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How Frequent Are Small Price Changes?†

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Recent empirical work suggests that small price changes are relatively common. This evidence has been used to criticize classic menu-cost models. In this paper, we use scanner data from a national supermarket chain and micro data from the Consumer Price Index 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 the evidence on the prevalence of small price changes is much too weak to be used as a litmus test of nominal rigidity models. (*JEL* C82, E31, L11, L81)

A classic issue in macroeconomics is how monetary policy affects economic activity. In many monetary models, inertia in nominal prices plays a key role in the monetary transmission mechanism. However, the literature has not reached a consensus on the micro-foundations of this inertia. Competing theories emphasize menu costs, rational inattention, sticky information, costs of re-optimizing and implementing new plans, and the negative reaction of consumers to large price changes.[1]

In the past decade there has been an explosion of work using detailed micro datasets to assess the plausibility of alternative models of price rigidity. An important finding in this literature is that firms often make small price changes.[2] This finding is inconsistent with classic menu-cost models.

There is a large literature aimed at developing variants of menu-cost models that can generate small price changes. For example, Dotsey, King, and Wolman (1999) and Caballero and Engel (1999) assume that the cost of changing price is stochastic.

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[1] For menu costs, see Barro (1972), Mankiw (1985), Caplin and Leahy (1991), Golosov and Lucas (2007), and Gertler and Leahy (2008). For rational inattention, see Sims (2003, 2010), Reis (2006), Woodford (2009), Maćkowiak and Wiederholt (2009), and Matejka (2010). For a combination of menu costs and rational innatention, see Alvarez, Lippi, and Paciello (2011). For sticky information, see Mankiw and Reis (2002). For costs of re-optimizing and implementing new plans, see Zbaracki et al. (2004); Burstein (2006), and Eichenbaum, Jaimovich, and Rebelo (2011). For negative reactions of consumers to large price changes, see Rotemberg (1982, 2005).

[2] See, for example, Klenow and Kryvtsov (2008), Wulfsberg (2009), Barros et al. (2009), Bhattarai and Schoenle (2010), and Midrigan (2011).

So, when the cost is low, firms might make small price changes. Lach and Tsiddon (2007), Midrigan (2011), and Alvarez and Lippi (2012) consider multi-product firms with economies of scope in price setting. Small price changes arise naturally in these models because once a firm pays a fixed menu cost, it can adjust the prices of more than one good.

In this paper, we address the empirical question: just how prevalent are small price changes? Using a new dataset from a large US supermarket retailer, we argue that the distribution of price changes is quite sensitive to a form of measurement error that arises in many scanner datasets. This error arises from the use of price measures constructed as unit value indices (UVIs), i.e., the ratio of sales revenue from a product to the quantity sold.[3] A unique feature of our dataset is that it includes both the prices and quantities sold in each transaction.

We show that UVI-based pricing induces a leftward shift in the distribution of price changes. A researcher using UVI-based prices would infer that there are many more small price changes and fewer large price changes than actually exist. In addition, the use of UVI prices induces a significant downward bias in the median size of price changes, a result that is particularly relevant to researchers calibrating menu-cost models.

To assess the robustness of our inference about the prevalence of small price changes, we also consider the Consumer Price Index (CPI) research dataset collected by the US Bureau of Labor Statistics (BLS). Again, we argue that the evidence of frequent small price changes is illusory.

In the CPI dataset, spurious small price changes arise from a variety of measurement problems. These problems fall into four broad categories. First, some prices are computed using UVIs. Second, some quoted prices pertain to bundles of goods. Third, some prices refer to goods sold at points of service that change over time. Finally, some prices are nontransactional or are affected by uncontrolled forms of quality changes. In practice, the first two categories are, by far, the most important. In Section II, we provide examples of 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 those considered by Klenow and Kryvtsov (2008, table 4). Our qualitative conclusions hold regardless of which of these values are used to define a small price change. For concreteness, we focus our discussion on price changes that are less than 1 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 1988 to July 2011) is 2.9 percent and 2.7 percent for headline and core inflation, respectively.

[3] In some scanner datasets, such as the Dominicks dataset, the weekly price of an item is chosen according to an algorithm based on the share of sales that occur at various prices. Changes in these shares induce spurious changes in reported prices of an individual item. We thank an anonymous referee for drawing our attention to this fact.

The fraction of small price changes in the CPI dataset 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 fraction of price changes that are small. He finds that 2.7 percent of price changes are smaller than 1 percent. Significantly, his evidence is based on retail catalogs, which do not suffer from most of the measurement error issues that arise in problematic categories of CPI goods. Carlton (1986) reports much higher percentages of small price changes than Kashyap (1995). However, there is a crucial difference between their studies. Carlton's data pertains to transactions between firms (the buyers are typically Fortune 500 firms). Moreover, with the exception of household appliances and truck motors, the goods in his data are commodities for which sticky prices are, presumably, not very important.

Our results are also consistent with the findings in Cavallo (2010) and Cavallo and Rigobon (2011) which are based on scraped price data. Cavallo (2010) reports that the share of price changes that are smaller than 1 percent in absolute value is 4.2 percent in Argentina, 4.3 percent in Brazil, and 3.6 percent in Chile. Using a dataset that spans 23 countries and 5 continents, Cavallo and Rigobon (2011) find that the median fraction of price changes smaller than 1 percent in absolute value is 3.8 percent.

Viewed as a whole, our results from the scanner and CPI datasets 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 evaluating the plausibility of menu-cost models or their competitors.

This paper is organized as follows. We discuss our results for scanner data and CPI data in Sections I and II, respectively. Section III concludes.

I. Spurious Small Price Changes in Scanner Data

An important source of evidence regarding the distribution of price changes is scanner data.[4] The price of an item is generally not directly recorded in these datasets. In many datasets, such as those used by Eichenbaum, Jaimovich, and Rebelo (2011); Burstein and Jaimovich (2011); and Gopinath, Itskhoki, and Rigobon (2010), researchers compute the price of an item as a UVI, i.e., they divide total sales of a product by quantity sold.

Computing prices in this way can generate spurious small price changes. For example, suppose that different consumers buy the same good at different prices. Then a small change in consumer composition can lead to a spurious small price change. 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

[4] See, for example, Burstein and Hellwig (2007); Campbell and Eden (2010); Nakamura (2008); Broda and Weinstein (2010); Midrigan (2011); and Eichenbaum, Jaimovich, and Rebelo (2011).

"two-for-one" types of promotions. Changes in the fraction of customers who take advantage of these types of discounts induce spurious changes in UVI-based prices.

To gauge the potential importance of this type of measurement error, we use a new dataset related to the one in Eichenbaum, Jaimovich, and Rebelo (2011). They use a scanner dataset from a large food and drug retailer that operates more than 1,000 stores in different US states and covers the period from 2004 to 2006. This dataset contains observations on weekly quantities and sales revenue for roughly 60,000 items in each of the retailer's stores. Here an item is a good, as defined by its universal product code (UPC), in a particular store. Most of the items in this dataset are in the processed food, unprocessed food, household furnishings, and "other goods" categories of the CPI.

In this paper, we use a new dataset from the same retailer that 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. Because prices are observed directly, there is no measurement error associated with time-varying uses of discounts, coupons, loyalty cards, and other promotions. Also, the price is not calculated using a revenue share-based algorithm, as in the Dominicks dataset, and so it is not subject to spurious price changes induced by such algorithms.

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/Store/Day that appear for at least seven days and in which at least three units were sold in each day. Applying these criteria to the dataset 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: the maximum, minimum, and modal price of a product. These statistics do not involve averaging the underlying prices. To assess the measurement error induced by the use of UVIs, we proceed as follows. First, we construct UVI-based prices using our dataset. 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, as well as in the minimum, maximum, and modal prices. Figure 2 displays the empirical distribution of price changes for the modal and UVI-based prices. In all cases, the distributions displayed are conditional on there being a price change.

Figures 1 and 2 show that the distribution of price changes is quite sensitive to the use of UVI prices. The cumulative distribution function for changes in UVI prices is significantly above the cumulative distribution of changes in the maximum, minimum, and modal price. This difference is particularly stark for all price changes less than 10 percent in absolute value. Figure 2 shows that UVI-based pricing induces a leftward shift in the distribution of prices. There are, in fact, many more large price changes and many fewer small price changes than one would infer using UVI-based pricing.

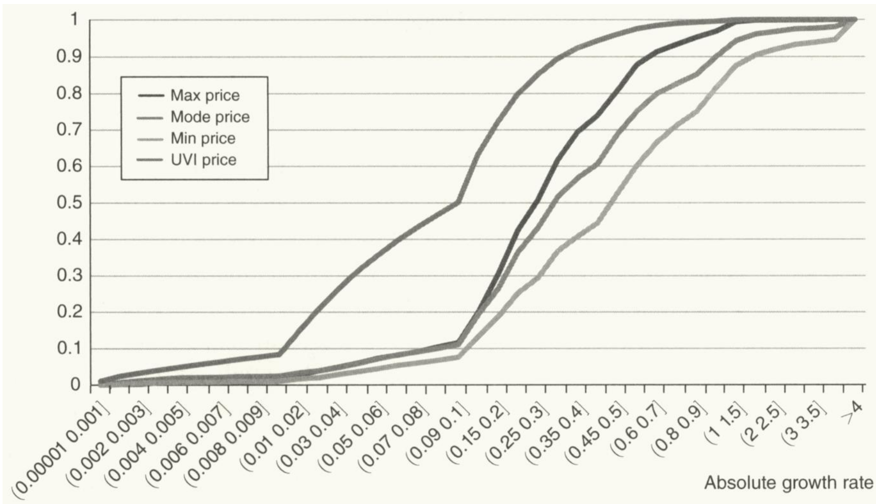

FIGURE 1. CUMULATIVE DISTRIBUTION OF PERCENTAGE PRICE CHANGES

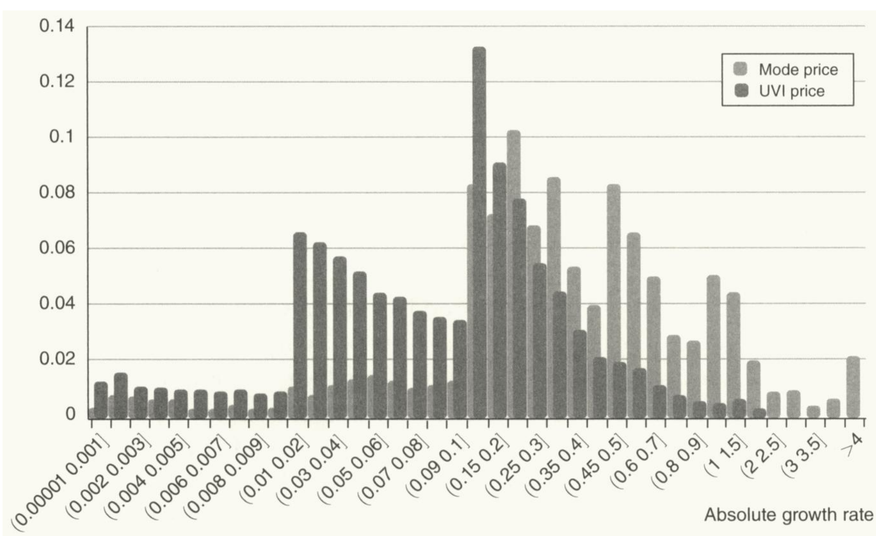

FIGURE 2. EMPIRICAL DISTRIBUTIONS OF PERCENTAGE PRICE CHANGES

The Size of Median Price Changes.—According to Figure 1, the median change in UVI-based prices is roughly 10 percent. This value is very close to the one used by Golosov and Lucas (2007) and Midrigan (2011) in calibrating their models. Figure 1 indicates that the actual median price change is roughly 30 percent.[5] So, according to this dataset, actual median price changes appear to be larger than the

[5] There are three median price changes depending on how prices are measured. Using the maximum, modal, and minimum price measure, the median price change is 23, 28, and 38 percent, respectively. The average of these numbers is 30 percent. The percentage of price changes smaller than 1 percent is 1.6, 2.5, and 1.1 percent for the maximum, modal and minimum price, respectively.

number used to calibrate menu-cost models. This result indicates that calibrations based on scanner data can be quite sensitive to the UVI problem.

The Number of Small Price Changes.—There is no unique definition of what constitutes a small price change. Recall that Klenow and Kryvtsov (2008, table 4) use threshold values of 1, 2.5, and 5 percent to define a small price change. In a similar vein, Midrigan (2011, 1160) uses threshold values of 3 and 5 percent. So, for robustness, we report results using 1, 2.5, and 5 percent as our small price thresholds.

Figure 1 indicates that 31.5 percent of the changes in the constructed UVI prices are smaller than 5 percent in absolute terms. The actual fraction of price changes smaller than 5 in absolute value is 5.2 percent.[6] The analogous numbers for the 1 percent threshold are 8.4 and 1.7. Clearly, using UVI-based prices leads the analyst to greatly overstate the frequency of small price changes. So, we are skeptical of evidence on the prevalence of small price changes that is based on scanner data.

One can always question the representativeness of the goods covered by scanner data. So, in the next section, we assess the robustness of inference about small price changes to using the whole spectrum of goods covered by the CPI.

II. Evidence from 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 nonshelter 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 64-ounce bottle of New Planet Organics Apple Juice purchased in a particular Whole Foods store in Chicago at a particular time. A time series of price quotes for a particular item is called a "quote-line." The BLS collects observations on 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 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 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 nonsale prices.

Tables 1 and 2 present our main results on small price changes for posted and regular prices, respectively.[7] We compute the percentage of price changes in the CPI dataset 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. Unless we state otherwise, we proceed as in Klenow and

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

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

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	5.9	11.0
Remove items that were replaced or quality-adjusted	59,774	5.8	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	12.8	22.9
Remove items that were replaced or quality-adjusted	130,604	12.6	23.0
Remove price changes less than 2.5 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	24.3	39.0
Remove items that were replaced or quality-adjusted	241,401	23.0	39.8
Remove price changes less than 5 percent in problematic ELIs	127,793	12.2	24.4

Kryvtsov (2008) and compute statistics applying sampling weights to items within ELIs.[8] In computing the weighted percentage of small price changes, we remove problematic price changes from both the numerator and the denominator.

In what follows, we focus our discussion on the fraction of price changes that are less than 1 percent in absolute value. The analogous results for 2.5 and 5 percent thresholds are reported in Tables 1 and 2. We begin by discussing changes in posted prices. In our dataset there are a total of 1,047,547 price changes out of 4,791,569 price observations, implying a raw frequency of price changes equal to 22 percent. The weighted frequency of price changes is also 22 percent. Abstracting from Jensen's inequality, this frequency implies an average price duration of 4.5 months. There are 69,720 posted small price changes less that 1 percent in our dataset. These represent 12.5 percent (6.7 percent) of all weighted (unweighted) price changes.[9]

We now examine the extent to which the observed small changes in posted prices 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

[8] We use the weights reported by Klenow and Kryvtsov (2008), which are available at: http://klenow.com/KK_Frequencies.xls.

[9] The weighted fraction of price changes smaller than 1 percent in absolute value reported by Klenow and Kryvtsov (2008, table IV) is 11.3 percent and 12.1 percent for posted and regular price changes, respectively. They do not report the analogue statistic for unweighted price changes.

Table 2—Regular Price Changes

	Total number	Percentage of all price changes (unweighted)	Percentage of all price changes (weighted)
Total number of price changes			636,728
Price changes smaller than 1 percent in absolute value			
No adjustment	66,906	10.5	14.0
Remove price changes that are less than a penny	59,210	9.4	12.0
Remove items that were replaced or quality-adjusted	58,043	9.2	12.6
Remove price changes less than one percent in problematic ELIs	12,194	2.1	5.0
Price changes smaller than 2.5 percent in absolute value			
No adjustment	136,481	21.4	27.0
Remove price changes that are less than a penny	127,394	20.3	25.7
Remove items that were replaced or quality-adjusted	125,233	20.0	26.0
Remove price changes less than 2.5 percent in problematic ELIs	46,010	8.4	13.8
Price changes smaller than 5 percent in absolute value			
No adjustment	242,357	38.1	46.0
Remove price changes that are less than a penny	231,863	37.0	45.0
Remove items that were replaced or quality-adjusted	228,111	36.6	45.8
Remove price changes less than 5 percent in problematic ELIs	116,124	22.7	32.2

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.[10] Eliminating these observations leaves us with 59,774 candidate small price changes.

Third, we identified a set of 27 problematic ELIs that are subject to types of measurement error that generate spurious small price changes.[11] These ELIs account for roughly 77 percent of the candidate small price changes. The remaining 23 percent small price changes are spread across many potentially problematic ELIs for which it was impossible to obtain detailed documentation. In what follows, we adopt the conservative assumption that the small price changes in these ELIs are not spurious. We eliminate the small price changes in the 27 problematic ELIs, leaving 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.

[10] 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.

[11] We describe these ELIs in detail in an Appendix that is available online.

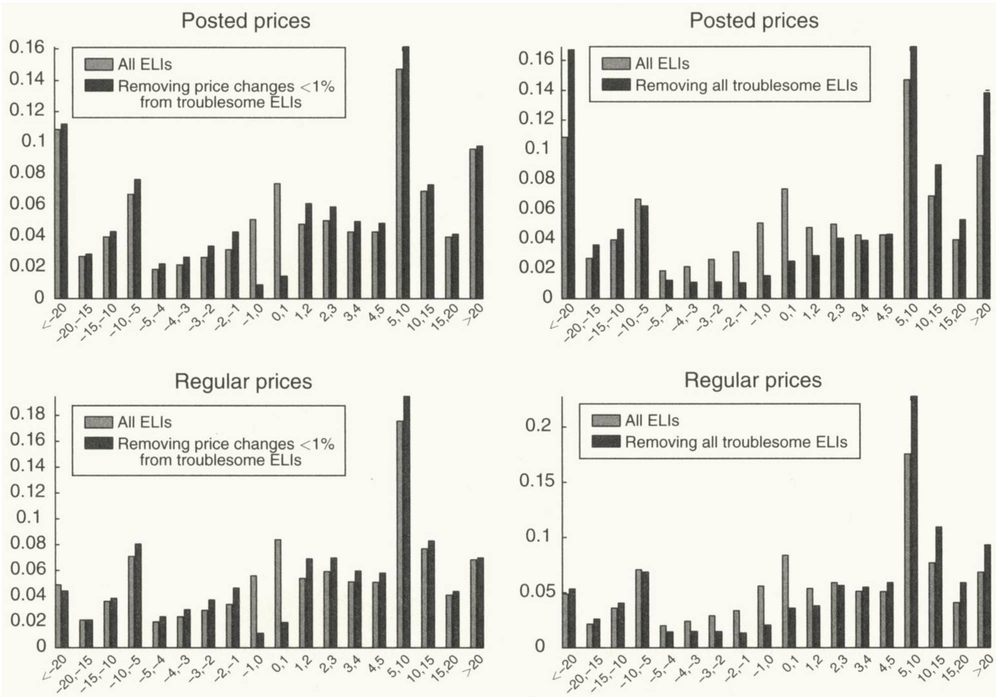

FIGURE 3

Panel A of Figure 3 displays, for posted prices, the impact of eliminating small changes in problematic ELIs. The $(1, 1)$ element of this panel shows two distributions. The first pertains to price changes across all the ELIs. Notice that a substantial fraction of these price changes fall between -1 and $+1$ percent. The second distribution results from removing all price changes that are less than 1 percent for troublesome ELIs. Notice that a much smaller fraction of price changes now lies between -1 and $+1$ percent.

One might be concerned that the dip around zero in the second distribution is an artifact of eliminating the small price changes for the troublesome ELIs. To address this concern we display in the $(1, 2)$ element of panel A a third distribution, obtained by eliminating all of the problematic ELIs from the sample. Like the second distribution, the third distribution has a much smaller fraction of price changes between -1 and $+1$ percent than the first distribution. The second and third distributions appear more bimodal than the first distribution. Interestingly, the shape of these distributions is similar to those displayed in Cavallo (2010) and Cavallo and Rigobon (2011).

Viewed overall, the net effect of our corrections for posted prices 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.

We now turn our attention to regular prices. There are 4,708,719 regular price observations in our dataset. According to Table 2, there are 636,728 price changes, representing 13.5 percent of all price observations. So, the frequency of regular price changes is 13.5 percent, implying an average price duration of 7.4 months.

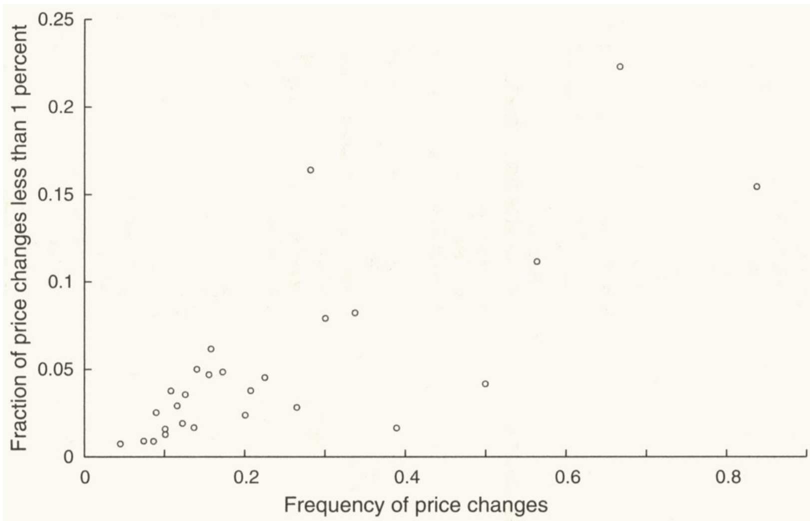

Figure 4

There are 66,906 regular small price changes less than 1 percent, which represents a weighted (unweighted) fraction of 14 (10.5) percent of all price changes. The analogue statistic in Klenow and Kryvtsov (2008) is roughly 12 percent. Proceeding as above, we eliminate subsets of those observations that we think are due to measurement error. First, there are 7,696 price changes that are less than a penny. Second, we eliminate 1,167 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. Panel B of Figure 3 is the analogue of panel A for regular price changes and displays a similar pattern of results.

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

It is interesting to ask the question: do small price changes occur in ELIs whose prices change infrequently? This type of behavior would be inconsistent with simple menu cost models. In fact the answer to this question is no. Figure 4 shows that, for regular prices in the problematic ELIs, there is a positive correlation (76 percent) between the frequency of price adjustment and the fraction of small price changes.[12] So, small price changes are more likely to occur in ELIs where prices change frequently. For example, the price of "Utility Natural Gas Service," has an average duration of 1 month and a large fraction (15 percent) of price changes that are small. In contrast, "College Tuition and Fixed Fees," has an average price duration of 12 months and a very small fraction (1 percent) of small price changes. The correlation

[12] The correlation between the frequency of regular price adjustment and the fraction of small regular price changes across all ELIs is 0.62. Interestingly, this correlation is only 0.32 for posted prices. This lower correlation presumably reflects the effects of sales.

between the frequency of price adjustment and the fraction of small price changes within the problematic ELIs is 70 percent for posted prices.

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 observations, they account for 77 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 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 nontransactional 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. Some of these assignments are based on the BLS documentation cited below. Others are based on discussions with BLS officials. As a check on our classifications, we reviewed with BLS officials the ELIs that we classify as problematic to receive feedback from them about our interpretation of the nature of measurement error.[13]

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 a UVI is cellular telephone 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."[14]

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 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.

[13] To be clear, the BLS has not officially endorsed our classification.
[14] See http://www.bls.gov/cpi/cpifactc.htm.

TABLE 3—PROBLEMATIC ELIs

ELI (Alpha-numeric)	ELI (Numeric)	Name	Potential problem	Regular price changes < 1%: Number	Regular price changes < 1%: Cumulative distribution	Posted price changes < 1%: Number	Posted price changes < 1%: Cumulative distribution	CPI weight (per KK (2008))
HF011	26011	Electricity	Unit value index	12,312	26.9	12,312	26.6	0.029
HF021	26021	Utility natural gas service	Unit value index	8,723	45.9	8,723	45.5	0.010
ED011	27011	Telephone services, local charges	Unit value index	2,887	52.2	2,887	51.7	0.011
ED021	27051	Interstate telephone services	Unit value index	971	54.3	971	53.8	0.007
RA021	27031	Community antenna or cable TV	Unit value index	772	56.0	768	55.5	0.007
HG011	27021	Residential water and sewer service	Unit value index	791	57.7	791	57.2	0.006
GA011	63011	Cigarettes	Unit value index	364	58.5	438	58.1	0.009
HG021	27041	Garbage and trash collection	Unit value index	416	59.4	416	59.0	0.002
AA011	36011	Men's suits	Unit value index	162	59.8	257	59.6	0.002
TG011	53011	Airline fares	Composite good	5,704	72.2	5,704	71.9	0.008
TA011	45011	New cars	Composite good	5,048	83.2	5,048	82.8	0.049
TD031	49021	Automotive drive train repair	Composite good	734	84.8	741	84.4	0.002
TC011	48011	Tires	Composite good	749	86.4	792	86.1	0.003
TD021	49031	Automotive maintenance and servicing	Composite good	552	87.6	561	87.4	0.005
TD011	49011	Automotive body work	Composite good	432	88.6	432	88.3	0.001
TA011	45021	New trucks	Composite good	322	89.3	322	89.0	0.018
EE011	69011	Personal computers and peripheral equipment	Composite good	236	89.8	289	89.6	0.003
EB011	67011	College tuition and fixed fees	Composite good	267	90.4	267	90.2	0.009
RA011	31011	Televisions	Composite good	231	90.9	305	90.9	0.003
TD031	49041	Automotive power plant repair	Composite good	197	91.3	197	91.3	0.004
HB021	21021	Lodging while out of town	Point of service	923	93.3	925	93.3	0.016
TA041	52051	Automobile rental	Point of service	1,064	95.7	1,068	95.6	0.005
TG023	53023	Ship fares	Point of service	337	96.4	387	96.4	0.001
MA011	54011	Prescription drugs and medical supplies	Miscellaneous	493	97.5	493	97.5	0.007
MD011	57011	Hospital room in-patient	Miscellaneous	479	98.5	479	98.5	0.006
TE011	50011	Automobile insurance	Miscellaneous	442	99.5	442	99.5	0.024
MD011	57021	Hospital in-patient services other than room	Miscellaneous	241	100.0	241	100.0	0.006
			UVI		59.8		59.6	0.083
			Composite goods		31.6		31.7	0.106
			Point of service		5.1		5.1	0.021
			Miscellaneous		3.6		3.6	0.041

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 changes 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 3.6 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." [15] 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. In this case, 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); Hospital In-patient Services, Other than Room (MD011); and Prescription Drugs and Medical Supplies (MA011). As discussed in Cardenas (1996), in all three cases the recorded price is the product of a complex procedure that combines elements of composite goods, UVIs, and nontransactional prices.

A Robustness Check.—Eliminating all sources of measurement error 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 corrected estimates provide lower bounds on the actual fraction of small price changes because we eliminated all price changes less than 1 percent in the problematic ELIs that we identified. However, in another sense, the corrected estimates 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.

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

To assess robustness of inference we redid our computations eliminating *all* problematic ELIs from the analysis, instead of eliminating only price changes that are smaller than 1 percent in the problematic ELIs. We find that inference is robust. For example, the fraction of price changes that is smaller than the 5 percent threshold, in absolute value, is almost identical in both cases (24.4 and 32.2 percent for posted and regular prices, respectively). The analogue numbers for the 1 percent threshold are 3.6 and 5.0 for posted and regular prices, respectively.

The Impact of Our Corrections on Other Statistics.—Micro-based estimates of the distribution of price changes are often used to calibrate competing models of the monetary transmission mechanism. A classic example is Golosov and Lucas (2007), who choose the size of menu costs to be consistent with the median size of price changes, as well as other moments of the distribution of price changes. To the extent that such moments are substantially affected by measurement error, the models are misspecified, potentially leading to misleading inference.

Consider first the impact of our measurement error corrections on the median size of weighted price changes. In the uncorrected data, this statistic is roughly 2 percent for posted prices and 2.5 percent for regular prices.[16] These statistics are basically unaffected if we make our measurement error corrections, including removing price changes lower than 1 percent in problematic ELIs. However, if we remove all the problematic ELIs from the sample, the median size of price change is 3 percent for posted prices and 5 percent for regular prices.[17] The reason this last correction has a bigger impact is that most of the small price changes are in the problematic ELIs.

Next, consider the impact of our measurement error corrections on the frequency with which prices are adjusted. Working with uncorrected data, we find, for posted prices, that the frequency of weighted price changes is 22 percent. This frequency rises to 25 percent when we make our measurement error corrections, including eliminating price changes lower than 1 percent in problematic ELIs.[18] Working with the same corrections but removing all the problematic ELIs, this frequency declines to 19 percent.

Finally, consider regular prices. Working with uncorrected data, we find that the frequency of weighted price changes is 17 percent. This frequency declines to 16 percent when we make our measurement error corrections, including eliminating price changes lower than 1 percent in problematic ELIs. Working with the same corrections, but removing all the problematic ELIs, this frequency declines to 9 percent.

We conclude that the median size of price changes and the frequency statistics are robust to our corrections with one exception. If one works with regular prices and insists on removing all the problematic ELIs from the sample, then the frequency

[16] The median size of the absolute weighted price change estimated using the distributions in Figure 3 is 8 percent for posted prices and 7 percent for regular prices.

[17] The analogue estimate of the median size of the absolute weighted price change is 12 percent for posted prices and 8 percent for regular prices.

[18] There is no a priori reason to think that the frequency of price changes should rise or fall after eliminating the problematic ELIs. There is a presumption that there are more frequent small price changes in these ELIs. But there could be more, or fewer, nonsmall price changes in the problematic ELIs. So, the net effect of removing these ELIs in the overall frequency of price changes is unclear. An additional complication is that we compute the frequency of price changes weighting categories by their importance in consumer expenditures. These weights are recalculated once we remove the problematic ELIs.

of price changes drops substantially. The median size of price changes doubles with this particular correction, and the price duration implied by the frequency statistic rises from roughly 6 to 11 months (abstracting from Jensen's inequality).

The analysis in Eichenbaum, Jaimovich and Rebelo (2011) suggests that the properties of regular prices are more relevant than those of posted prices in assessing the monetary transmission mechanism. So, we think that the results for regular prices are particularly noteworthy. That said, we do not see any compelling reason to remove all of the problematic ELIs from our sample.

III. Conclusion

In this paper, we study the frequency of small price changes. Using both scanner data and the CPI research dataset, we argue that the vast majority of small price changes reflects measurement error. 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 in the CPI.

Small price changes may exist but they occur much less frequently than the existing evidence suggests. Menu-cost models have been criticized because they do not generate small price changes. We think that the evidence on the prevalence of small price changes is much too weak to be used as a litmus test for assessing these 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.

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.

A. *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 the 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 the 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 the 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 the 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 the 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.

B. *Composite Goods*

- Airline fares (TG011): Airline fares are a composite good made up of the actual airline fare (e.g., nonstop 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 30 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 changes 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.

C. *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 nontaxed 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.

D. *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.

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