the Medicare COB data to examine all ages. Details of the analytic file construction are available in Appendix 1.

To keep this project manageable, we limited the analysis to three metropolitan areas that serve as primary sampling units (PSUs) for the CPI and that have significant numbers of people captured in MarketScan databases. They are: New York-A109, Philadelphia-A102, and Boston-A103. While the number of covered lives in each of the cities varies by year, MarketScan has many more respondents in Boston (146,000 in 1998) than Philadelphia (104,901) or New York (43,520).

### **3. Replication of the Medical CPI**

The main purpose of replicating the current BLS methodology is to compare prices captured in the claims database with those collected in the BLS sample. In particular, replicating BLS indexes will provide answers to the following two questions:

- Is the distribution of reimbursements for the various types of medical goods and services in the MarketScan database significantly different from the distribution in the BLS production data set?
- Is the BLS MCPI affected by different sample sizes?

#### **3.1. BLS Method**

The BLS CPI is constructed using a two stage process. In the first stage, price indexes are generated for 201 different items for 38 cities. The indexes in the first stage are then used to generate an “All-Items-All Cities” Index. The following categories are included in the medical

care CPI: 1) Internal and Respiratory Over the Counter Drugs, 2) Nonprescription Medical Equipment and Supplies, 3) Physician Services, 4) Dental Services, 5) Eyeglasses and Eye Care, 6) Services by other Medical Professionals, 7) Hospital Services, and 8) Nursing Homes and Adult Day Care. The overall Medical CPI is an expenditure weighted average of these item indexes.

The initial sample at the “item-area” level is implemented with two surveys. The first is a “Telephone Point of Purchase Survey” (TPOPS) where randomly selected households are asked where they purchase their medical goods and services, and how much they spend at each outlet. In the second survey, the results of TPOPS are used to select outlets and then select an item within the outlet where the probability of selection for a particular outlet is proportional to its expenditure share in TPOPS.

Once an outlet is drawn then the BLS field representative goes to the outlet to select either a good or a service that falls within a certain item category. There is a detailed checklist of important characteristics of the item. The field representative determines the expenditure share for each characteristic. And the probability that an item is drawn is proportional to the expenditure share of its characteristics within the outlet. For pharmaceuticals a key characteristic is the National Drug Code (NDC), for physicians, it is the Current Procedure Terminology (CPT) code, and for hospitals it is based on the Diagnosis Related Group (DRG).

Once the outlets and items are selected they stay in the sample for five years. The implicit assumption of this fixed sample is that the inputs used to treat each specific disease are constant. As Cutler et al. (1996) and Shapiro and Wilcox (1996) show, if less expensive inputs are substituted for more expensive ones, this will not show up in the BLS price index.



On a monthly basis, BLS reprices the items in its sample, and for all medical items except pharmaceuticals, will generate a Laspeyres type price index.<sup>7</sup> For pharmaceuticals, a geometric mean index is computed. Sometimes, when the BLS field representative attempts to reprice an item in the sample, it is no longer available. In the first month that this occurs, the price of the missing item is imputed by multiplying its last observed price times the price index of the other items. The field representative then tries to find the most similar item to replace the missing item. If the replacement item is very similar to the missing item, then this is treated as a *comparable substitution*, and there is no price adjustment. Otherwise, it is treated a *non comparable substitution* and the price is quality adjusted

The expenditure weights used for the first stage indexes in the derivation of the second stage are based solely of out of pocket costs. As a result medical care receives a 5.8% weight even though health care expenditures represent 14.8% of GDP, and over 20% of personal consumer expenditures.

### 3.2. Indexes Created using MarketScan Data and the BLS Method

No claims database contains the information needed to precisely mimic BLS procedures of constructing CPI. Appendix 1 provides the detailed ten steps we took to create analytic files that would provide as much of the information described above. Table 1 shows the maximum numbers of providers of different types in each of the three cities. In each case the claims database identifies a significant number of physicians and pharmacies. The number of hospitals and hospital outpatient departments is more limited but still large enough to support the planned analyses.

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<sup>7</sup> Most areas have an “on cycle” and “off cycle” months. For some areas the “on cycle” months are the even ones, and for others they are the odd ones. Repricing is only done in the “on cycle” months and the price index represents the price change over a two month period.

For prescription price indexes, we first identified suppliers of prescription drugs in the three cities by the location of the provider. For each unique pharmacy ID, we selected a NDC code in proportion to its expenditure share in that pharmacy. Inpatient hospital prescriptions and prescriptions paid by Medicaid or worker's compensation are ineligible for the medical price index and not included in the database.

All pharmacy IDs and the selected NDCs were included in the analytic file. To sample a given number of pharmacies, we randomly selected the same number of pharmacy IDs in proportion to their expenditure share within a PSU using probability proportion to size (PPS) with replacement sampling method, and then calculated the price indexes using the selected NDC for each selected pharmacy. Because MarketScan databases do not record the total annual expenditure of any pharmacy, we summed up all payment to a given pharmacy in a year recorded in MarketScan to calculate the probability of that pharmacy being selected. The computed total payment to a pharmacy could differ from its actual annual revenue as some large pharmacies may have a small number of patients in our sample. With those compromises, we were able to replicate the current CPI for prescription drugs. Two sets of price indexes were calculated: the first set was based on the same sample size currently used by the BLS (small-sample index) and the second set was based on a much larger sample size (large-sample index), which is ten times the BLS sample size. The next subsection provides results of the comparison of the prescription drug prices.

Similarly, analytic files for physician office visits, inpatient hospital stays, and outpatient hospital visits were created using the PPS with replacement sampling method. The small-sample and large-sample price indexes were also calculated for physician office visits and hospital

stays/visits. Subsequent drafts will provide more detail of the results for physician office visits and hospital stays/visits.

The small- and large-sample overall indexes are presented in Section 5 when we compare the episode-based index with the BLS index. It is worth noting that all indexes that are constructed based on claims data are only price indexes for those in the US that are covered by health plans. They cannot and do not estimate price indexes for the uninsured population.

### 3.3. Comparisons of Pharmaceutical Databases

We first compared drug prices collected by the BLS and the drugs prices in MarketScan from 1999 to 2002. The Medicare Modernization Act passed in 2003 highlighted the role that insurance-negotiated discounts for prescription drugs are currently a widespread phenomenon. The comparison analysis reported here answers the question: “Are time trends in drug prices affected by insurance reimbursement techniques? Or have the discounts been changing significantly over time?”

We recreated with the claims database the strategy outlined above for the current CPI procedures. That is, for each PSU, we selected the precise NDC codes used in the current CPI in 1999-2002. Since the prescriptions of each NDC could come from more than one pharmacy, could have more than one metric quantity, and could have more than one service date in a given month, we used the following rules to select just one prescription for each NDC in each month:

- For each NDC, we selected the most commonly prescribed metric quantity in a given PSU.
- We then selected the pharmacies that had the most prescription of the BLS NDCs.

- Since most NDCs have more than one service date in a given month, we selected the prescription that was closest to the 15<sup>th</sup> of the month.
- For those NDCs that do not have a prescription in a given month, we used the payment in the previous month whenever possible. If a previous month prescription was not available, we used the prescription in the following month when there was one.
- If there was no prescription in the give month, previous month, or the following month within the selected pharmacy, we calculated the missing price according to the price growth rate from MarketScan with NDCs that have complete prices in all months.
- Whenever the list of BLS NDCs changed for the first time, we priced both the old list of NDCs and the new list of NDCs in that month. For example, if BLS rotates NDCs in June, then we price the old list of NDCs and the new list of NDCs separately in June. The price change from May to June is calculated using the prices of the old list of NDCs in June, and the price change from June to July is based on prices from the new list of NDCs.
- Some of the BLS NDCs do not show up in relevant years in a given PSU in MarketScan. They were dropped from price comparison analysis.
- For each NDC, both the insurance reimbursement and the patient co-pay, if any, were included to arrive at the total reimbursement for that prescription

We calculated a prescription price index using the resulting sample. Figure 1 shows the BLS-measured monthly growth rate of prescription prices compared to the price changes we calculated using MarketScan data for each of the three cities. The correlation between the two series varies from a low of 0.78 in Boston to a high of 0.96 in Philadelphia. The correlation in New York was 0.88. It is difficult to know what factors might explain the differences between

the cities. Part of the story relates to the size of the claims database in each city. Boston is the largest city in MarketScan but the smallest PSU. Another part of the story could be differences in the healthcare delivery systems in the three cities.

We then further restricted the MarketScan NDC sample by only including NDCs that have the same metric quantity as that of the BLS NDC sample, and by including only those NDCs whose prescription came from the same pharmacy within a year. Prescription prices of the resulting sample were compared with the prices from the BLS sample using t-tests. Test statistics show that the price distribution in the MarketScan sample and the BLS sample is significantly different in each PSU separately and in all three PSU's combined (t-test statistics are -7.56 in Philadelphia, -8.10 in Boston, -17.76 in New York, and -16.78 in all three cities combined). As expected, prices collected in the claim database are lower than the prices collected by the BLS in all three cities because of discounts. (All of these comparisons have been conducted with the small sample – one with the same number of observations in both the BLS and MarketScan samples.

#### **4. Episode-based Price Indexes**

A number of studies cited above have examined the changing cost of treating specific illnesses by examining episodes of care for those illnesses and how the cost of a treatment episode changed over time. Based on that literature, the CNSTAT recommended study of a generalization of this approach.

Recommendation 6-1. BLS should select between 15-40 diagnoses from the ICD (International Classification of Diseases), chosen randomly in proportion to their direct medical treatment expenditures and use information from retrospective claims databases to identify and quantify the inputs used in their treatment and to estimate their cost. On a monthly basis, the BLS could re-price the current set of specific items (e.g., anesthesia, surgery, and medications), keeping quantity

weights temporarily fixed. Then, at appropriate intervals, perhaps every year or two, the BLS should reconstruct the medical price index by pricing the treatment episodes of the 15 to 40 diagnoses—including the effects of changed inputs on the overall cost of those treatments. The frequency with which these diagnosis adjustments should be made will depend in part on the cost to BLS of doing so. The resulting MCPI price indexes should initially be published on an experimental basis. The panel also recommends that the BLS appoint a study group to consider, among other things, the possibility that the index will “jump” at the linkage points and whether a prospective smoothing technique should be used.

In order to implement the committee’s recommendation with the data available for this study we needed a tool that transforms a stream of claims data into episodes of care for the full range of conditions covered by the ICD system. There are several commercially available software products that embody episode grouping methods. We used the Medstat Episodes Grouper (MEG). MEG is predicated on the Disease Staging patient classification system developed initially for the Healthcare Cost and Utilization Project (HCUP). MEG uses sophisticated logic to create clinically relevant, severity-rated, and disease-specific groupings of claims. There are 593 episode groups. Episodes can be of several types:

*Acute Condition* type includes episodes of care of acute conditions, which are generally reversible—such as an episode of sinusitis or otitis media.

*Chronic Maintenance* episodes refer to episodes of routine care and management for a chronic, typically non-reversible condition or life-long illness—such as diabetes mellitus episodes. All cancers are considered chronic.

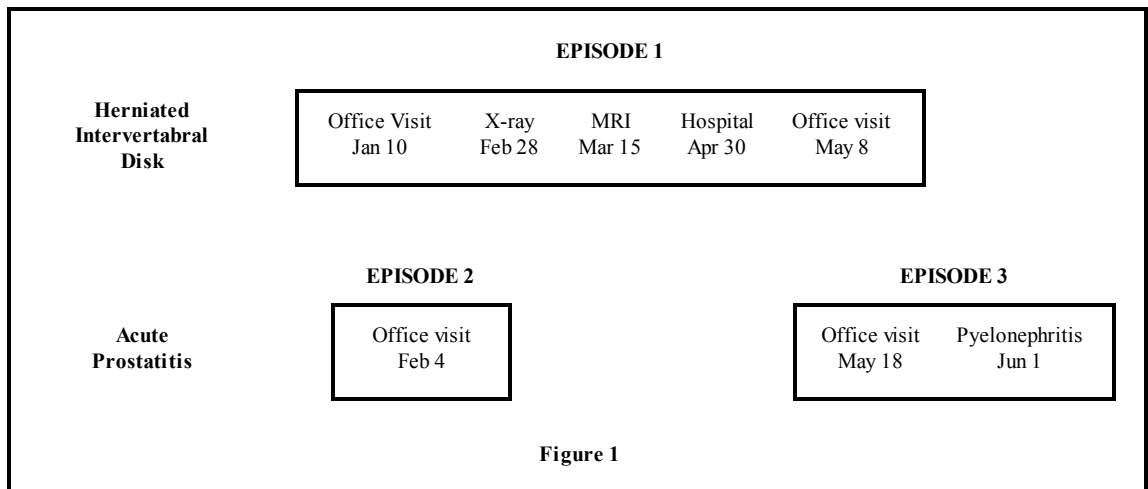
*Acute Flare-Up* type includes episodes of acute, generally reversible, and ideally preventable exacerbations of chronic conditions—such as an episode of diabetes with gangrene.

*Well Care* type includes administrative and preventative care provided to a patient for ongoing health maintenance and wellness.

For the acute conditions and flare ups gaps in services, identified in the claims, define clean periods that mark the beginning or end of an episode of care. For chronic maintenance episodes the first occurrence of the diagnosis can open an episode and the calendar year is used to define endpoints.

The following figure illustrates how a stream of claims can be transformed into three episodes of care for a 55-year-old male patient. In this example, episodes of care occur for two conditions: acute prostatitis and a herniated disc.

An episode for the care of the herniated disc (Episode 1) *begins* with an office visit on January 10. It includes all services related to an identified *health problem* of low back pain, including diagnostic imaging and a hospitalization. The episode *ends* with a follow-up physician office visit on May 8.



The treatment of acute prostatitis is divided into two episodes (Episodes 2 and 3). First, the patient is seen in his physician’s office for acute prostatitis on February 4. The length of time between the February 4 visit and the May 18 visit is sufficiently long enough begin a new episode rather than continue the first episode. Consequently, a second episode (Episode 3) is initiated with the office visit for acute prostatitis on May 18. A complication of prostatitis, pyelonephritis, occurs within a short time, so the June 1 visit is a continuation of the second prostatitis episode.

The above example also illustrates the difference between complications and comorbidities. A disease complication arises from the progression of an underlying disease. For example, pyelonephritis is a complication of acute prostatitis, and is therefore a part of the episode for acute prostatitis. Disease comorbidities are diseases that are concurrent, but not related to one another. For instance the acute prostatitis and the herniated disc are comorbidities unrelated to one another. Therefore, separate disease episodes are created for the two comorbidities.

An episode of care is initiated with a contact with the health delivery system. In a claims-based methodology, the beginning of an episode is the first claim received for an episode grouping. The MEG methodology allows physician office visits and hospitalizations to open or extend patient episodes. As the coding of claims for laboratory tests and x-rays are not always reliable, these services can join existing episodes but cannot open an episode. Frequently, in the practice of medicine, a physician will order a test prior to seeing a patient. To recognize this, a look-back mechanism has been incorporated MEG. When a lab or x-ray service is encountered that occurred prior to the date of the claim that established an episode, MEG checks to see if an episode with the same episode group number has been opened within 15 days following the test. If so, the lab or x-ray will be added to the episode.

An episode ends when the course of treatment is completed. Since the end of an episode is not designated on a claim, the clean period decision rule has been employed to establish the end date. Clean periods represent the period of time for a patient to recover from a disease or condition. If a subsequent visit for a disease occurs within the clean period, then it is assumed to be a part of the episode containing previous visits for that disease. If a visit for a disease occurs



later than the clean period, then it defines the beginning of a new episode. The duration of clean periods was empirically and clinically reviewed and varies by disease.

Non-specific, initial diagnoses are relatively common in the billing of treatments of patients. For instance, an initial visit may be coded as abdominal pain, but later be classified as appendicitis. MEG incorporates logic to link non-specific diagnoses and costs to specific episodes. The linkage occurs when a non-specific claim has a date close in time to the specific episode and the linkage makes clinical sense.

MEG incorporates drug claims into episode groups even though the drug claims do not themselves contain diagnostic information. The process of integrating pharmacy information into MEG begins with obtaining National Drug Code (NDC) information from Micromedex, a Thomson Healthcare affiliate of Medstat. Micromedex staff, made up of recognized pharmacological experts, map NDC codes from product package inserts to ICD-9-CM codes. This information is then reviewed by MEDSTAT clinical and coding experts and mapped to MEG episode groups.

For this analysis, we identified all claims for patients residing in the three metropolitan areas in the study. We processed this group of claims with the episode software and created a file containing all of the episodes of care. We randomly selected 40 episodes with probability proportional to total expenditure. The selection was carried out independently in each metropolitan area. For the conditions represented in the selected episodes (there could be more than one episode of a specific type chosen in this random selection), all episodes of the same type in the city were selected and the inputs used in these episode types were identified.

Appendix 2 provides information about the samples in each of the three cities.

Standard grouping methods were utilized to compute the inputs into each episode type. For inpatient stays we examined DRGs. For physician services and hospital outpatient services we used the CMS-developed Berenson-Eggers-Holahan Type of Service codes (a transformation of the CPT-4 codes). For prescription drugs we used Red Book therapeutic classes. This represents a departure from the replication analysis reported above. The motivating factor in the decision to use grouped data was the desire to examine the full range of services that might appear in the episode and the concern with the magnitude of the detail that would need to be captured. The more detailed the data we use the bigger the concern with adequate cell size for monthly reporting. That is, grouping helps avoid months with no observations on price for detailed inputs that are rarely used. As we use grouped data, however, we introduce the potential for month-to-month changes in within group service mix.

For each year  $t$  we identify all the inpatient, outpatient, and prescription drugs used to treat episodes of care of each type in each city. This captures local variation in practice patterns that have been the subject of much discussion. Given the mix of inputs in year  $t$ , we capture monthly prices for each input in each city in year  $t+1$  and compute a Laspeyres index. To link across years, we use the input mix in year  $t$ , the prices in December of year  $t$  and the prices of January  $t+1$  normalized to the index value in December  $t$ . This version of the overall index is labeled annual update in Figure 2. For comparison, we computed indexes based on the 1998 bundle of services for each episode type and location. Figure 2 also reports results based on episodes prices using the average bundle for all years.

An important compromise is used in this preliminary draft. The hospital prices driving the index number creation in each city are not city-specific but reflect monthly changes observed across all locations covered by MarketScan. We were concerned that there would be a large

number of months with no observation of a discharge in specific DRGs that occasionally appear in the treatment episode. Our general strategy for months with no relevant observation on price was to assume that the price was the same as the last month with a valid observation. Initial views of the data suggested that we might be imputing a substantial number of hospital price observations. To avoid the small sample issues with hospital stays we used the nationwide database for this version. The physician services and prescription drug price data are city specific because the frequency is high enough to avoid any imputation problems.

The results reported in Figure 2 are remarkably different from the BLS city-specific medical care indexes included in Figure 2. Instead of tracing a story of consistently rising prices, the episode based indexes suggest that the cost of treatment has remained constant between January 1999 and December 2002. In fact, the correlation between the BLS index and the annual update version of the episode indexes is  $-.75$  in Boston,  $-.75$  in New York, and  $0.00$  in Philadelphia. This preliminary result is similar to the findings reported for depression (Berndt et al.) and acute myocardial infarction (Cutler et al.) and in this case the finding of a substantially different trend in “price” change is for a randomly selected set of diagnoses selected from a sampling frame that contains virtually all potential diagnoses. (We excluded less than ten episode groups computed by MEG because they represent a collection of disparate conditions. This group contains only a small dollar amount.)

Figures 3 and 4 show the time trend for episode costs for acute myocardial infarction and diabetes mellitus type 2 with hyperglycemic states maintenance. That is, one acute treatment episode and one maintenance episode. These relatively expensive episode types were randomly selected for analysis in each of the three cities. The results are interestingly different for the two episodes. For AMI we found similar patterns of decline in Boston and New York while

treatment costs were constant in Philadelphia. In Boston and New York there was an initial increase in treatment costs followed by a decline that overshadowed the initial increase. There were considerable differences among the cities. For diabetes treatment, the differences among the cities were larger and the impression was more of increasing costs in Boston and Philadelphia that contrast with a considerable decline in New York.

## 5. Comparisons of BLS MCPI and Disease-Based Index

We compared the various price indexes to answer the following questions:

- Is there a difference between the BLS MCPI and the claims-data input-based indexes for each of the selected PSUs? If differences exist, do they come from sample size differences or from differences in the distribution of prices or both?
- Is there a difference between an index that uses the current BLS method and an index that is disease-based?
- What is the decomposition of the difference between the current BLS index and a disease-based index? There are three potential sources that contribute to the difference: different index construction methods, different sample sizes, and different price distributions. We decomposed the difference according to the following formula:

$$DPIMDT_{m,y} - MPIBLS_{m,y} = (DPIMDT_{m,y} - MPIMDTL_{m,y}) + (MPIMDTL_{m,y} - MPIMDTS_{m,y}) + (MPIMDTS_{m,y} - MPIBLS_{m,y})$$

Total Difference=Method+Sample Size+Different Price Distributions

where

$m,y$  = index month and year

$DPIMDT$  = the disease index generated with claims data

$MPIBLS$  = the BLS Medical CPI index with BLS data

$MPIMDTL$  = the large sample BLS CPI index with claims data

$MPIMDTS$  = the BLS CPI index with claims data using BLS sample sizes.

We used bootstrap methods to decompose the differences and test their statistical significance. Since we would be generating random noise around the BLS index at each iteration, the BLS index and the claims-based index will be independent at each iteration. Therefore, we did 1,000 replications of the claims-based index to obtain an estimate of the Claim Variance. Then we estimated the standard error of the difference as the square root of (BLS Variance + Claims Variance).

The BLS Variance is the square of the BLS standard error. The results should be the same as those we would get by generating noise for the BLS index at each iteration (then calculating the difference) because the two indexes will be independent of one another. Thus the best way to present the results would be to plot the monthly difference (y-axis) vs. month (x-axis) along with 95 % confidence intervals around the difference. Also, we put a horizontal line at zero on the graph. If the horizontal line at zero falls between the confidence intervals, then the difference is not statistically significant for that month. The 95 percent confidence interval = difference +/- 1.96 \* standard error of the difference. The difference is tested separately in each of the 60 months in 1998-2002.

The decomposition analysis was conducted for the three cities separately. Table 2 presents the month-to-month percentage changes and standard errors of the episode-based indexes, BLS MCPI, large-sample indexes using claims data, and the small-sample indexes using claims data.

Figure 5 plots the differences and the lower and upper bound of the confidence intervals of these differences. For all three cities, the horizontal line falls between the 95% confidence interval of the differences in most months, which implies that most of the differences (difference in index construction methods, difference in sample sizes, and difference in price distribution)

are not statistically significant. Especially, the episode-based index and the BLS index are not statistically significant in most months for all three cities.

## **6. Conclusions and Next Steps**

This paper reports the findings of an ongoing study using medical claims data to measure price changes in healthcare. For prescription drug data, we find that the prescription prices reported in a sample of health insurance claims are statistically lower than prescription prices collected by the BLS, but pricing procedures currently used by the BLS and the claim prices yield about the same price trends.

The analysis of trends in treatment costs for a randomly selected set of diseases yields a very different picture than the BLS overall medical care price index. Where the current methods indicate consistent price increases over time, the disease-based indexes suggest that treatment prices (i.e., cost for an episode of care) have not changed dramatically during the past three years. But the decomposition analyses show that the monthly differences between the disease-based index and the BLS index are not statistically different in almost every month of the 60 months in 1998-2002. While there is much more to be done to be sure that the new measures are doing what they are intended to, these preliminary results on the trends in treatment costs are similar to and a generalized version of the findings in cataract surgery, depression and acute myocardial infarction reported by Shapiro et al., Berndt et al., Busch et al., and Cutler et al.

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Appendix 1  
*Analytic File Construction for Replication Analysis*

The analytic file was built from the MarketScan databases following the steps summarized below.

1. Using the first three digits of providers' ZIP codes, we selected all inpatient admissions, inpatient services, outpatient services, and pharmacy claims for the following PSUs from the CC&E and Medicare Databases between January 1, 1998 and December 31, 2002: New York City-A109, Philadelphia-A102, and Boston-A103.
2. We combined the resulting datasets from the CC&E and Medicare Databases.
3. For each unique pharmacy ID, we randomly selected one NDC from the BLS list of currently used codes in proportion to its expenditure share within that pharmacy at yearly intervals. All drugs and medical supplies dispensed by prescription, including prescription-dispensed over-the-counter drugs, were included in this random selection. Inpatient hospital prescriptions and prescriptions paid by Medicaid or worker's compensation were ineligible for the medical price index. For each NDC selected, both the insurance reimbursement and the patient co-pay, if any, were included to arrive at the total reimbursement for that prescription. The probability that a prescription will be selected is calculated as:  $(\text{reimbursements of a NDC} / \text{total reimbursements that the pharmacy received}) * 100$ .
  - i. All pharmacy IDs and their selected NDCs were included in the analytic file. One calculation of the price index will be based on the same sample size currently used by the BLS (small-sample index). To sample a given number of pharmacies, we will randomly select the same number of

pharmacy IDs in proportion to their expenditure share within a PSU, and then calculate the price indexes using the selected NDC for each selected pharmacy. Because MarketScan databases do not record the annual expenditure of any pharmacy, we will sum up all payment to a given pharmacy in a year recorded in MarketScan to calculate the probability of that pharmacy being selected. The computed total payment to a pharmacy could differ from its actual annual revenue as some large pharmacies may have a small number of patients in our sample.

4. We excluded HMO-owned-and-operated hospitals because they are not eligible for CPI pricing. But since hospital ownership is not included in the MarketScan databases, HMO-owned-and-operated hospitals cannot be identified directly. Instead, we excluded all services that are paid by the capitation method, and by default, HMO-owned-and-operated hospitals will be excluded from our sample.
5. Because MarketScan outpatient services database does not contain the same hospital ID that is contained in the inpatient admissions and inpatient services databases, we cannot link inpatient stays and outpatient visits that occur within the same hospital. Medstat will use hospital ID (UNIHOSP) in the inpatient data sets to identify hospitals, and use provider ID (PROVID) in the outpatient data set to identify hospitals.
6. For each remaining unique hospital ID, we randomly selected one hospital stay from inpatient stays in proportion to its expenditure share within all inpatient hospital stays; for each remaining unique provider ID, we randomly selected one outpatient visit from outpatient hospital visits in proportion to its expenditure share within all outpatient services. Thus for each hospital ID, we selected one inpatient stay; for each provider ID,

we selected one outpatient visit. All random selection happens at yearly intervals.

Hospital outpatient services will be identified using the “place of service” variable STDPLAC.

7. All hospitals and their selected stays/visits were included in the analytic file. To sample a given number of hospitals for the small-sample indexes, we randomly selected the same number of hospitals in proportion to their expenditure share within a PSU, and then use the selected stays/visits for each selected hospital to calculate the small-sample indexes. Because MarketScan databases do not record the annual revenue of any hospital, we summed up all payment to a given hospital in a year recorded in MarketScan to calculate the probability of choosing that hospital. It is important to note that the computed total payment to a hospital could differ from its actual annual revenue as some large hospitals may have a small number of patients in our sample.
8. We included all physician provider IDs in the MarketScan database. We relied on the provider type variable (STDPROV) to exclude ophthalmologists, dentists, podiatrists, and other medical practitioners who are not medical doctors or osteopaths from our sample because they are not eligible for medical price indexes. We also excluded services reimbursed by capitation. For each remaining unique physician ID, we randomly selected one Current Procedure Terminology (CPT) code in proportion to its expenditure share of that physician at yearly intervals.
9. All physicians and their randomly-chosen CPTs were included in the analytic file. To calculate small-sample indexes, we first randomly selected a given number of physicians in proportion to their expenditure share within a PSU, and then used the randomly selected CPTs to calculate small-sample price indexes. Because MarketScan databases do

not record the annual revenue of any physician, we summed up all payment to a given physician in a year recorded in MarketScan to calculate the probability of selecting that physician. It is important to note that the computed total payment to a physician could differ from his/her actual annual revenue.

10. We calculated the final reimbursements for each selected NDC, CPT, and hospital stay/visit in each month. The PAY variable in MarketScan measures total payment reimbursed from all sources.

## Appendix 2 Sampling Characteristics

Conditions Sampled for Boston

13:41 Monday, May 3, 2004 1

Episode Group Number	Episode Label	Total MarketScan Payments	Number of Times Drawn	Expected Number of Times Drawn
10	Angina Pectoris, Chronic Maintenance	\$27,424,386	4	2.690
374	Osteoarthritis	\$16,971,880	3	1.665
11	Acute Myocardial Infarction	\$16,192,922	1	1.588
13	Essential Hypertension, Chronic Maintenance	\$13,013,202	2	1.277
397	Cerebrovascular Dis with Stroke	\$11,187,732	2	1.097
187	Renal Failure	\$10,737,384	2	1.053
92	Cataract	\$8,905,881	1	0.874
500	Chronic Obstructive Pulmonary Disease	\$8,752,026	1	0.859
6	Arrhythmias	\$8,653,448	1	0.849
212	Neoplasm, Malignant: Breast, Female	\$8,542,333	1	0.838
348	Fracture: Femur, Head or Neck	\$7,267,359	2	0.713
426	Complications of Surgical and Medical Care	\$6,681,475	1	0.655
50	Diabetes Mellitus Type 2 and Hyperglycemic States Maintenance	\$5,312,060	1	0.521
24	Tibial, Iliac, Femoral, or Popliteal Artery Disease	\$5,176,366	1	0.508
203	Delivery, Vaginal	\$4,850,220	1	0.476
398	Dementia: Primary Degenerative (Alzheimer's or Pick's Disease)	\$2,540,752	1	0.249
536	Neoplasm, Malignant: Carcinoma, Basal Cell	\$2,236,696	1	0.219
209	Neoplasm, Benign: Breast	\$1,994,974	1	0.196
361	Fracture, Dislocation, or Sprain: Humerus (Head) or Shoulder	\$1,968,915	2	0.193
164	Peptic Ulcer Disease	\$1,916,376	1	0.188
88	Sinusitis	\$1,915,297	1	0.188
23	Thrombophlebitis	\$1,848,311	2	0.181
357	Fracture or Sprain: Ankle	\$1,589,749	1	0.156
149	Functional Digestive Disorders	\$1,564,679	1	0.153
491	Schizophrenia	\$1,021,690	1	0.100
2	Aneurysm, Thoracic	\$888,311	1	0.087
355	Fracture: Tibia	\$624,201	1	0.061
516	Pulmonary Embolism	\$515,951	1	0.051
387	Injury: Other and Ill-Defined Musculoskeletal Sites	\$427,259	1	0.042
		=====	=====	
		\$180,721,837	40	

Conditions Sampled for Philadelphia

13:41 Monday, May 3, 2004 2

Episode Group Number	Episode Label	Total MarketScan Payments	Number of Times Drawn	Expected Number of Times Drawn
10	Angina Pectoris, Chronic Maintenance	\$16,594,049	6	2.965
187	Renal Failure	\$9,538,311	2	1.704
11	Acute Myocardial Infarction	\$8,740,579	2	1.562
374	Osteoarthritis	\$8,349,565	1	1.492
397	Cerebrovascular Dis with Stroke	\$6,531,667	2	1.167
426	Complications of Surgical and Medical Care	\$5,092,074	1	0.910
212	Neoplasm, Malignant: Breast, Female	\$4,802,802	1	0.858
336	Neoplasm, Malignant: Prostate	\$3,671,757	2	0.656
274	Cholecystitis and Cholelithiasis	\$2,868,658	1	0.513
51	Diabetes Mellitus with Complications	\$2,393,106	1	0.428
189	Urinary Tract Infections	\$2,231,736	2	0.399
405	Injury: Spine and spinal cord	\$1,955,954	1	0.349
50	Diabetes Mellitus Type 2 and Hyperglycemic States Maintenance	\$1,779,928	1	0.318
535	Infections of Skin and Subcutaneous Tissue	\$1,359,153	1	0.243
1	Aneurysm, Abdominal	\$1,103,927	1	0.197
411	Neoplasm: Central Nervous System	\$967,351	1	0.173
357	Fracture or Sprain: Ankle	\$899,572	1	0.161
285	Pancreatitis	\$812,379	1	0.145
149	Functional Digestive Disorders	\$805,771	1	0.144
556	Injury: Other	\$690,768	1	0.123
138	Appendicitis	\$591,180	1	0.106
204	Dysfunctional Uterine Bleeding	\$387,773	1	0.069
366	Infectious Arthritis	\$372,816	1	0.067
386	Anomaly: Musculoskeletal system	\$336,946	2	0.060
206	Endometriosis	\$288,676	1	0.052
220	Pelvic Inflammatory Disease	\$125,016	1	0.022
547	Adverse Drug Reactions	\$119,754	1	0.021
304	Herpes Simplex Infections	\$77,815	1	0.014
58	Neoplasm, Benign: Adenoma, Parathyroid, or Hyperparathyroidism	\$63,178	1	0.011
		=====	=====	
		\$83,552,260	40	

Episode Group Number	Episode Label	Total MarketScan Payments	Number of Times Drawn	Expected Number of Times Drawn
203	Delivery, Vaginal	\$3,580,789	5	1.816
10	Angina Pectoris, Chronic Maintenance	\$2,737,849	3	1.388
374	Osteoarthritis	\$2,379,435	1	1.207
212	Neoplasm, Malignant: Breast, Female	\$1,868,716	2	0.948
11	Acute Myocardial Infarction	\$1,407,383	1	0.714
411	Neoplasm: Central Nervous System	\$1,173,222	2	0.595
508	Neoplasm, Malignant: Lungs, Bronchi, or Mediastinum	\$1,150,206	1	0.583
6	Arrhythmias	\$989,755	1	0.502
209	Neoplasm, Benign: Breast	\$926,921	1	0.470
341	Bursitis	\$880,225	1	0.446
510	Pneumonia: Bacterial	\$632,472	1	0.321
211	Neoplasm, Benign: Uterus (Leiomyomas)	\$574,949	1	0.292
152	Hernia, External	\$552,161	1	0.280
427	Encounter for Chemotherapy	\$533,949	1	0.271
158	Neoplasm, Benign: Adenomatous Polyps, Colon	\$530,215	1	0.269
274	Cholecystitis and Cholelithiasis	\$528,935	1	0.268
85	Otitis Media	\$433,414	1	0.220
50	Diabetes Mellitus Type 2 and Hyperglycemic States Maintenance	\$425,695	1	0.216
317	Rheumatic Fever	\$357,445	1	0.181
173	Gastroenteritis	\$330,471	1	0.168
213	Neoplasm, Malignant: Cervix Uteri	\$307,638	1	0.156
370	Injury, Open Wound, or Blunt Trauma: Lower Extremity	\$209,390	1	0.106
163	Neoplasm, Malignant: Stomach	\$177,219	1	0.090
289	Neoplasm, Malignant: Other Hepatobiliary Tract	\$166,445	1	0.084
398	Dementia: Primary Degenerative (Alzheimer's or Pick's Disease)	\$152,349	1	0.077
114	Macular Degeneration	\$136,377	1	0.069
434	Neoplasm, Benign: Other Sites	\$122,331	1	0.062
487	Eating disorders: Anorexia Nervosa	\$85,993	1	0.044
443	Anomaly: Defects of Kidney	\$67,282	1	0.034
190	Neoplasm, Benign: Urinary Tract	\$40,339	1	0.020
307	Infectious Mononucleosis	\$22,333	1	0.011
343	Dislocation: Knee	\$14,330	1	0.007
		=====	=====	
		\$23,496,233	40	

**Table 1. Number of Unique Pharmacies, Hospitals, and Physicians in Each PSU**

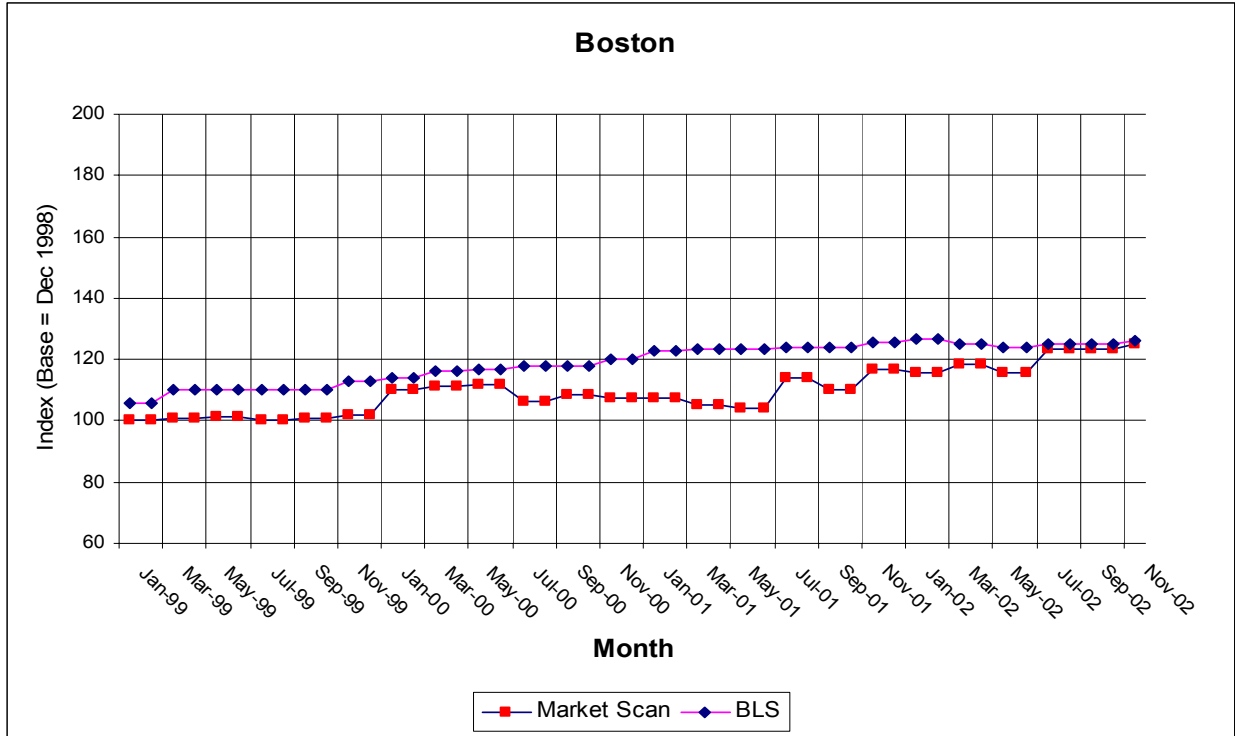
	1998	1999	2000	2001	2002
<b>New York</b>					
Pharmacy	1,406	1,219	1,279	1,329	1,460
Hospital (Inpatient)	69	58	47	53	66
Hospital (Outpatient)	321	117	101	113	250
Physician	11,905	6,677	6,048	5,636	8,536
<b>Philadelphia</b>					
Pharmacy	1,763	1,455	1,477	1,402	1,454
Hospital (Inpatient)	134	99	92	83	93
Hospital (Outpatient)	1,084	353	315	337	676
Physician	19,448	7,517	6,763	5,430	8,440
<b>Boston</b>					
Pharmacy	1,439	1,313	1,324	1,419	1,584
Hospital (Inpatient)	195	181	173	132	144
Hospital (Outpatient)	854	592	528	549	881
Physician	27,788	22,868	20,816	21,715	26,621

Source: Medstat MarketScan.

Note: We used the first three digits of the providers' ZIP codes to select claims for the three PSUs -- Philadelphia A102, Boston A103, and New York City A109.



Figure 1: Comparison of BLS Prescription Index to MarketScan Prescription Index Based on the Same NDCs



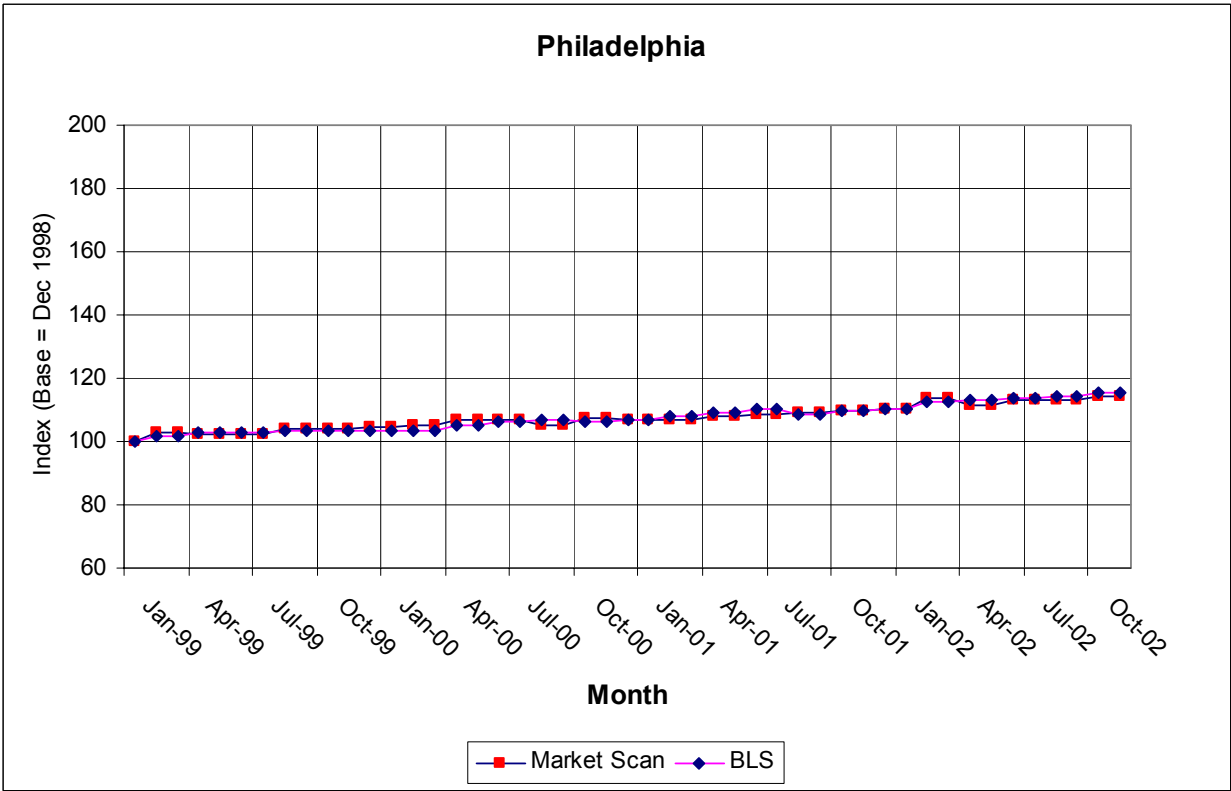
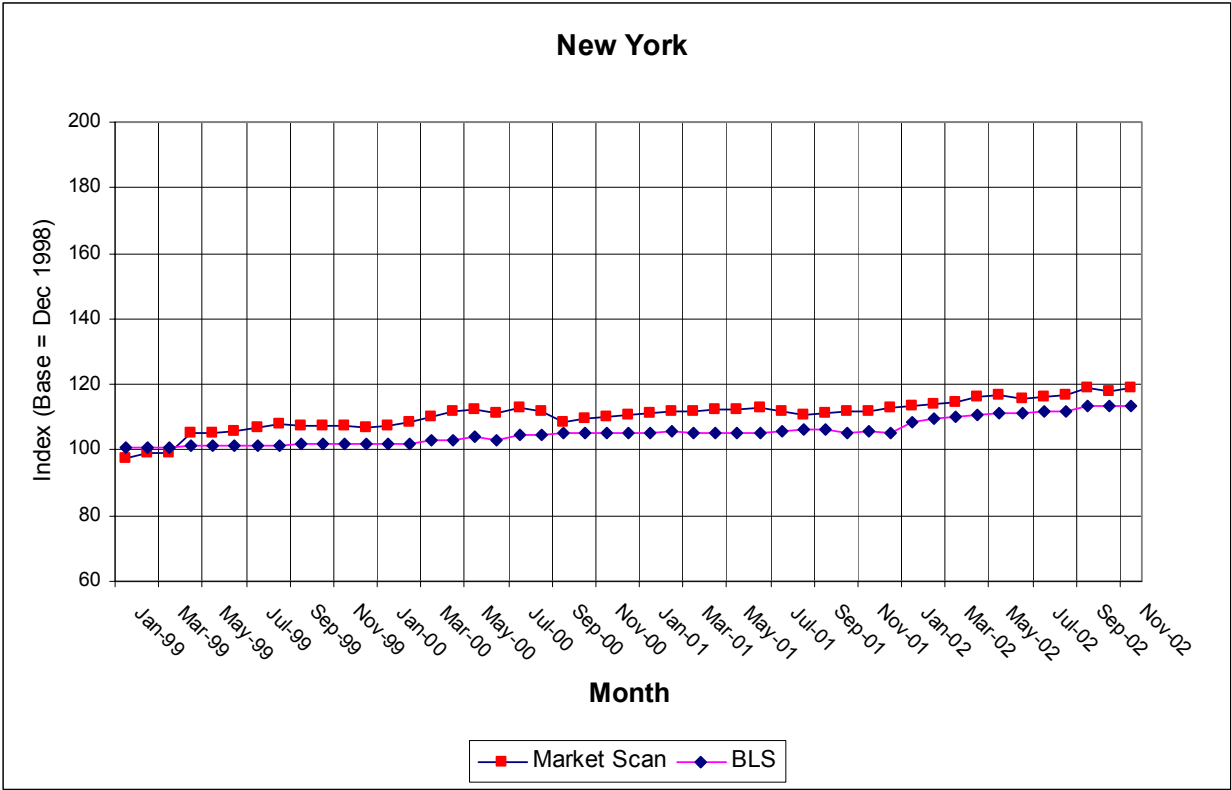


Figure 2. Disease-Based Index of Medical Treatment Costs -

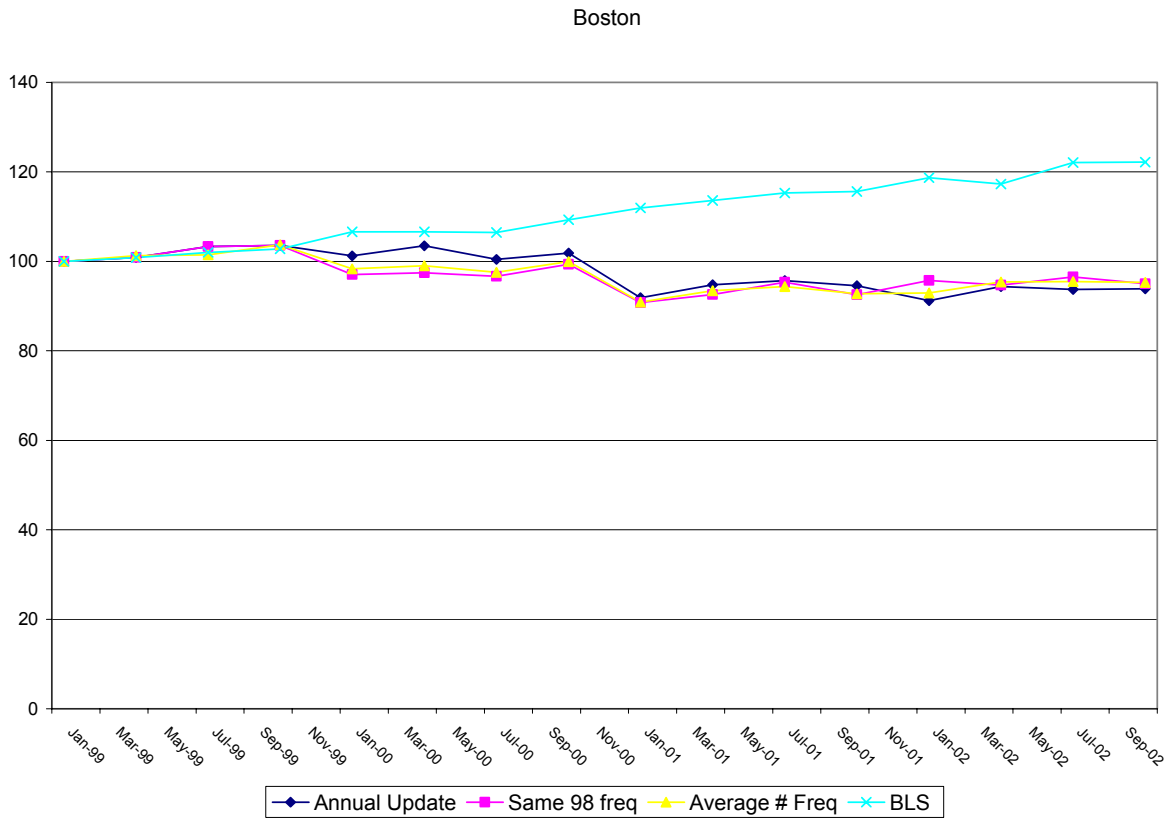


Figure 2b

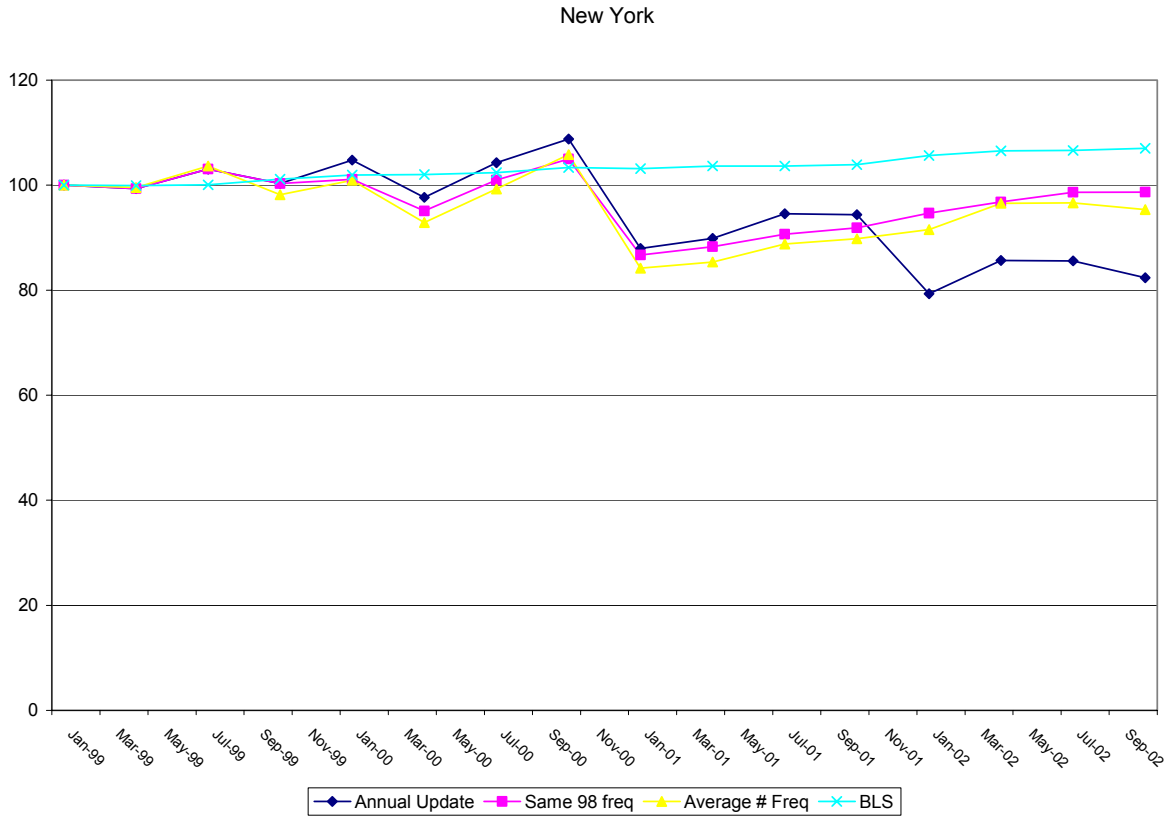


Figure 2c

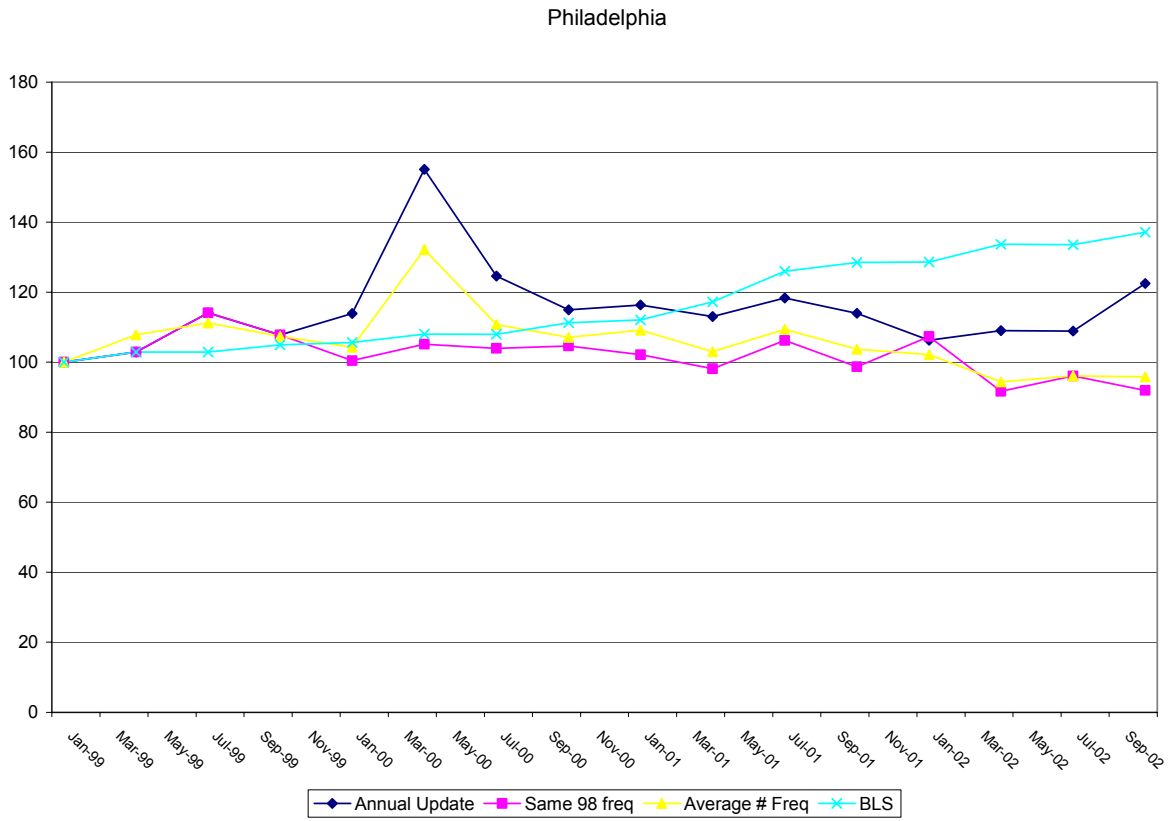


Figure 3: Cost of Treating Acute Myocardial Infarction in Three Cities.

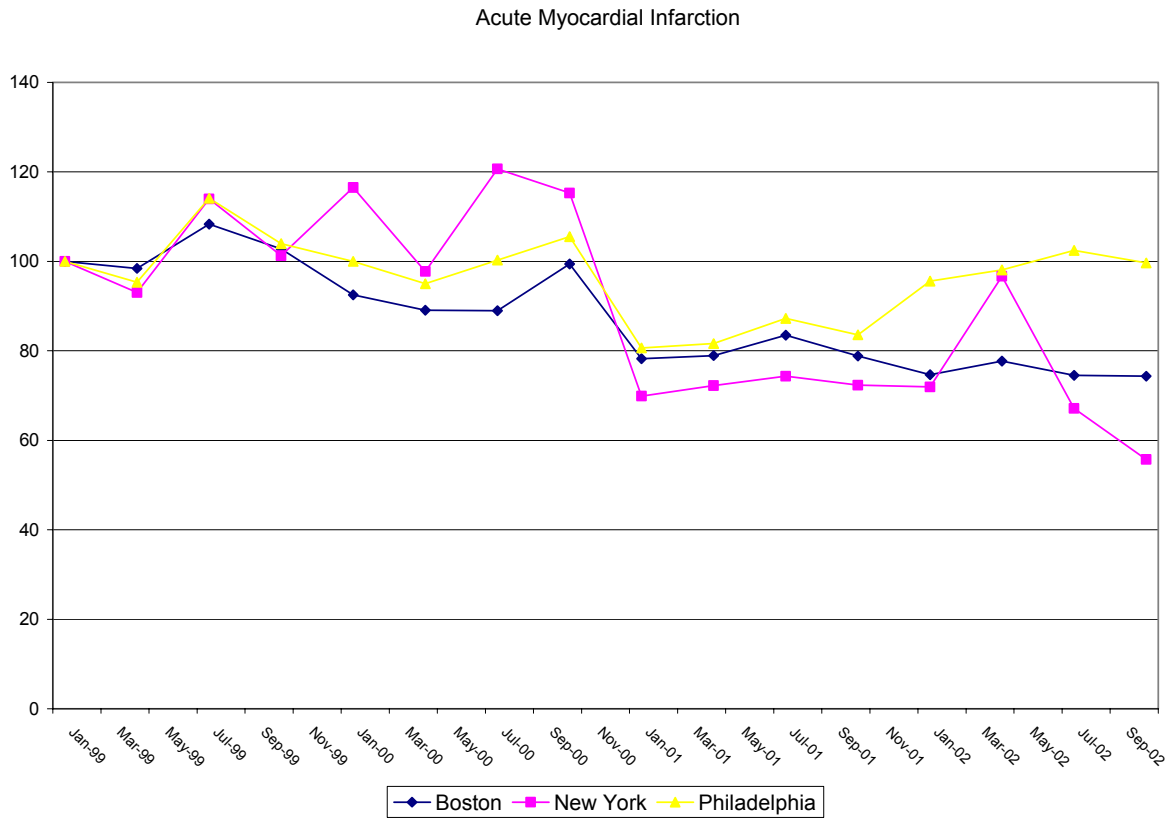
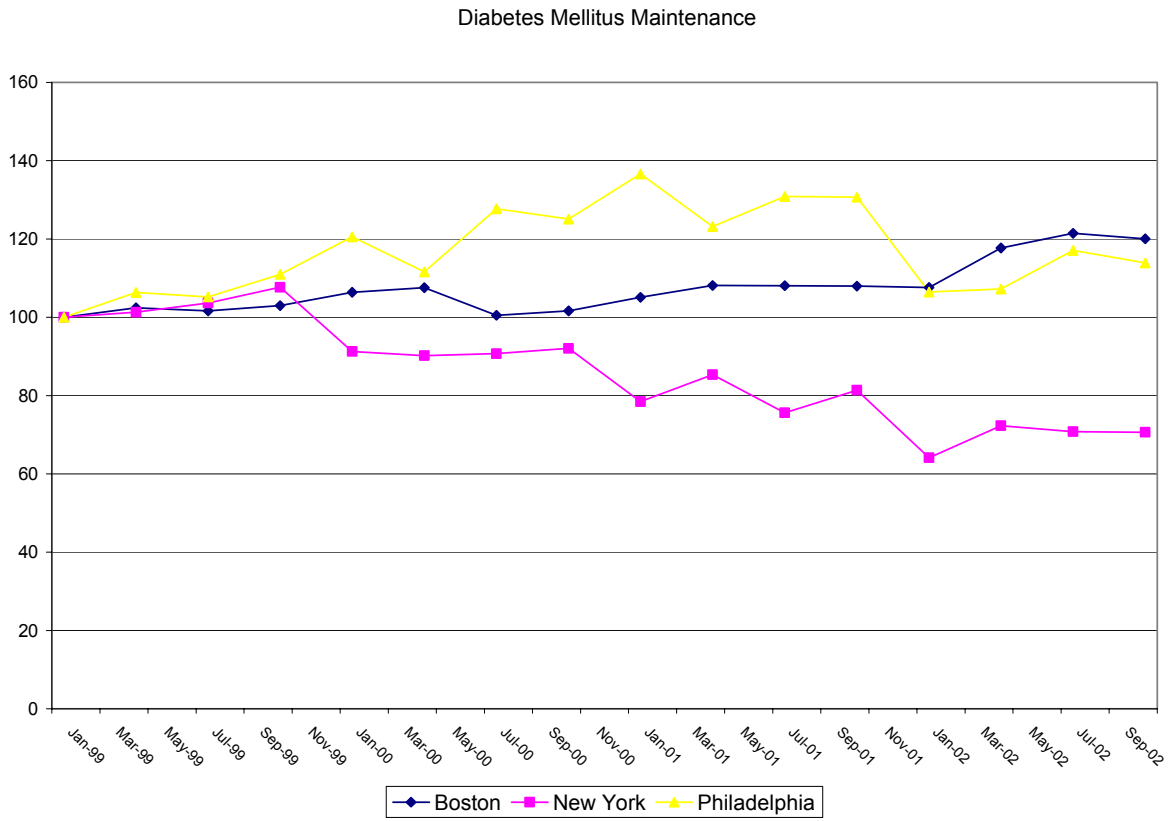


Figure 4: Cost of Treating Diabetes Mellitus (maintenance) in Three Cities.



**Table 2. Comparison of Episode-Based Index, BLS MCPI, Large-Sample Index, and Small-Sample Index**

**Philadelphia**

<i>Months</i>	<i>BLS</i>		<i>Episode-Based</i>		<i>Large Sample</i>		<i>Small Sample</i>	
	<i>month-to-month percentage change</i>	<i>standard errors</i>	<i>month-to-month percentage change</i>	<i>standard errors</i>	<i>month-to-month percentage change</i>	<i>standard errors</i>	<i>month-to-month percentage change</i>	<i>standard errors</i>
Jan_98	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Feb_98	0.0074	0.0157	0.0011	0.0110	0.0048	0.0159	-0.0162	0.0347
Mar_98	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Apr_98	-0.0075	0.0071	0.0176	0.0519	0.0116	0.0515	-0.1491	0.1630
May_98	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Jun_98	0.0092	0.0073	-0.0235	0.0442	0.4581	0.3934	0.3319	0.3841
July_98	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Aug_98	0.0087	0.0226	0.0240	0.0070	0.0281	0.0602	0.0713	0.0601
Sep_98	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Oct_98	-0.0167	0.0136	0.0231	0.0221	0.2888	0.2868	-0.1939	0.2774
Nov_98	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Dec_98	-0.0015	0.0081	-0.0339	0.0267	-0.3560	0.2682	-0.2338	0.2221
Jan_99	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Feb_99	0.0092	0.0124	-0.0003	0.0112	-0.3024	0.1178	0.0696	0.3603
Mar_99	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Apr_99	0.0117	0.0308	0.0294	0.0189	0.0524	0.0467	0.1078	0.0601
May_99	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Jun_99	-0.0199	0.0035	-0.0130	0.0068	0.3057	0.7329	0.3037	0.8741
Jul_99	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Aug_99	0.0027	0.0121	-0.0190	0.0297	0.2153	0.2235	0.4805	0.3417
Sep_99	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Oct_99	0.0141	0.0287	0.0818	0.0470	-0.0961	0.0305	-0.0764	0.0923
Nov_99	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Dec_99	-0.0101	0.0195	0.0493	0.0427	-0.1687	0.2442	-0.2089	0.2295
Jan_00	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Feb_00	0.0030	0.0187	0.0581	0.0375	-0.0188	0.0209	-0.0066	0.0561
Mar_00	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Apr_00	0.0033	0.0100	-0.0110	0.1087	-0.0064	0.0689	-0.0592	0.1019
May_00	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Jun_00	-0.0136	0.0157	0.0588	0.0824	-0.0125	0.0518	-0.0262	0.0727
Jul_00	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Aug_00	0.0302	0.0260	-0.0690	0.0187	-0.1129	0.2514	-0.1134	0.5354
Sep_00	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Oct_00	-0.0271	0.0253	0.0097	0.0148	0.4965	0.4177	0.2240	0.2080
Nov_00	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Dec_00	0.0063	0.0225	-0.0021	0.0307	-0.2892	0.1909	-0.1983	0.2186
Jan_01	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Feb_01	0.0244	0.0588	-0.0296	0.0150	-0.0045	0.0254	0.0453	0.0498
Mar_01	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Apr_01	-0.0188	0.0180	-0.0099	0.0255	0.0872	0.0663	0.0865	0.1152



<i>Months</i>	<i>BLS</i>		<i>Episode-Based</i>		<i>Large Sample</i>		<i>Small Sample</i>	
	<i>month-to-month percentage change</i>	<i>standard errors</i>	<i>month-to-month percentage change</i>	<i>standard errors</i>	<i>month-to-month percentage change</i>	<i>standard errors</i>	<i>month-to-month percentage change</i>	<i>standard errors</i>
May_01	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Jun_01	0.0612	0.1506	0.0141	0.0294	0.3062	0.3001	0.4205	0.5543
Jul_01	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Aug_01	-0.0490	0.0080	0.0128	0.0124	-0.0546	0.1920	0.0700	0.3737
Sep_01	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Oct_01	-0.0237	0.0083	-0.0205	0.0362	-0.0108	0.0843	-0.0958	0.1219
Nov_01	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Dec_01	0.0029	0.0191	0.0807	0.0285	0.2210	0.2448	0.4145	0.4065
Jan_02	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Feb_02	0.0373	0.0764	-0.1494	0.0494	-0.0136	0.0194	0.0235	0.0480
Mar_02	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Apr_02	-0.0353	0.0065	0.0043	0.0098	-0.1505	0.0992	-0.1044	0.0922
May_02	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Jun_02	-0.0028	0.0081	0.0386	0.0226	0.1308	0.1022	0.4738	0.3282
Jul_02	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Aug_02	0.0178	0.0016	-0.0199	0.0083	0.3904	0.3918	0.3540	0.3794
Sep_02	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Oct_02	-0.0060	0.0193	-0.0149	0.0219	0.1766	0.2994	0.0278	0.5170
Nov_02	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Dec_02	0.0079	0.0376	0.0249	0.0349	0.0009	0.0526	0.0325	0.1017

**Boston**

<i>Months</i>	<i>BLS</i>		<i>Episode-Based</i>		<i>Large Sample</i>		<i>Small Sample</i>	
	<i>month-to-month percentage change</i>	<i>standard errors</i>	<i>month-to-month percentage change</i>	<i>standard errors</i>	<i>month-to-month percentage change</i>	<i>standard errors</i>	<i>month-to-month percentage change</i>	<i>standard errors</i>
Jan_98	0.1225	0.0184	0.0083	0.0128	0.1164	0.0926	0.3837	0.2232
Feb_98	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Mar_98	-0.0003	0.0342	0.0222	0.0261	0.1350	0.0911	0.3025	0.2004
Apr_98	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
May_98	0.0029	0.0385	0.0014	0.0044	0.0125	0.0671	-0.1792	0.1268
Jun_98	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
July_98	-0.0032	0.0244	-0.0539	0.0253	-0.1602	0.1210	-0.1012	0.5132
Aug_98	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Sep_98	-0.0142	0.0130	-0.0196	0.0041	-0.1120	0.0798	0.0686	0.1452
Oct_98	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Nov_98	0.0223	0.0167	0.0886	0.0271	-0.1785	0.1530	-0.4146	0.1828
Dec_98	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Jan_99	-0.0024	0.0302	-0.0072	0.0082	0.0952	0.0854	0.4262	0.4357
Feb_99	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Mar_99	-0.0090	0.0326	-0.0163	0.0229	-0.0704	0.1503	-0.0366	0.2100
Apr_99	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
May_99	-0.0105	0.0043	0.0206	0.0357	-0.0430	0.0347	-0.1278	0.0774
Jun_99	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Jul_99	0.0171	0.0405	-0.0075	0.0136	-0.0023	0.0352	0.0600	0.0465
Aug_99	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Sep_99	-0.0068	0.0119	0.1279	0.0788	0.0421	0.1242	0.6791	0.5631
Oct_99	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Nov_99	0.0135	0.0329	-0.1015	0.0700	-0.0917	0.0904	-0.0055	0.1669
Dec_99	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Jan_00	-0.0053	0.0196	0.0154	0.0178	-0.0045	0.0199	0.0186	0.0316
Feb_00	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Mar_00	-0.0155	0.0256	0.0053	0.0098	0.0724	0.0519	0.0392	0.0617
Apr_00	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
May_00	-0.0063	0.0247	-0.0015	0.0148	-0.0096	0.0409	0.0623	0.0459
Jun_00	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Jul_00	0.0114	0.0101	-0.0174	0.0123	-0.0815	0.0892	0.0038	0.0448
Aug_00	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Sep_00	0.0212	0.0379	-0.0069	0.0176	0.0871	0.2073	-0.0966	0.2342
Oct_00	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Nov_00	-0.0172	0.0343	0.0224	0.0164	-0.0146	0.1461	-0.2027	0.2759
Dec_00	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Jan_01	0.0069	0.0118	0.0110	0.0119	0.5215	0.5213	0.6019	0.6940
Feb_01	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Mar_01	-0.0009	0.0182	0.0165	0.0064	0.5789	0.5370	0.5612	0.7141
Apr_01	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
May_01	-0.0011	0.0117	0.0364	0.0153	-0.1320	0.0992	-0.1952	0.1721
Jun_01	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Jul_01	-0.0125	0.0079	-0.0113	0.0162	0.0227	0.0809	0.0202	0.1094
Aug_01	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Sep_01	0.0022	0.0096	0.0645	0.0717	0.3253	0.3736	0.7034	1.3844

<i>Months</i>	<i>BLS</i>		<i>Episode-Based</i>		<i>Large Sample</i>		<i>Small Sample</i>	
	<i>month-to-month percentage change</i>	<i>standard errors</i>	<i>month-to-month percentage change</i>	<i>standard errors</i>	<i>month-to-month percentage change</i>	<i>standard errors</i>	<i>month-to-month percentage change</i>	<i>standard errors</i>
Oct_01	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Nov_01	0.0176	0.0143	-0.0559	0.0622	-0.4224	0.2084	-0.5398	0.1018
Dec_01	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Jan_02	-0.0149	0.0250	-0.0079	0.0123	0.0292	0.0303	0.0316	0.0675
Feb_02	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Mar_02	-0.0176	0.0303	-0.0040	0.0160	0.0312	0.0382	0.0557	0.0650
Apr_02	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
May_02	0.0496	0.1079	0.0246	0.0087	-0.1136	0.0690	-0.0613	0.0628
Jun_02	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Jul_02	-0.0316	0.0109	0.0103	0.0118	0.1128	0.1743	0.3123	0.2802
Aug_02	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Sep_02	-0.0032	0.0034	-0.0113	0.0093	-0.0334	0.0657	-0.0689	0.0848
Oct_02	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Nov_02	0.0188	0.0106	-0.0008	0.0038	-0.2056	0.1448	-0.2576	0.1262
Dec_02	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

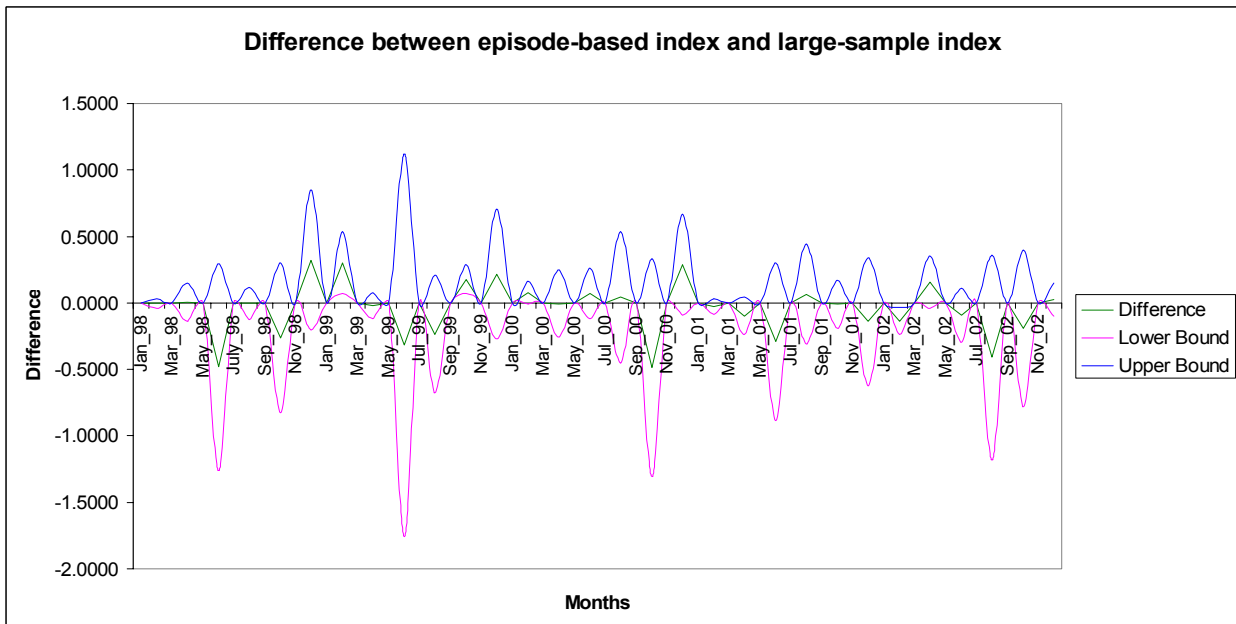
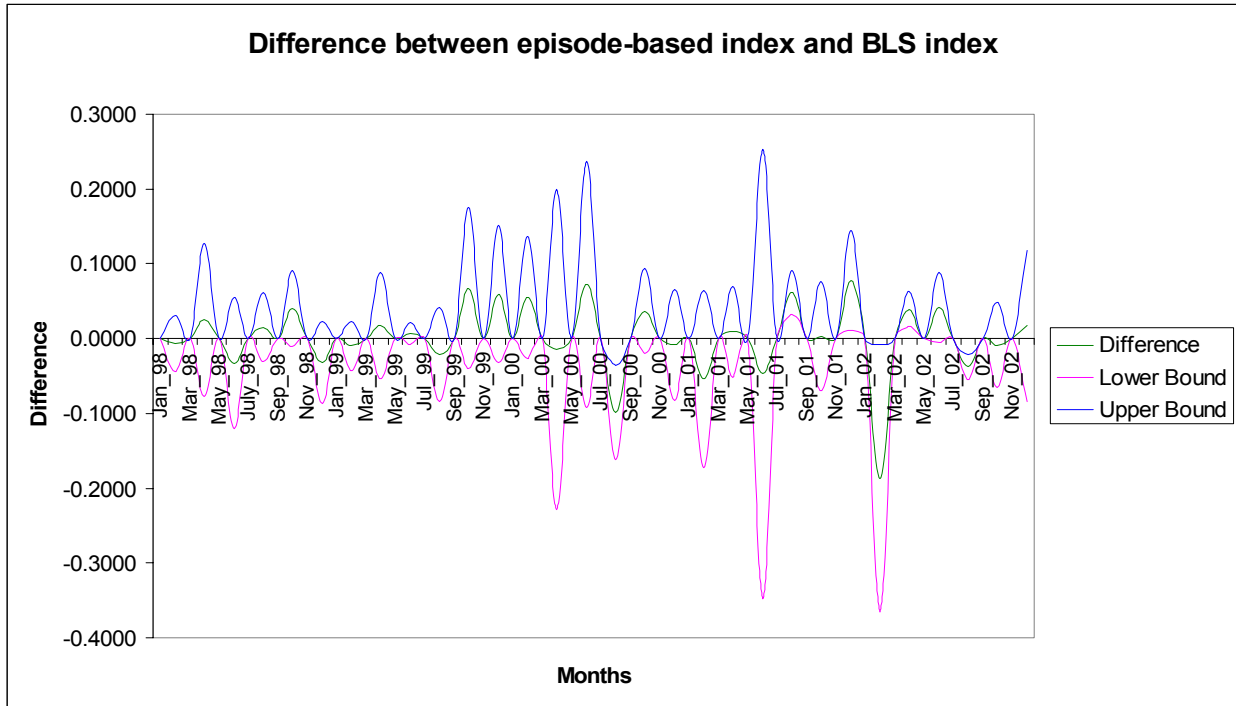
**New York**

<i>Months</i>	<i>BLS</i>		<i>Episode-Based</i>		<i>Large Sample</i>		<i>Small Sample</i>	
	<i>month-to-month percentage change</i>	<i>standard errors</i>	<i>month-to-month percentage change</i>	<i>standard errors</i>	<i>month-to-month percentage change</i>	<i>standard errors</i>	<i>month-to-month percentage change</i>	<i>standard errors</i>
Jan_98	0.0017	0.0245	0.0313	0.0204	-0.0063	0.0244	0.0721	0.0615
Feb_98	0.0181	0.0235	0.0313	0.0208	-0.0063	0.0235	0.0721	0.0607
Mar_98	-0.0191	0.0015	-0.0370	0.0191	-0.0326	0.0439	-0.0750	0.1082
Apr_98	0.0265	0.0270	0.0059	0.0195	0.0154	0.0539	-0.0774	0.0449
May_98	-0.0257	0.0113	-0.0087	0.0223	-0.0703	0.0484	-0.0643	0.0394
Jun_98	-0.0015	0.0098	0.0203	0.0162	0.0805	0.1931	0.1139	0.1993
July_98	0.0027	0.0021	-0.0067	0.0095	-0.2103	0.1137	-0.2937	0.1255
Aug_98	-0.0004	0.0068	0.0080	0.0221	0.0501	0.0513	-0.0721	0.0831
Sep_98	0.0004	0.0061	0.0035	0.0126	0.0441	0.1997	0.3074	0.2738
Oct_98	-0.0015	0.0000	0.0011	0.0155	0.0079	0.0477	0.0119	0.0863
Nov_98	0.0000	0.0000	0.0076	0.0084	0.0276	0.0297	-0.0042	0.0645
Dec_98	0.0065	0.0075	-0.0205	0.0107	-0.1348	0.1665	-0.1386	0.1645
Jan_99	0.0031	0.0112	-0.0118	0.0162	-0.0113	0.0196	0.0038	0.0815
Feb_99	-0.0096	0.0000	-0.0118	0.0164	-0.0109	0.0202	0.0070	0.0839
Mar_99	0.0006	0.0031	0.0159	0.0098	0.1330	0.1588	-0.0200	0.1085
Apr_99	-0.0018	0.0020	0.0178	0.0235	-0.0287	0.0676	-0.0277	0.0527
May_99	-0.0048	0.0074	0.0290	0.0500	-0.0722	0.0648	-0.0206	0.1111
Jun_99	0.0065	0.0007	-0.0319	0.0362	-0.0155	0.0227	-0.1169	0.0673
Jul_99	0.0060	0.0327	0.0228	0.0230	-0.0590	0.0675	-0.0088	0.0534
Aug_99	-0.0019	0.0152	-0.0203	0.0336	0.0095	0.0295	-0.0327	0.0479
Sep_99	-0.0036	0.0063	0.0092	0.0133	0.0243	0.0574	0.0812	0.0759
Oct_99	0.0041	0.0152	-0.0049	0.0161	0.1842	0.1678	0.2320	0.1987
Nov_99	-0.0099	0.0058	-0.0170	0.0125	-0.3827	0.1675	-0.6204	0.1826
Dec_99	0.0038	0.0029	0.0183	0.0203	-0.3233	0.2430	-0.0837	0.1792
Jan_00	0.0149	0.0143	-0.0204	0.0376	-0.0011	0.0179	0.0591	0.0342
Feb_00	-0.0136	0.0000	-0.0204	0.0376	0.1947	0.0145	0.0585	0.0368
Mar_00	0.0028	0.0186	0.0199	0.0383	0.1584	0.2283	0.1752	0.2715
Apr_00	-0.0046	0.0134	-0.0062	0.0215	-0.0423	0.0201	-0.0527	0.0610
May_00	0.0045	0.0066	-0.0109	0.0247	-0.1209	0.1399	-0.0088	0.1158
Jun_00	-0.0038	0.0112	0.0593	0.0466	-0.1952	0.1412	-0.2499	0.2110
Jul_00	0.0033	0.0097	-0.0487	0.0311	-0.0034	0.0290	-0.0611	0.0529
Aug_00	-0.0018	0.0019	0.0954	0.0658	0.1430	0.1559	0.0465	0.0799
Sep_00	0.0034	0.0060	-0.0642	0.0342	0.0016	0.0838	0.0674	0.1482
Oct_00	0.0013	0.0081	0.0164	0.0344	0.3625	0.4710	0.2113	0.3262
Nov_00	-0.0061	0.0025	-0.0196	0.0284	0.0042	0.3176	-0.2073	0.3638
Dec_00	-0.0025	0.0048	-0.0057	0.0318	-0.4160	0.2229	-0.3890	0.1853
Jan_01	0.0060	0.0052	0.0300	0.0233	0.0420	0.0603	0.1069	0.1359
Feb_01	0.0027	0.0074	0.0300	0.0232	0.0420	0.0605	0.1127	0.1383
Mar_01	-0.0058	0.0312	-0.0094	0.0247	-0.0179	0.0150	-0.1456	0.0553
Apr_01	0.0010	0.0034	0.0199	0.0263	-0.0433	0.0189	0.1006	0.0654
May_01	-0.0004	0.0000	0.0100	0.0169	0.0844	0.0894	0.1048	0.0682
Jun_01	-0.0011	0.0020	-0.0311	0.0258	0.5121	0.6013	0.6311	0.7805
Jul_01	0.0022	0.0139	0.0456	0.0141	0.0424	0.0323	0.0820	0.0743
Aug_01	-0.0003	0.0123	0.0254	0.0203	0.0560	0.0881	0.0602	0.0583
Sep_01	-0.0008	0.0000	-0.0454	0.0260	-0.2456	0.1043	-0.2856	0.1177

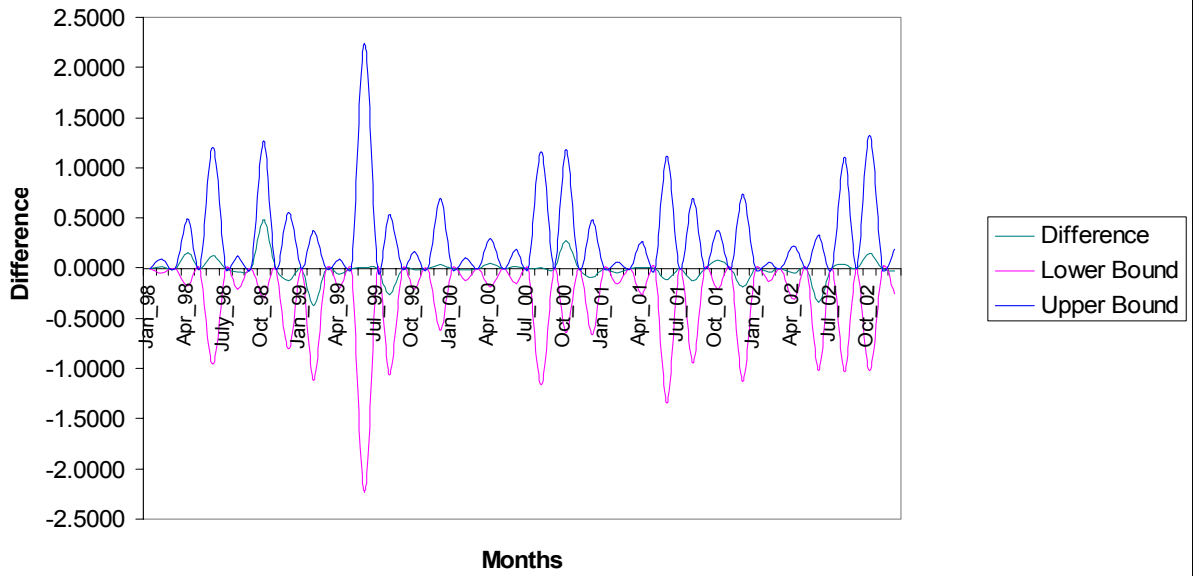
	<i>BLS</i>		<i>Episode-Based</i>		<i>Large Sample</i>		<i>Small Sample</i>	
	<i>month-to-month percentage change</i>	<i>standard errors</i>	<i>month-to-month percentage change</i>	<i>standard errors</i>	<i>month-to-month percentage change</i>	<i>standard errors</i>	<i>month-to-month percentage change</i>	<i>standard errors</i>
<i>Months</i>								
Oct_01	0.0017	0.0142	0.0073	0.0177	-0.0247	0.0200	-0.0617	0.0444
Nov_01	-0.0005	0.0098	0.0027	0.0125	0.0168	0.0589	-0.0480	0.0673
Dec_01	-0.0020	0.0077	-0.0118	0.0270	0.2626	0.1737	0.3227	0.2771
Jan_02	0.0174	0.0193	-0.0413	0.0227	-0.0021	0.0243	-0.0228	0.0320
Feb_02	-0.0145	0.0202	-0.0413	0.0222	-0.0114	0.0253	-0.0176	0.0339
Mar_02	-0.0026	0.0294	0.0044	0.0235	0.2209	0.2641	0.4970	0.4680
Apr_02	0.0076	0.0133	0.0715	0.0695	-0.0342	0.0246	-0.0920	0.0416
May_02	-0.0061	0.0067	-0.0504	0.0914	0.0086	0.0274	0.0484	0.0556
Jun_02	-0.0013	0.0032	-0.0117	0.0315	-0.0165	0.0860	-0.1092	0.1185
Jul_02	0.0015	0.0021	0.0306	0.0227	0.3364	0.5257	0.3989	0.7729
Aug_02	-0.0001	0.0024	-0.0171	0.0248	0.0034	0.0489	0.0417	0.0930
Sep_02	0.0021	0.0107	0.0472	0.0510	-0.1806	0.1519	-0.3565	0.2248
Oct_02	-0.0025	0.0042	-0.0394	0.0488	-0.0431	0.0515	0.0749	0.0543
Nov_02	0.0001	0.0009	-0.0374	0.0306	-0.5955	0.1970	-0.6262	0.2285
Dec_02	-0.0003	0.0006	0.0453	0.0473	0.1510	0.3049	0.0565	0.1497

**Figure 5. Differences between Episode-Based Index, BLS MCPI, Large-Sample Index, and Small-Sample Index**

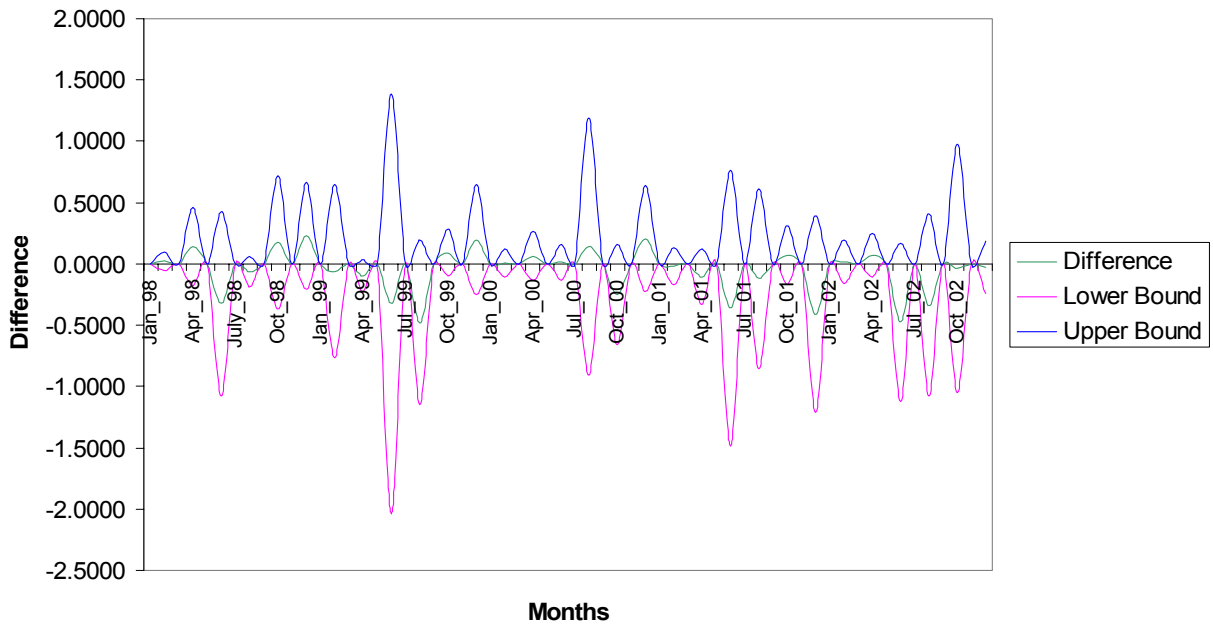
**Philadelphia**



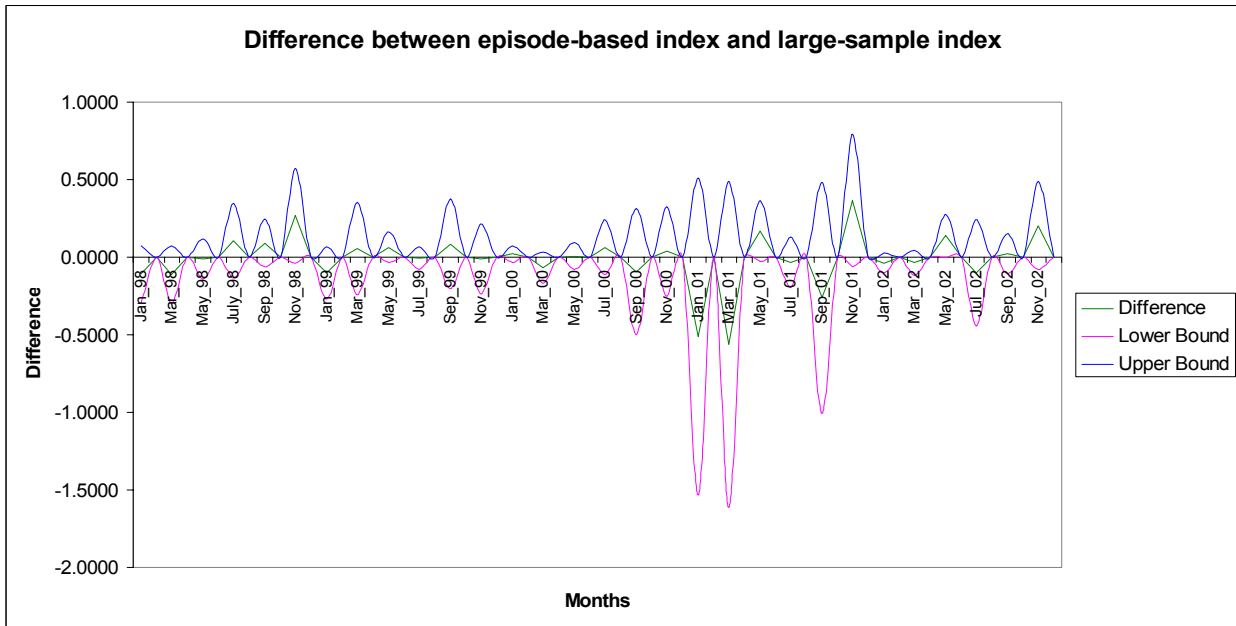
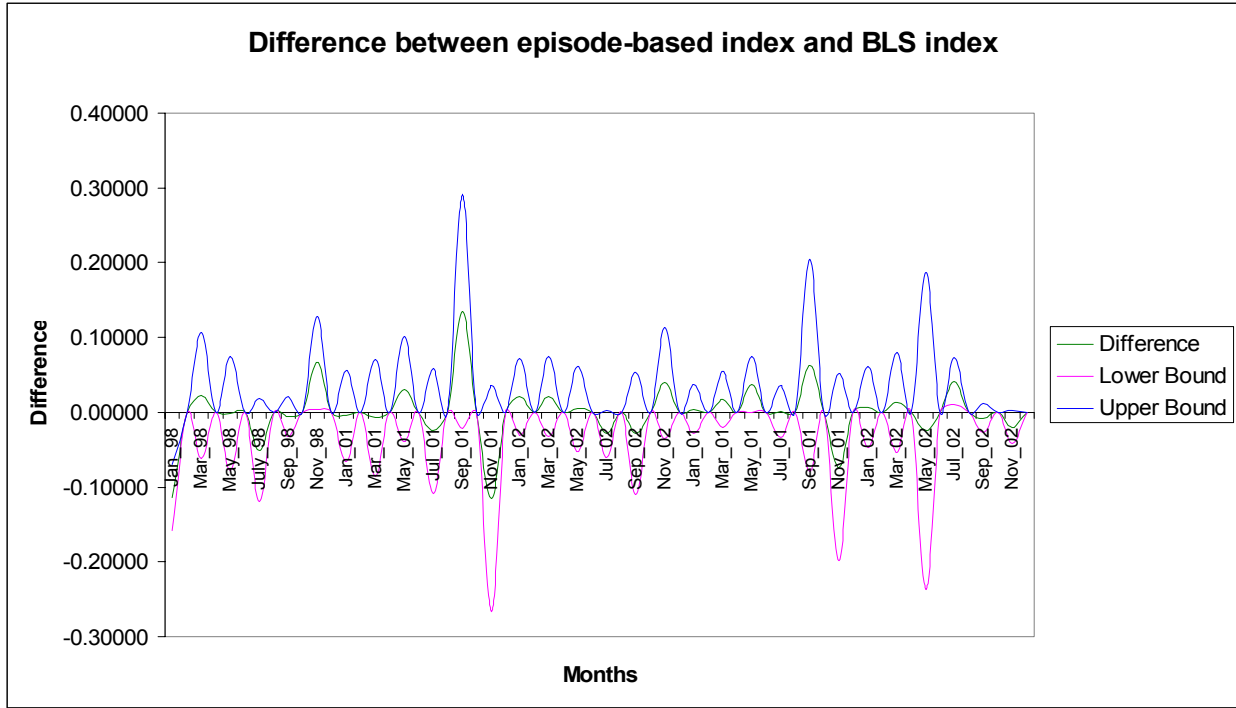
**Difference between large-sample index and small-sample index**



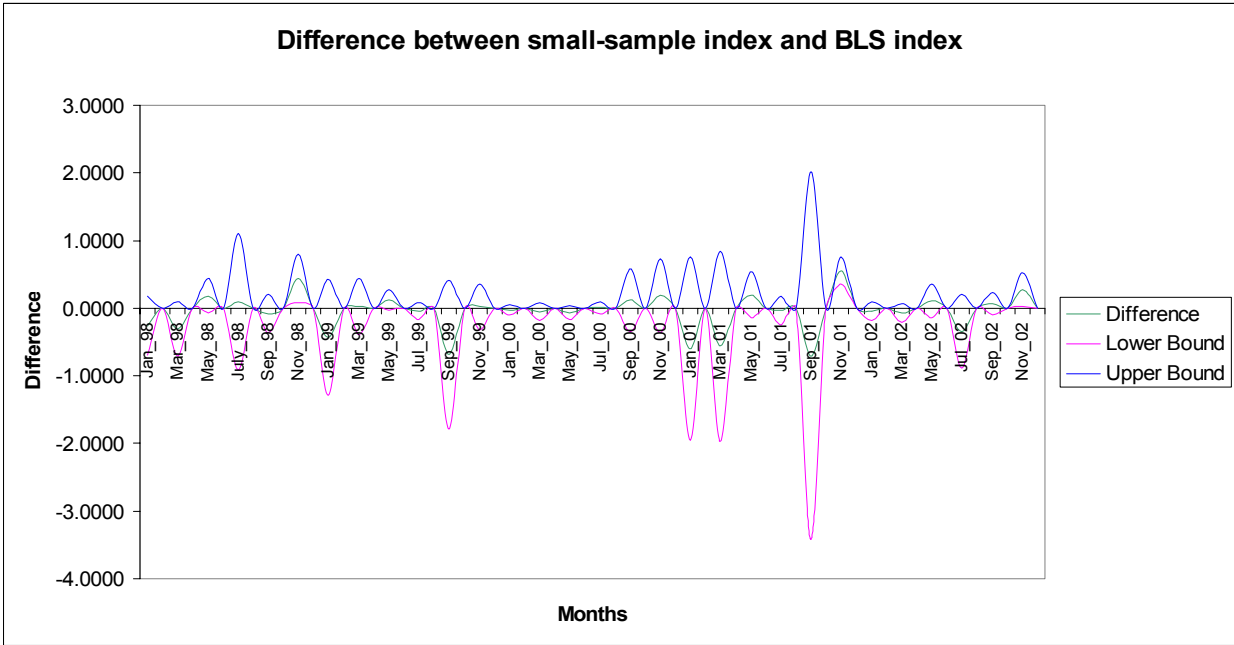
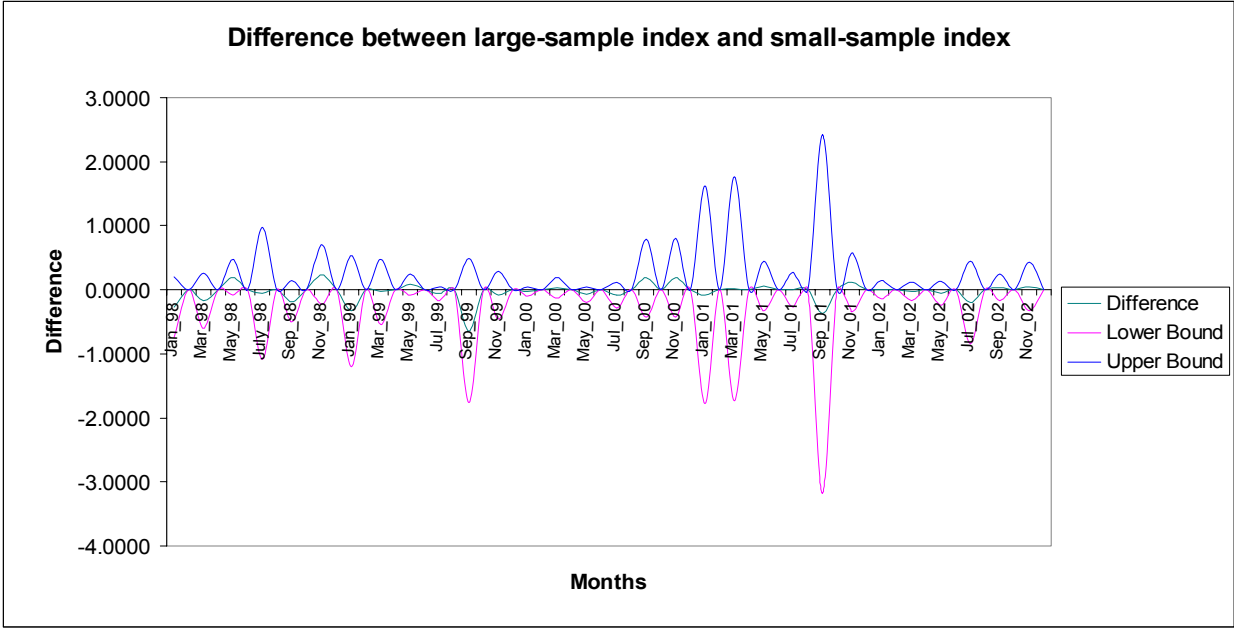
**Difference between small-sample index and BLS index**



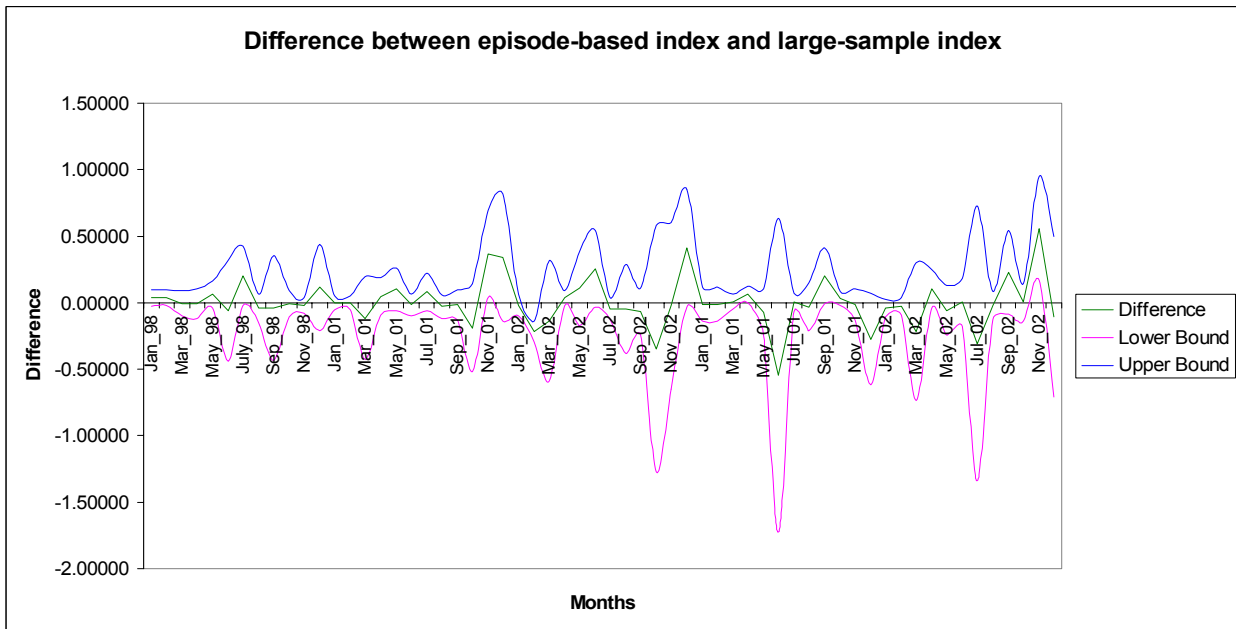
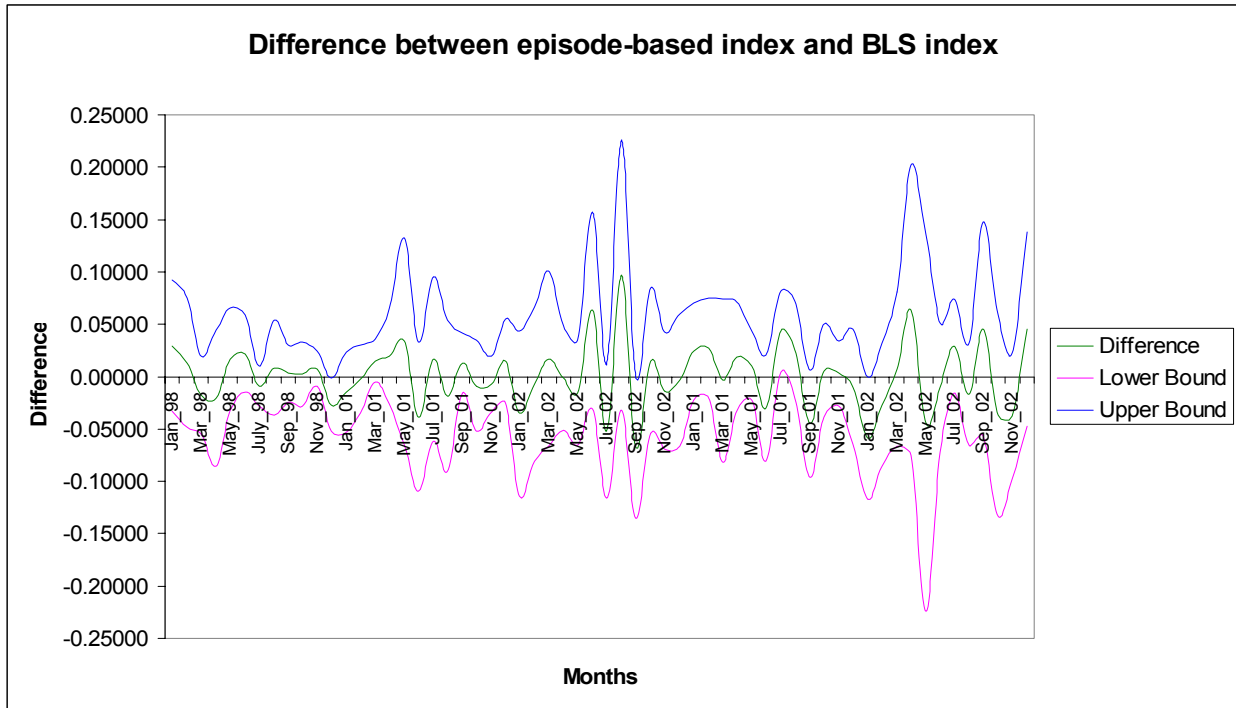
# Boston







# New York



Difference between large-sample index and small-sample index

