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ABSTRACT

Recent empirical work suggests that small price changes are relatively common. These findings have been used to evaluate competing theories of nominal price rigidities. In this paper we use micro data from the consumer price index and a scanner data set from a national supermarket chain to reassess the importance of small price changes. We argue that the vast majority of these changes are due to measurement error. We conclude that small price changes are too small a phenomenon for macro modelers to be concerned with.

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1. Introduction

A classic issue in macroeconomics is how monetary policy affects economic activity. Many monetary models assume that nominal prices adjust slowly to economic shocks. Competing theories emphasize menu costs (e.g. Mankiw (1985), Midrigan (2011)), rational inattention (e.g. Sims (2003, 2010), Reis (2006), Woodford (2009), Maćkowiak and Wiederholt (2009), and Matejka (2010)), sticky information (e.g. Mankiw and Reis (2002)), the costs of re-optimizing and implementing new plans (e.g. Zbaracki, Ritson, Levy, Dutta, and Bergen (2004), Burstein (2006), Eichenbaum, Jaimovich, and Rebelo (2011)), and the negative reaction of consumers to large price changes (e.g. Rotemberg (1982, 2005)).

Competing theories of the monetary transmission mechanism lead to policy recommendations that differ on important dimensions (see, for example, Levin, López-Salido, Nelson, and Yun (2008)). Prior to the availability of detailed microeconomic price data, it was difficult to convincingly discriminate between alternative theories of nominal price rigidity. Aggregate data is simply too coarse a filter to distinguish between these theories.

In the past decade there has been an explosion of work using detailed micro data sets to assess the plausibility of alternative forms of price rigidity. One strand of this literature emphasizes the implications of different theories for how often firms make small price changes. The conventional view is that firms make many small price changes. This view is based on empirical work by Klenow and Kryvtsov (2008), Wulfsberg (2009), Barros, Bonomo, Carvalho, and Matos (2009), and Midrigan (2011).

Klenow and Malin (2009) discuss the implications of the view that there are many small price changes for the plausibility of alternative models. For example, they argue that the prevalence of small price changes is inconsistent with models that emphasize large menu costs of the sort considered by Lucas and Golosov (2007). It is also inconsistent with versions of Mankiw and Reis' (2002) sticky information models in which there are large but infrequent updates to agents' information sets.[1] On the other hand, Midrigan's (2011) model where firms can change more than one price when they incur a menu cost is consistent with the presence of many small price changes. Such changes are also consistent with Rotemberg (1982), in which firms face quadratic costs of changing prices. They also arise naturally in behavioral theories like Rotemberg (2005, 2007) in which consumers react negatively to large price changes. Small price changes also emerge from rational inattention models in which there are no costs of changing prices (e.g. Maćkowiak and Wiederholt (2009)), and from models in which it is costly for firms to change their pricing plans (Burstein (2006) and Eichenbaum, Jaimovich, and Rebelo (2011)). The previous examples make clear why the size distribution of price changes is viewed as providing important information in evaluating competing theories of nominal price rigidities.

In this paper we re-evaluate the evidence on the prevalence of small price changes. Using both the consumer price index (CPI) research data set, collected by the U.S. Bureau of Labor Statistics (BLS), and a scanner data set from a large U.S. supermarket retailer, we argue that the evidence of frequent small price changes is illusory.

In the CPI data set, spurious small price changes arise from a variety of measurement problems. These problems fall into four broad categories. First, some prices are computed using unit value indexes (UVIs), i.e. the ratio of sales revenue to quantity sold. Second, some quoted prices include taxes or fees or pertain to bundles of goods. Third, some prices refer to goods sold at points of service that

[1] Of course, if there are small but infrequent updates to agents' information sets, Mankiw and Reis' (2002) model implies that we would see small price changes.

change over time. Finally, some prices are non-transactional or are affected by uncontrolled forms of quality changes. In Section 2, we detail specific CPI items that are subject to these forms of measurement error and discuss why they lead to spurious small price changes. We show that removing the problematic CPI items has a large impact on inference about the prevalence of small price changes.

The definition of what constitutes a "small" price change is, inevitably, somewhat arbitrary. In our empirical work, we study price changes that are smaller, in absolute terms, than 1, 2.5, and 5 percent. These values are the ones considered by Klenow and Kryvtsov (2008). For concreteness, we focus our discussion on price changes that are less than one percent in absolute value, which we refer to as small price changes. As a reference point, the average rate of inflation over the period that our CPI data covers (January 1998 to July 2011) is 2.9 percent and 2.7 percent for headline and core inflation, respectively,

The fraction of small price changes in the CPI data set is 12.5 and 14 percent for posted and regular prices, respectively. These fractions are very close to those reported by Klenow and Kryvtsov (2008). Removing problematic CPI items has a dramatic impact on the fraction of small price changes: this fraction declines to 3.6 and 5 percent, for posted and regular prices, respectively. Interestingly, these statistics are in line with early findings by Kashyap (1995) on the frequency of small price changes. Significantly, his evidence is based on retail catalogs which do not suffer from most of the measurement error problems in problematic categories of CPI goods.

Are there literally no small price changes? The answer to this question is obviously no. The relevant question is whether small price changes are empirically important. One way to think about this question is to ask: how long does an econometrician have to wait, on average, to observe a price change less than one percent in absolute value? The answer is roughly 28 months and 20 months, for posted and regular prices, respectively. Based on this simple metric it seems hard to conclude that small price changes are a first-order phenomenon that macroeconomists should be concerned with.

The second source of evidence on the importance of small price changes comes from scanner data (e.g. Midrigan (2011)). Therefore, it is important to assess whether our conclusions hold up with respect to that data. Scanner data sets do not generally contain direct measures of prices. Examples include the widely used Dominicks data set and the data from a large supermarket retailer used by Eichenbaum, Jaimovich, and Rebelo (2011). Researchers using such data sets compute prices as UVIs. This practice can easily generate spurious small price changes. To examine the actual impact of UVIs on estimates of the fraction of price changes that are small, we exploit a data set from the same large supermarket retailer studied by Eichenbaum, Jaimovich, and Rebelo (2011). A unique feature of this new data set is that it has both the prices and quantities sold in each transaction. We show that in this new data set there are very few small price changes. We then argue that UVIs account for the vast majority of small price changes in the original UVI-based scanner data set from this retailer.

Viewed as a whole, our results from the CPI data set and the scanner data set are consistent with the view that most small price changes are artifacts of measurement error. To the extent that such changes occur they are far too rare to be used as a litmus test for competing models of nominal rigidities.

This paper is organized as follows. We discuss our results for BLS data and scanner data in Sections 2 and 3, respectively. Section 4 concludes.

2. Spurious small price changes in the CPI

Our analysis is based on an updated version of the BLS's CPI research database used by Klenow and Kryvtsov (2008). This database covers the non-shelter component of the CPI. Our sample period is from January 1988 to July 2011.

The basic unit of observation is the price of a particular item at a specific location and point in time; for example, a six-ounce bottle of Coke purchased in a particular Whole Foods store in Chicago. A time series of price quotes for a particular item is called a 'quote-line.' The BLS collects observations on roughly 75,000 quote-lines on a monthly basis in New York, Los Angeles, and Chicago and on a bimonthly basis in other urban areas. The BLS organizes quote-lines into 388 categories called entry-level items (ELIs). For example, ELI TA011 is New cars. An example of a quote-line within this ELI might be a 2005 Ford Focus LX Sedan with a particular set of features as outlined in the BLS's ELI checklist. The BLS distinguishes between posted and regular prices. Posted prices include temporary price changes that the BLS flags as "sales." Regular prices are non-sale prices.

Tables 1 and 2 present our main results on small price changes for posted and regular prices, respectively.[2] We compute the percentage of price changes in the CPI data set that are smaller, in absolute value, than 1, 2.5, and 5 percent. We report both the raw number of small price changes and the weighted percentage of price changes in parentheses, weighted by the importance of different ELI categories in consumer expenditures.[3]

Recall that, for concreteness, we define small price changes as those that are less than one percent in absolute value. We begin by discussing changes in posted prices. In our data set there are a total of $1,047,547$ price changes out of $4,791,569$ price observations, implying a raw frequency of price changes of 22 percent.[4] Abstracting from Jensen's inequality, this frequency implies an average price duration

[2]See Nakamura and Steinsson (2008) for a detailed analysis of the different properties of posted and regular prices in the CPI.

[3]Unless we state otherwise, we proceed as in Klenow and Kryvtsov (2008) and compute statistics weighting each category of items by its CPI weight. We use the weights reported by Klenow and Kryvtsov (2008), which are available at: http://klenow.com/KK_Frequencies.xls.

[4]The weighted frequency of price changes is also 22 percent.

of 4.5 months. There are 69,720 posted small price changes less that one percent in our data set. These represent 12.5 percent (6.7 percent) of all unweighted (weighted) price changes.[5]

We now examine the extent to which the observed small price changes can be attributed to various forms of measurement error. First, there are 8,703 price changes that are less than a penny. These changes are clearly due to measurement error. Eliminating them reduces the candidate pool of small price changes from 69,720 to 61,017. Second, we eliminate 1,243 observations that are flagged by the BLS because the new price pertains to a substitute item or a quality adjustment has been made. We eliminate these observations because small differences between the substitute and original item or small errors in the quality adjustment result in spurious small price changes.[6] Eliminating these observations leaves us with 59,774 small price changes.

Third, we eliminate small price changes in problematic ELIs that are subject to types of measurement error that generate spurious small price changes. Doing so leaves us with 13,518 small price changes. Since these problematic ELIs account for the vast majority of the small price changes, it is important to discuss them in more detail. We return to this issue below. Due to feasibility considerations, we could only analyze a subset of the potentially problematic ELIs. This subset contains roughly 75 percent of all small price changes.

Viewed overall, the net effect of our corrections is to reduce the ratio of small price changes to all price changes from an unweighted 6.7 percent to 1.3 percent. The analogue statistic for weighted price changes falls from 12.5 percent to 3.6 percent.

[5] The weighted frequency of posted price changes reported by Klenow and Kryvtsov (2008) is 14 percent. They do not report the analogue statistic for unweighted price changes.

[6] We eliminate these items by restricting our sample to items for which the BLS flag COMP is equal to CC. Other potential values for COMP include COMP = QC, which means there is a quality adjustment, or COMP = SR, which means that there is a substitution.

We now turn our attention to regular prices. According to Table 2, there are $636,728$ price changes in our data set, representing 13.5 percent of all price observations. So, the frequency of regular price changes is 13.5 percent, implying and average price duration of 7.4 months. There are $66,906$ regular small price changes less than one percent, which represents a weighted (unweighted) fraction of 14 (10) percent of all price changes. Again, the analogue in Klenow and Kryvtsov (2008) is around 12 percent. Proceeding as above, we eliminate subsets of those observations that we think are due to measurement error. First, there are $7,687$ price changes that are less than a penny. Second, we eliminate $1,176$ observations flagged by the BLS because the new price pertains to a substitute item or a quality adjustment has been made. Third, we eliminate $45,849$ small price changes in the problematic ELIs. After these corrections we are left with $12,194$ small price changes.

Viewed overall, the net effect is to reduce the ratio of small price changes to all price changes from a unweighted 10 percent to 2 percent. The analogue statistic for weighted price changes falls from 14 percent to 5 percent.

Understanding the problematic ELIs Clearly, the problematic ELIs are the major source of measurement error in computing small price changes. While they account for roughly 25 percent of all price changes, they account for nearly 75 percent of all small price changes. So, it is clearly important to discuss why the problematic ELIs are likely to be associated with spurious small price changes.

The problematic ELIs fall into four categories. Category 1 consists of prices computed as UVIs. Category 2 consists of prices that include taxes or fees or prices that pertain to a bundle of goods. Category 3 consists of prices for goods that, at least prior to 2007, were sold at points of service that change over time. Category 4 includes miscellaneous forms of measurement error, such as non-transactional prices or uncontrolled forms of quality changes. In practice some ELIs can be placed in more than one category. Table 3 lists the problematic ELIs and the major category to which we assign them. Categories 1 and 2 are, by far, the most important source of spurious small price changes. These two categories alone account for 90 percent of the small price changes in problematic ELIs.

Table 3 lists the nine ELIs that are subject to the UVI problem. These ELIs account for approximately 45 percent of the posted and regular small price changes. A concrete example of an item whose price is computed as an UVI is cellular telephones services, which is part of Interstate telephone services (ELI ED021). According to the BLS: "Data supplied by some cellular providers to the CPI (as well as the data shared by the PPI) are types of average revenue figures from the company's internal computer system. Some cellular companies feel average revenue is a good pricing measure since it encompasses many different customers, and a wide array of cellular calling characteristics. These data may be supplied as average revenue per minute, per customer, per bill, or per account."[7]

To see how UVI-based prices can generate spurious small price changes, suppose that different consumers buy the same good at different prices because of quantity discounts, coupons or promotions. If the price is computed as sales revenue/quantity, then a small change in consumer composition can lead to a spurious small price change.

From Table 3 we see that 11 ELIs are subject to the composite-good problem. These ELIs account for approximately 23 percent of the regular and posted small price change observations. An example of a composite-good ELI is Airline fares (ELI TG011). The price paid by the consumer for an airplane ticket includes the price charged by the airline as well as a myriad of taxes and fees, such as the September 11 security fee, a passenger facility fee, the Federal excise tax, a travel

[7] See http://www.bls.gov/cpi/cpifactc.htm

facilities tax, a Federal Domestic flight segment fee, and departure and arrival fees. These taxes or fees often represent a very small percent of the price charged by the airline. A change in these taxes or fees would result in a small change in the price recorded by the BLS, even though the airline did not change its fare price.

Another example of a composite good is College tuition and fees (ELI EB011). College tuition and fees are known to change on an annual basis for most institutions. However, the BLS often collects pricing data on a monthly basis for a particular quote-line that includes financial aid. Therefore, a small change in private loan rates can induce a small price change. For example, suppose that a change in market interest rates affected financial aid and, therefore, a student's out-of-pocket expenses. The result would be a small change in the price recorded by the BLS, even though the college did not change its price.

From Table 3 we see that three ELIs are subject to the point of service problem. These ELIs account for approximately 4.1 percent of the regular and posted small price changes. An example of such an ELI is Automobile rental (TA041). The BLS can obtain information on the price of car rentals from the internet. Prior to 2007, it was not always the case that the BLS recorded the precise location from which a car was picked up. If there are small differences in taxes, fees, or prices at each different point of service, then changes in the point of service would generate small change in the prices recorded by the BLS.

From Table 3 we see that four ELIs are subject to miscellaneous forms of measurement error. These ELIs account for approximately 2.6 percent of the regular and posted small price change observations. While these ELIs are less important quantitatively than the other categories, they are still instructive because they highlight the problems that can arise in measuring prices. Consider, for example, Automobile insurance (ELI TE011). In this case, small price changes are induced by small changes in quality that are not controlled for. According to the BLS: "Each year in October/November, the model year of each vehicle in our sample is updated by one year in order to keep the age of our sample vehicles constant; e.g., a three year old vehicle stays three years old from year to year. This annual updating process often results in premium changes."[8] Because car safety has slowly improved over time, the nature of a three-year-old used car has changed over time. Presumably, insurance premia fall to reflect this fact. Under this circumstance the BLS would record a small price change. In our view, this change is spurious because the good itself has changed.

The other three goods included in this category are Hospital in-patient room (ELI MD011) and Hospital in-patient services, other than room (MD011), and Prescription drugs and medical supplies (MA011). In all three cases the recorded price is the product of a complex procedure that combines elements of composite goods, UVIs, and non-transactional prices.[9]

Eliminating the problematic ELIs dramatically reduces the percentage of weighted small price changes from 12.5 to 3.6 percent for posted prices and from 14 and 5 percent for regular prices. The analogue reduction for unweighted small price changes is from 6.7 percent to 1.3 percent for posted prices and from 10.5 percent to 1.9 percent for regular prices.

In one sense, the correct percentages provide lower bounds on the actual fraction of small price changes because we eliminated all price changes less than one percent in the problematic ELIs that we identified. However, in another sense, the correct percentages overstate the true fraction of small price changes since we only corrected for a subset of the total ELIs we think might be contaminated by forms of measurement error.[10]

[8] http://www.bls.gov/cpi/cpifacmvi.htm

[9] See Cardenas (1996) for a discussion.

[10] We communicated with BLS officials about the major ELIs that we eliminated to receive

Viewed overall, in this section we argue that the impact of measurement error on the number of measured small price changes is very large. A simple way to summarize the argument is as follows. Eliminating small price changes contaminated by measurement error reduces the number of small price changes by roughly 80 percent for both posted and regular prices.

Our results indicate that small price changes are, in fact, a rare phenomenon. A particularly stark way of describing just how rare they are is to compute the average amount of time that an econometrician would have to wait to see a small price change. The answer is 28 months and 20 months, for posted and regular prices, respectively.[11] Viewed from this perspective, small price changes seem too infrequent to be used as evidence to evaluate competing theories of how prices are set .

3. Spurious small price changes in scanner data

Some of the evidence regarding small price changes comes from scanner data. One example includes the widely-used Dominicks supermarket data set (see e.g. Midrigan (2011)). In this data set, the price of an item is generally not directly observed. Instead, the price is computed as an UVI. As discussed above, this procedure can generate spurious small price changes when the same good is sold at different prices. This problem is particularly acute with respect to supermarket transactions for three reasons. First, some items are sold at a discount to customers who have a loyalty card. Second, some items are discounted with coupons. Third, there are "two-for-one" types of promotions. Changes in the fraction of customers who take advantage of these types of discounts induce spurious changes

feedback from them about our interpretation of the nature of measurement error. As a practical matter we could not interview BLS officials about all the ELIs.

[11] We compute this statistic as the inverse of the frequency of raw price changes, so we are abstracting from Jensen's inequality.

in UVI-based prices.

To gauge the potential importance of this type of measurement error, we use two data sets. The first, used in Eichenbaum, Jaimovich, and Rebelo (2011), is a scanner data set from a large food and drug retailer that operates more than 1,000 stores in different U.S. states and covers the period from 2004 to 2006. It contains observations on weekly quantities and sales revenue for roughly 60,000 items in each of the retailer's stores. By an item we mean a good, as defined by its universal product code (UPC), in a particular store. Most of the items in this data set are in the processed food, unprocessed food, household furnishings, and "other goods" categories of the CPI. We use our data on sales revenue and quantities sold to compute the price for each individual item as a UVI. Using this constructed price measure we find that 7.8 percent of all price changes are smaller than one percent in absolute value.

The second data set is from the same retailer but contains the actual price associated with each transaction for 374 stores in Arizona, California, Colorado, Oregon, Washington, and Wyoming, for the period from January 4, 2004 to December 31, 2004. The sample we use includes goods that are included in the data set for at least seven days. Because prices are observed directly, there is no measurement error associated with time-varying uses of discounts, coupons, loyalty cards, and other promotions.

We are interested in understanding whether a given good is sold at different prices on a given day. To this end, we identify all UPC/Stores/Days that appear for at least 7 days and in which at least 3 units were sold in each day. Applying these criteria to the data set leaves us with 1.7 million transactions. In 70 percent of these observations, the same good is sold at the same price in all transactions that occur in the same store and on the same day. In the remaining 30 percent of observations, the same good is sold at more than one price on the same day. As discussed previously, these different prices could reflect affinity purchases, coupons or other promotions.

We compute summary statistics for the daily distribution of the price of each good. We focus on three statistics: the daily maximum, minimum and modal price of a product. These statistics do not involve averaging the underlying prices. Figure 1 displays the cumulative distribution of changes in these three price statistics. Our key finding is that only 1.6, 1.1, and 2.5 percent of the price changes are smaller than one percent in absolute value for the daily maximum, minimum and modal price, respectively. In other words, there are very few small price changes.

To assess the measurement error induced by the use of UVIs, we proceed as follows. First, we construct UVI-based prices for the stores where we have actual transactions data. For every day in our sample we divide total sales revenue for item i in store j by the total quantity sold of item i in store j. Second, we compute the absolute percentage price change for the constructed UVI prices. Figure 1 displays the cumulative distribution of changes in these constructed UVI prices. A key feature of this figure is that the cumulative distribution function for changes in UVI prices is significantly above the cumulative distribution of changes in the max, min and mode price. This difference is particularly stark for all price changes less than 10 percent in absolute value.

Turning to small price changes per se we see that 8.4 percent of the changes in the constructed UVI prices are smaller than one percent in absolute terms. The actual fraction of small price changes is only 1.7 percent.[12] Clearly, using UVI-based prices leads the analyst to greatly overstate the frequency of small price changes. On this basis, we are very skeptical of the evidence for the prevalence of small price changes that is based on existing scanner data sets.

[12] This statistic is computed as the average of the fraction of small price changes in the minimum, maximum, and medium price.

4. Conclusion

In this paper we investigate the evidence for the frequency of small price changes. Using both the CPI research data set and a scanner data set we argue that the vast majority of small price changes reflects measurement error. Small price changes may exist but they occur much less frequently than the existing evidence suggests. An important class of macro models has been criticized because they do not generate small price changes. We think that small price changes are too rare to be used as evidence against this class of models.

We conclude by emphasizing that our results do not cast doubt on the efficacy of the BLS's methods for measuring the overall CPI or the rate of inflation. The methods that the BLS uses were not developed to accurately isolate small price changes. And they don't.

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5. Appendix: Description of Troublesome ELIs

In this appendix we briefly discuss the rationale for labeling an ELI problematic. By problematic, we mean that spurious small price changes arise because of the method used to measure prices.

5.1. UVI-based prices

- Electricity (HF011): Prices are constructed as UVIs because it is impossible to price exactly the same electricity service every month. The BLS collects the total amount of energy purchases (broken down into several categories) and the total expenditures on energy. Using these inputs, they construct a measure of price per unit of electricity purchase.

- Utility natural gas services (HF021): Prices are constructed as UVIs because it is impossible to price exactly the same utility natural gas service every month. The BLS collects total amount of utility natural gas purchases (broken down into several categories) and total expenditures on utility natural gas. Using these inputs, they construct a measure of price per unit of utility natural gas purchase.

- Telephone services, local charges (ED011): Prices are constructed as UVIs because it is impossible to price exactly the same local telephone services every month. The BLS collects total amount of local telephone services purchases (broken down into several categories) and total expenditures on local telephone services. Using these inputs, they construct a measure of price per unit of local telephone services. In addition, average revenue figures are often used to compute price quotes.

- Interstate telephone services (ED021): Prices are constructed as UVIs because it is impossible to price exactly the same interstate telephone services every month. The BLS collects total amount of interstate telephone services purchases (broken down into several categories) and total expenditures on interstate telephone services. Using these inputs, they construct a measure of price per unit of interstate telephone services. In addition, average revenue figures are often used to compute price quotes.

- Community antenna or cable TV (RA021): Prices are constructed as UVIs because it is impossible to price exactly the same community antenna or cable TV services every month. The BLS collects total amount of community antenna or cable TV purchases (broken down into several categories) and total expenditures on community antenna or cable TV. Using these inputs, they construct a measure of price per unit of community antenna or cable TV.

- Residential water and sewer services (HG011): Prices are constructed as UVIs because it is impossible to price exactly the same residential water and sewer services every month. The BLS collects total amount of residential water and sewer services purchases (broken down into several categories) and total expenditures on residential water and sewer services. Using these inputs, they construct a measure of price per unit of residential water and sewer services.

- Cigarettes (GA011): The price of a specific cigarette package size is sometime imputed from other sizes. For example, the price of a single pack of cigarettes may be derived from the price of a five-pack carton of cigarettes. A spurious small price change can be induced if the price of a five-pack carton is not equal to five times the price of a single pack of cigarettes.

- Garbage and trash collection (HG021): Prices are constructed as UVIs because it is impossible to price exactly the same garbage and trash collection services every month. The BLS collects total amount of garbage and trash collection purchases (broken down into several categories) and total expenditures on garbage and trash collection. Using these inputs, they construct a measure of price per unit of garbage and trash collection.

- Men's suits (AA011): These prices are sometimes computed as UVIs. For example, when there is a "two-for-one" deal, the price per suit is computed as a UVI.

5.2. Composite goods

- Airline fares (TG011): Airline fares are a composite good made up of the actual airline fare (e.g. non-stop United ticket from EWR to LHR), taxes and fees, and baggage fees. The actual airline fare is generally large relative to the other price components. So, for example, a change in an airport surcharge fee will induce a small price change on the price of the airline fare recorded by the BLS.
- New cars (TA011): The BLS price quote for new cars includes additional charges and/or discounts such as dealer markups, dealer concessions and discounts, and consumer rebates. The BLS measures some of these additional charges and discounts using a moving average over the past thirty days for the particular vehicle quote-line. This averaging induces spurious small price changes.
- Automotive drive train repair (TD031): As with airline fares, the price refers to a composite good that includes disposal fees and other surcharges.
- Tires (TC011): Same issues as automotive drive train repair.
- Automotive maintenance and servicing (TD021): Same issue as automotive drive train repair.
- Automotive bodywork (TD011): Same issues as automotive drive train repair.
- New trucks (TA011): Same issues as new cars.
- Personal computers and peripheral equipment (EE011): The BLS price quote for computers includes warranties and rebates, which are collected based on average data for a particular model over a given period of time. In addition, attribute values (e.g. processor speed, RAM, hard drive size, etc.) can change,

and early quotes collected before the BLS established a concise attribute value schematic for pricing could lack proper flagging of such changes and thus induce small price changes.

- College tuition and fixed fees (EB011): College tuition and fees are known to change on an annual basis for most higher education institutions. However, the BLS collects pricing data for a particular quote-line that includes financial aid. Small change in private loan rates and averaging across students can induce small price changes.

- Televisions (RA011): Same issues as personal computers and peripheral equipment.

- Automotive power plant repair (TD031): Similar issues as in Automotive maintenance and servicing, disposal and environmental fees can induce small price changes.

5.3. Point of service

- Lodging while out of town (HB021): The point of service information can be inaccurate and induce small price changes. There are also non-taxed charges, fees, and surcharges that can affect the price quote outside of the actual pricing done by the producer of lodging.

- Automobile rental (TA041): The BLS price quote for automobile rentals includes additional charges, which may include average revenue figures in the computation. In addition, changes in the point of service information for rental cars (particularly given the increase in internet and/or telephone rentals) can induce spurious small price changes.

- Ship fares (TG023): Same issue as automobile rental.

5.4. Miscellaneous

• Prescription drugs and medical supplies (MA011): When calculating price quotes, the BLS collects data on insurance reimbursement for the particular medication. The providers of this data may report figures that are based on averages across patients or on preliminary estimates for insurance reimbursement. In addition, unmeasured changes in medication dosage can induce spurious small price changes.

• Hospital room in-patient (MD011): A variety of factors impact the BLS price quote of the hospital in-patient room. In particular, the chargemaster, or the master list of prices served (for health insurance purposes), is the main factor in determining the price of the hospital in-patient room. It is well documented that prices in this chargemaster, which changes periodically, do not actually capture the price paid by a patient admitted for a particular service.

• Automobile insurance (TE011): The BLS carefully tracks particular individual policies over a given time period. However, it annually adjusts the sampling vehicle. The measured price can change simply because the new sampling vehicle is safer than the previous sampling vehicle. This situation can result is a small price change even though the actual price of insurance per unit of car safety has not changed. In addition, issuance of dividends to policyholders affects how prices are measured. Depending on how dividends are issued, the BLS either considers them to be a price reduction or not.

• Hospital in-patient services, other than room (MD011): Same issues as hospital room in-patient.

Table 1: Posted price changes

Total number of price changes	1,047,547

Price changes smaller than 1 percent in absolute value

	Total number	Percentage of all price changes (unweighted)	Percentage of all price changes (weighted)
No adjustment	69,720	6.7	12.5
Remove price changes that are less than a penny	61,017	5.8	11.0
Remove items that were replaced or quality-adjusted	59,774	5.7	11.0
Remove price changes less than one percent in problematic ELIs	13,518	1.3	3.6

Price changes smaller than 2.5 percent in absolute value

	Total number	Percentage of all price changes (unweighted)	Percentage of all price changes (weighted)
No adjustment	142,822	13.6	24.0
Remove price changes that are less than a penny	132,935	12.7	22.9
Remove items that were replaced or quality-adjusted	130,604	12.5	23.0
Remove price changes less than one percent in problematic ELIs	50,504	4.8	10.5

Price changes smaller than 5 percent in absolute value

	Total number	Percentage of all price changes (unweighted)	Percentage of all price changes (weighted)
No adjustment	256,303	24.5	40.6
Remove price changes that are less than a penny	245,519	23.4	39.0
Remove items that were replaced or quality-adjusted	241,401	23.0	39.8
Remove price changes less than one percent in problematic ELIs	127,793	12.2	24.4

Table 2: Regular price changes

Total number of price changes	636,728

Price changes smaller than 1 percent in absolute value

	Total number	Percentage of all price changes (unweighted)	Percentage of all price changes (weighted)
No adjustment	66,906	10.5	14.0
Remove price changes that are less than a penny	59,210	9.3	12.0
Remove items that were replaced or quality-adjusted	58,043	9.1	12.6
Remove price changes less than one percent in problematic ELIs	12,194	1.9	5.0

Price changes smaller than 2.5 percent in absolute value

	Total number	Percentage of all price changes (unweighted)	Percentage of all price changes (weighted)
No adjustment	136,481	21.4	27.0
Remove price changes that are less than a penny	127,394	20.0	25.7
Remove items that were replaced or quality-adjusted	125,233	19.7	26.0
Remove price changes less than one percent in problematic ELIs	46,010	7.2	13.8

Price changes smaller than 5 percent in absolute value

	Total number	Percentage of all price changes (unweighted)	Percentage of all price changes (weighted)
No adjustment	242,357	38.1	46.0
Remove price changes that are less than a penny	231,863	36.4	45.0
Remove items that were replaced or quality-adjusted	228,111	35.8	45.8
Remove price changes less than one percent in problematic ELIs	116,124	18.2	32.2

Table 3: Problematic ELIs

ELI (Alpha-numeric)	ELI (Numeric)	Name	Potential Problem	Regular price changes < 1%		Posted price changes < 1%		CPI Weight
				Number	Cumulative distribution	Number	Cumulative distribution	(per KK (2008))
HF011	26011	Electricity	Unit value index	12999	26.0	12999	25.8	0.029
HF021	26021	Utility natural gas service	Unit value index	8965	44.0	8965	43.5	0.010
ED011	27011	Telephone services, local charges	Unit value index	3320	50.6	3320	50.1	0.011
ED021	27051	Interstate telephone services	Unit value index	1615	53.8	1615	53.3	0.007
RA021	27031	Community antenna or cable TV	Unit value index	1070	56.0	1071	55.4	0.007
HG011	27021	Residential water and sewer service	Unit value index	1010	58.0	1010	57.4	0.006
GA011	63011	Cigarettes	Unit value index	478	59.0	581	58.6	0.009
HG021	27041	Garbage and trash collection	Unit value index	455	59.9	455	59.5	0.002
AA011	36011	Men's suits	Unit value index	178	60.2	298	60.1	0.002
TG011	53011	Airline fares	Composite good	5755	71.8	5755	71.5	0.008
TA011	45011	New cars	Composite good	5352	82.5	5352	82.1	0.049
TD031	49021	Automotive drive train repair	Composite good	840	84.2	847	83.8	0.002
TC011	48011	Tires	Composite good	802	85.8	853	85.5	0.003
TD021	49031	Automotive maintenance and servicing	Composite good	649	87.1	666	86.8	0.005
TD011	49011	Automotive body work	Composite good	502	88.1	502	87.8	0.001
TA011	45021	New trucks	Composite good	342	88.7	342	88.5	0.018
EE011	69011	Personal computers and peripheral equipment	Composite good	279	89.3	337	89.1	0.003
EB011	67011	College tuition and fixed fees	Composite good	272	89.8	272	89.7	0.009
RA011	31011	Televisions	Composite good	257	90.4	341	90.3	0.003
TD031	49041	Automotive power plant repair	Composite good	210	90.8	210	90.8	0.004
HB021	21021	Lodging while out of town	Point of service	1250	93.3	1255	93.2	0.016
TA041	52051	Automobile rental	Point of service	1186	95.7	1190	95.6	0.005
TG023	53023	Ship fares	Point of service	345	96.4	396	96.4	0.001
MA011	54011	Prescription drugs and medical supplies	Miscellaneous	569	97.5	570	97.5	0.007
MD011	57011	Hospital room in-patient	Miscellaneous	551	98.6	551	98.6	0.006
TE011	50011	Automobile insurance	Miscellaneous	452	99.5	452	99.5	0.024
MD011	57021	Hospital in-patient services other than room	Miscellaneous	251	100.0	251	100.0	0.006
			UVI		60.2		60.1	0.083
			Composite goods		30.5		30.7	0.106
			Point of service		5.6		5.6	0.021
			Miscellaneous		3.6		3.6	0.041

Figure 1: Cumulative distribution of percentage price changes