No. 7
June 2009

StaffPAPERS

FEDERAL RESERVE BANK OF DALLAS

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Excluding Items from Personal Consumption Expenditures Inflation

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Abstract

Core inflation measures constructed by excluding particularly volatile items from the price index have a long history. The most common such measures are indexes excluding the prices of food and energy items. This paper attempts to shed some statistical light on the impact of excluding certain items from the personal consumption expenditures (PCE) price index. In particular, I am interested in the trade-off between reducing short-run volatility (relative to the volatility of the headline index) and possibly distorting the measurement of inflation over longer horizons. Some of the questions this paper addresses are: Which items have the highest time series volatility? Among the items with high volatility, are there meaningful patterns in the distribution of volatility across high and low frequencies? Which items, by their exclusion, have the largest impact on longer-horizon measures of inflation? And which, by their exclusion, contribute the most to reducing high-frequency volatility in measured inflation? Excluding items that answer the last question yields a PCE index which compares favorably to PCE ex food and energy along several dimensions, while excluding only half as many items by expenditure weight.

JEL codes:: C43, E31
Keywords:: PCE inflation, core inflation

I thank the editor, Mark Wynne, for many useful comments.

Exclusion-based measures of core inflation—the traditional "inflation ex…" measures—have a long history. The Bureau of Labor Statistics (BLS) produced versions of the Consumer Price Index (CPI) excluding food and excluding shelter at least since the late 1950s, when those series first appeared in the annual *Economic Report of the President.* "CPI ex food and energy"—now taken almost synonymously with core inflation—made its first appearance in the report in 1980. Many national statistical agencies produce inflation measures of this sort, and many central banks refer to these measures as guides for monetary policy.

For example, from 2004 to 2007, the Federal Reserve cast the inflation forecasts in its semiannual reports to Congress in terms of the price index for personal consumption expenditures (PCE) excluding food and energy; since 2008, the Fed has released forecasts for both headline PCE and PCE excluding food and energy. While "ex food and energy" seems to be the most common exclusion-based measure, others are in use. The Sveriges Riksbank refers in its public communications to a measure of consumer price inflation excluding mortgage interest costs and energy, while the Bank of Canada uses a CPI excluding the eight most volatile items as an operational guide for monetary policy.

Academic interest in exclusion-based core inflation measures began with Blinder (1982), who used them to analyze the high rates of inflation experienced in the United States in the 1970s. In the 27 years since Blinder's work, a number of alternative, nonexclusion-based measures of core inflation have been proposed. Silver (2007) provides a nice survey of this growing literature. Rich and Steindel (2007) present a comprehensive "horse race" among competing core inflation measures. Despite the proliferation of alternative core inflation measures, exclusion-based measures appear to remain the most popular among policymakers, judging by the number of central banks that make some reference to exclusion-based core measures.[1]

In the core measures adopted by the Riksbank and the Bank of Canada, the main rationales are evident for the exclusion of certain items from a measure of inflation. One is that the prices of some items, such as the service flow from owner-occupied housing, are difficult to measure. It is unclear whether proxies for those prices—or even the prices themselves—convey useful information about inflation (as distinct from the cost of

[1] A comprehensive list would include not just the Federal Reserve, Sveriges Riksbank and Bank of Canada but also the European Central Bank, the Bank of Japan, the Reserve Bank of Australia, and the Reserve Bank of New Zealand. Some central banks make reference in their public statements to measures of core inflation in addition to exclusion-based measures, but I know of none that reference a nonexclusion-based measure without also referencing an exclusion-based measure. The Bank of England is alone among major central banks in making no references to core inflation in its public statements.

living).[2] If the cost of owner-occupied-housing services is proxied by mortgage interest expenses, then including that cost in a measure of inflation could mean, perversely, that a tighter monetary policy (a higher policy interest rate) causes a rise in measured inflation.[3] The other main rationale for exclusion, evident in the Bank of Canada's description of its core price index, is the elimination of highly volatile items from the inflation measure.[4] This rationale, the reduction of volatility, will be my focus in this paper.

While PCE ex food and energy holds a special status as the core measure preferred by the Federal Reserve, the practices of other central banks make clear that there are alternatives to excluding all food and energy items (and only food and energy items). A look at disaggregated PCE data reveals that while food and energy items figure prominently among the components with the highest time series volatility, not all of the most volatile items are food or energy, and not all food and energy items rank among the most volatile.[5] This fact suggests a closer examination of which items should be excluded if the aim is to produce an index with lower volatility than the headline index and still capture the longer-run trend in headline inflation.

In the next section, I begin the analysis by asking, simply, what are the most volatile items in the PCE? Rather than identifying the *N* most volatile items, for some *N*—à la the Bank of Canada's core measure—I ask a somewhat different question. Food and energy make up roughly 20 percent of the PCE by expenditure. What, then, are the most volatile items with aggregate weight of 20 percent? The list may be somewhat surprising. There are certainly plenty of food and energy items on the list but also computers, used autos, small electric appliances, women's and girls' clothing, airline services, and more. Also, many food items do not make the list—for example, cereals, bakery products, and "purchased meals: other than at schools," which represents the price of meals at restaurants and bars. A common characteristic of food items not on the list (except for fish and seafood) is that they involve relatively more processing than raw items such as meats, eggs, fruits, and vegetables.

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[2] Inflation is commonly understood as a persistent and general increase in prices or an erosion of the purchasing power of a unit of money. More precise (and more operational) definitions are model-dependent. A cost of living index has a precise definition as the money cost to an economic unit (a household or individual) of maintaining a given level of well-being in the face of changing prices. Astin (1999), in discussing the challenges of constructing harmonized inflation indexes for the euro area, provides a nice discussion of the different ends for which price indexes are constructed.

[3] As stated on the Riksbank website (www.riksbank.com/templates/Page.aspx?id=10578), "Households' mortgage interest expenditure is excluded more for reasons of clarity. It may in some cases be problematic for the Riksbank to explain why the immediate effect of a tighter monetary policy is that CPI inflation rises."

[4] Coincidentally, mortgage interest cost is also among the eight most volatile items excluded in the Bank of Canada's core measure.

[5] Bryan and Cecchetti (1994) make a similar point in reference to the exclusion of the component "food away from home" from CPI ex food and energy.

The price index that would result from excluding the 20 percent most volatile items would certainly look odd. Moreover, we know that the prices of some of these items—computers, televisions, and other consumer electronics—have pronounced downward trends. Their monthly rates of change are consistently negative, though volatile. Excluding items whose prices are consistently falling risks introducing an upward bias into the resulting "inflation ex..." measure.

A distinguishing feature of items like computers and other consumer electronics is the amount of low-frequency power their price-change series have. The variance of changes in the price index for computers is high, but much of that variance is concentrated at very low frequencies. In section 2, I briefly examine the power spectral densities of the component series to identify the components with the greatest power at high and low frequencies. Gasoline, fuel oil, computers, and software emerge as unique, as do several other items. For some of these items, the distribution of power across high and low frequencies suggests a trade-off, or tension, in the decision of whether to exclude the items. Gasoline and fuel oil, for example, rank at the top in terms of high-frequency power but also possess significant low-frequency power relative to almost all other items. Computers and software, by contrast, rank highest in terms of low-frequency power and possess high-frequency power that, while non-negligible, is not especially distinguishable from the majority of other items. If the goal is to construct a core measure with less high-frequency volatility than the headline index, one would hope for a sharp division between items with substantial volatility at high frequencies and those with substantial volatility at low frequencies. Liquid fuels and a few other items, unfortunately, occupy a middle ground, with relatively high volatility at both high and low frequencies.

In section 3, I examine the impact of excluding each of the underlying PCE components on several measures of the longer-run behavior of "PCE ex item j"—the price index that results from excluding only item j. The measures of longer-term behavior include (1) the resulting average rate of inflation in the ex j indexes over the entire sample period, (2) average inflation over periods of a few years, and (3) a band-pass filter estimate of the long-run trend in ex j inflation.

Several components emerge as unique in their impact on these longer-run criteria, including gasoline and computers but also owner-occupied housing, women's and girls' clothing, tobacco, and "brokerage/investment counseling services." The difference between headline PCE and "PCE ex item j" depends on both the time series properties of the excluded component and its weight in the headline index. Thus, an item like fuel oil—which has time series properties similar to gasoline but a much smaller weight—does not emerge as a high-impact item in these experiments.

The third measure of longer-term impact mentioned above—the effect of an item's exclusion on the band-pass trend in PCE inflation—suggests a converse measure of the impact an item's exclusion has on higher-frequency volatility in inflation: the reduction in volatility of the band-pass cyclical component one obtains from an item's exclusion. I examine this measure in section 4. Interestingly, the set of items which, by their exclusion, yield lower high-frequency volatility is small—only 19 items have this property, and those items have an aggregate expenditure weight equal to about half the weight of food and energy. The list contains food and energy items, but others as well. Most food is not on the list, nor, among energy items, is electricity. The "PCE ex…" measure that results from excluding these 19 items looks to be an improvement over "ex food and energy" in terms of its volatility (both cyclical and overall volatility); its ability to track the trend in PCE inflation; and its ability to forecast future headline inflation at horizons of 12, 18, 24, and 36 months.

Data and Notation

The price series for 186 components of PCE are taken from underlying detail Table 2.4.4U, "Chain-Type Price Indexes for Personal Consumption Expenditures," from the Bureau of Economic Analysis (BEA). The list almost exhausts PCE, though two items for which prices or real quantities could potentially be negative—net foreign remittances and net foreign travel—have been excluded.

These 186 items are the series underlying the Federal Reserve Bank of Dallas' Trimmed Mean PCE inflation rate. A list of the 186 items is given in Dolmas (2005). The sample period is January 1987 to August 2008. Note that all the series are seasonally adjusted by BEA.

Let P^i_t denote the price index for component i at date t, $p^i_t = ln\ P^i_t$, and $\pi^i_{t,k} = (1200/k)(p^i_t - p^i_{t-k})$. For simplicity, let $\pi^i_{t,1} \equiv \pi^i_t$, which will be the basic unit of analysis through most of the paper. The same set of variables, without the superscript i, refers to the headline PCE index. The same set of variables, with a superscript "ex j," denotes the price index or inflation rates for PCE excluding item j.

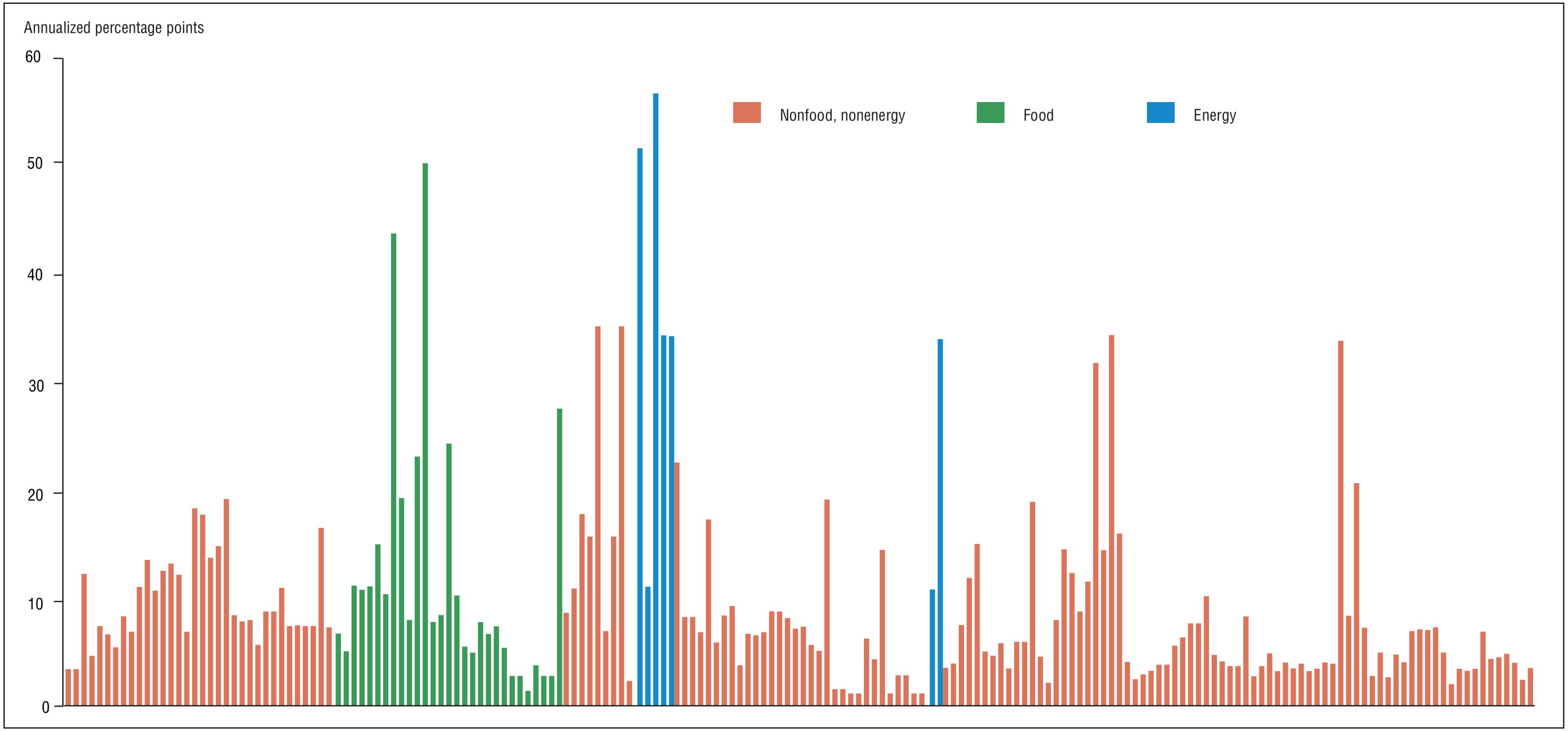
1. THE MOST VOLATILE PCE COMPONENTS

Suppose that, as an alternative to PCE ex food and energy, one wished to construct a "PCE ex…" index analogous to the Bank of Canada's CPI ex the eight most volatile items. What would it contain? Would any nonfood or nonenergy items be excluded? Would any food or energy items be included?

Figure 1 presents the sample standard deviations of the annualized log monthly rates of change for each of the 186 PCE components that I use in this paper—i.e., the sample standard deviations of π^i_t for $i = 1, \ldots, 186$. Energy items are shown in blue, and food items are shown in green.[6] Clearly, while the majority of food and energy items are among the most volatile, this is not true of all food and energy items. Excluding food and energy (and only food and energy) thus misses some high-volatility items while excluding some items that have relatively low volatility.

[6] The items are ordered in the figure as they are in the BEA's underlying detail tables: durables (items 1–34), nondurables (35–97), and services (98–186).

Figure 1: Standard Deviations of Annualized Log Monthly Price Changes for 186 Components of PCE



Rather than rank the N most volatile items, for an arbitrary N (e.g., N=8, 10, 25, or what have you), I think a better way to characterize the extent to which excluding only food and energy differs from excluding the most volatile items is as follows. In recent years, the expenditure weight of food and energy in the PCE has been around 20 percent. Imagine ordering all components by their standard deviation, from highest to lowest, then finding the N such that the aggregate expenditure weight of items 1 through N is approximately 20 percent.

At the level of disaggregation we are working, that exercise yields the 52 items shown in Table 1.[7] Nonfood, nonenergy items are shown in bold in the table.

Several features of the data in Table 1 are worth noting. First and most obviously, the majority of items on the list are items other than food or energy. Less obviously, the majority of items by expenditure weight are also items other than food or energy: The aggregate expenditure weight of the items in Table 1 is 20.87 percent, of which 11.34 percent consists of items other than food or energy.

What's also striking is the expenditure weight of gasoline; at 4.32 percent, it is more than double the second-largest expenditure share on the list (women's and girls' clothing, item 50, with a weight of 1.71 percent). Thus, of the roughly 20 percent of expenditure shown in the table, gasoline makes up a little over one-fifth. The same is true, obviously, of gasoline's weight in food and energy.

The list includes all energy components of the PCE but not all food components. Food items not making the 20 percent-most-volatile cut are shown in Table 2. If we imagine ordering food components on a spectrum from crude to processed (with, say, fresh vegetables at one end and meals at restaurants at the other), then the food components in Table 2, with perhaps the exception of fish and seafood, are all from the more processed end of the spectrum. Note, too, that while some items on Table 2 have standard deviations close to the minimum in Table 1—that is, they just missed the cutoff—others have standard deviations well below those shown in Table 1. In particular, "purchased meals: other than at schools"—or meals purchased at restaurants—is both one of the largest PCE components (its weight is roughly the same as that of gasoline) and one of the least volatile. With a standard deviation of 1.36 annualized percentage points, it actually ranks 181st out of 186 when items are ranked by volatility. Only five components—all parts of housing services—are less volatile. No reasonable exclusion-based measure would throw out this item.

Some of the nonfood, nonenergy items in Table 1 are generally regarded as having high volatility over short horizons—tobacco, for example, or the apparel components. Items like airline services and the other transportation components no doubt inherit some of their volatility from energy's role as an important input. The presence of other items on the list may

[7] There is one exception. As a result of the 9/11 attacks, the price index for "personal business services: cost of handling life insurance" plunged 46 percent in September 2001, then rose 46 percent in October 2001. Due to this singular event, the otherwise smooth series of log price changes for the cost of handling life insurance would rank as one of the most volatile PCE components. The analysis that follows uses a "pasted" life insurance series that assigns to September 2001 the midpoint of the price index's values in August and October 2001.

Table 1: The 20 Percent of Components (Expenditure Weighted) with the Highest Sample Volatility

Rank	Component name (Nonfood, nonenergy items in bold)	Standard deviation	Expenditure weight
1	Purchased fuel oil	55.93	.16
2	Gasoline and other motor fuel	50.91	4.32
3	Food: fresh vegetables	49.55	.40
4	Food: eggs	43.13	.10
5	**Women's luggage**	**34.66**	**.04**
6	**Men's luggage**	**34.66**	**.02**
7	**Transportation services: airlines**	**33.85**	**.37**
8	Purchased LP gas and other fuel	33.83	.13
9	Farm fuel	33.75	.00
10	**Household operation services: natural gas**	**33.48**	**.79**
11	**Personal business services: brokerage/ investment counseling**	**33.33**	**1.13**
12	**Transportation services: intercity railroad**	**31.31**	**.01**
13	Food produced and consumed on farms	27.13	.01
14	Coffee, tea, and beverage materials	23.95	.20
15	Food: fresh fruit	22.76	.28
16	**Tobacco**	**22.22**	**.96**
17	**Personal business services: commercial bank imputed interest**	**20.33**	**1.07**
18	Food: fresh milk and cream	18.97	.21
19	**Durable house furnishings: textile products**	**18.88**	**.07**
20	**Flowers, seeds and potted plants**	**18.84**	**.21**
21	**Other household operation: postage**	**18.62**	**.12**
22	**Computers and peripherals**	**18.03**	**.49**
23	**Infants' clothing**	**17.51**	**.13**
24	**Software**	**17.45**	**.16**
25	**Semidurable house furnishings**	**17.01**	**.46**
26	**Jewelry and watches**	**16.25**	**.66**
27	**Other transportation services**	**15.73**	**.10**
28	**Women's sewing goods**	**15.45**	**.07**
29	**Men's sewing goods**	**15.45**	**.01**
30	**Interstate toll telephone calls**	**14.77**	**.14**

Table 1: The 20 Percent of Components (Expenditure Weighted) with the Highest Sample Volatility (continued)

Rank	Component name (Nonfood, nonenergy items in bold)	Standard deviation	Expenditure weight
31	Food: poultry	14.74	.46
32	**Durable house furnishings: clocks, lamps, and artwork**	**14.58**	**.41**
33	**Transportation services: bridge and road tolls**	**14.29**	**.08**
34	**Housing services: hotels and motels**	**14.23**	**.67**
35	**Transportation services: intercity buses**	**14.21**	**.03**
36	**Other durable house furnishings: floor coverings**	**13.52**	**.20**
37	**China, glassware, tableware, and utensils**	**13.32**	**.40**
38	**Audio equipment**	**12.99**	**.33**
39	**Video equipment other than TVs**	**12.33**	**.14**
40	**Transportation services: net auto insurance premiums**	**12.12**	**.19**
41	**Net purchases of used autos**	**12.05**	**.53**
42	**Records, tapes, and disks**	**11.96**	**.21**
43	**Intrastate toll telephone calls**	**11.67**	**.06**
44	**Transportation services: taxicab**	**11.34**	**.05**
45	Food: beef and veal	10.97	.38
46	Food: other meat	10.90	.24
47	Lubricants	10.86	.06
48	**Small electric appliances**	**10.85**	**.06**
49	**Photographic equipment**	**10.77**	**.05**
50	**Women's and girls' clothing**	**10.71**	**1.71**
51	Household operation services: electric	10.62	1.51
52	Food: pork	10.59	.30

NOTES: Items are ranked by the standard deviation of annualized monthly log price changes, π_t^i. An item's weight is its percentage of total expenditure at the end of the sample.

be surprising, particularly the consumer electronics items: computers, software, audio equipment, and video equipment. Among these, computers, software, and video equipment are items whose log price changes have pronounced longer-run trends. Computers and software, for example, underwent a sustained period of more rapid price decline in the second half of the 1990s, compared with the rates of decline that prevailed before and after. The long-run trend in the log price changes for these items is thus roughly U-shaped. As we'll see in the next section, while price changes for these items have high volatility, a substantial amount of that volatility derives from their lower-frequency movements.

Table 2: Food Items Not Among the 20 Percent of Components (Expenditure Weighted) with the Highest Sample Volatility Listed in Table 1

Rank	Component name	Standard deviation	Expenditure weight
54	Food: fish and seafood	10.19	.16
55	Food: fats and oils	10.07	.14
64	Food: juices and nonalcoholic beverages	8.28	.76
73	Food: processed dairy products	7.83	.46
77	Food: processed fruit and vegetables	7.66	.24
78	Pet food	7.64	.33
87	Alcohol: wine and brandy, off-premise consumption	7.25	.23
102	Food: cereals	6.59	.35
104	Alcohol: beer and ale, off-premise consumption	6.55	.77
116	Food: sugar and sweets	5.40	.45
118	Alcohol: distill spirits, off-premise consumption	5.30	.20
120	Food: bakery products	4.97	.63
124	Other prepared food	4.85	1.31
147	Alcohol in purchased meals and beverages	3.69	.57
167	Food furnished to civilian employees	2.72	.12
168	Purchased meals: elementary school lunch	2.72	.07
169	Food furnished to military employees	2.72	.02
170	Purchased meals: higher-education school lunch	2.72	.09
181	Purchased meals: other than at schools	1.36	4.43

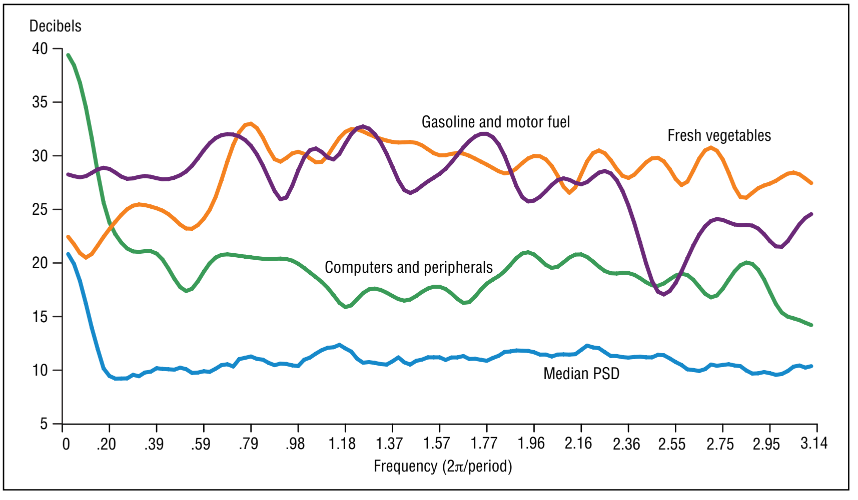
NOTE: The first column gives the item's rank when all 186 items are ordered by the standard deviations of their annualized monthly log price changes, π_t^i.

2. VOLATILITY ACROSS FREQUENCIES

Mishkin (2007) captured well the common-sense rationale behind ex food and energy measures of inflation when he wrote: "When a cold snap freezes the Florida orange crop or a tropical storm hits the gasoline refineries along the Gulf Coast, monetary policy cannot reverse the resulting spikes in prices for fresh orange juice or for gasoline at the pump. Temporary supply shocks such as these raise the prices of food and energy relative to other prices and can have substantial effects on inflation in the short run."

Price changes for food and energy items, it is supposed, display high volatility at high frequencies.[8] Fresh vegetables, the most volatile food component by standard deviation, at first glance appears to come close to this ideal. Figure 2 plots the power spectral density (PSD) of the log monthly price changes (π_t^i) for fresh vegetables.[9] Very roughly, the PSD of a time series provides a graphical representation of the way in which the series' overall volatility is accounted for by movements in the series occurring over different frequencies, much as a graphic equalizer breaks down the content of an audio signal into the parts occupying bass, mid-range and treble frequencies.[10]

Figure 2: Power Spectral Densities of Fresh Vegetables, Gasoline and Other Motor Fuel, and Computers and Peripherals with Median Power Spectral Density of 186 PCE Components



The vertical axis in the figure is in decibel units; that is, if $f_i(\omega)$ denotes the PSD of fresh vegetables at some frequency ω, what's plotted is $10\log_{10}f_i(\omega)$. Thus, a difference of 10 between values of the rescaled PSD at some frequencies ω_1 and ω_2 corresponds to a factor of 10 difference

[8] Mishkin does note the same point made in section 1: that not all food and energy is highly volatile, while other nonfood, nonenergy items are.

[9] The power spectral densities reported in this section are estimated using Welch's nonparametric method with a Hamming window. In particular, I use the pwelch function in MATLAB's Signal Processing toolbox.

[10] More precise definitions can be found, among other places, in Sargent (1979, ch. 11) or Hamilton (1994, ch. 6).

between the values of the unscaled PSD—for example, if the rescaled PSD shown in Figure 2 is 10 units higher at frequency ω_2 than at ω_1, this means $f_i(\omega_2) = 10f_i(\omega_1)$. The horizontal axis is in units of angular frequency, equivalently $2\pi/T$, where T is the period in months. Thus, a value of, say, 0.5 corresponds to a period in months of $2\pi/0.5 \cong 12.6$.

The log monthly price changes for fresh vegetables have considerably more power at frequencies above roughly 0.6—corresponding to a period of about 10 months—than at frequencies below. As a result, a much larger portion of the substantial volatility of this item is concentrated at periods shorter than 10 months than at periods longer than 10 months. On the other hand, compared with the typical PCE item, this item has considerably higher power at all frequencies, except the very lowest. This can be seen by comparing the PSD of fresh vegetables with the series marked "median PSD," which plots the median of the PSDs of all 186 components.[11] Compared with the typical item, fresh vegetables have substantially higher power at all periods shorter than roughly five years (corresponding to 0.10 on the horizontal scale in the figure). The PSD below five years is similar to the median PSD.

Fresh vegetables are not alone among the most volatile items in having relatively high power at what would seem to be fairly low frequencies. Figure 2 also shows the PSDs for log monthly price changes in computers and gasoline. The PSD for computers has a spectral shape similar to the median PSD—relatively abundant power at the lowest frequencies, Granger's (1966) "typical spectral shape"—though with greater power than the median item at all frequencies. Software, video equipment, and televisions have similar spectra.

Gasoline, by contrast, has power that's uniformly high, except for frequencies above roughly 2.3, or about three months in terms of period. Bearing in mind the decibel scale, for all periods longer than roughly three months, the PSD for gasoline displays about 30 to 100 times the power along the median PSD.

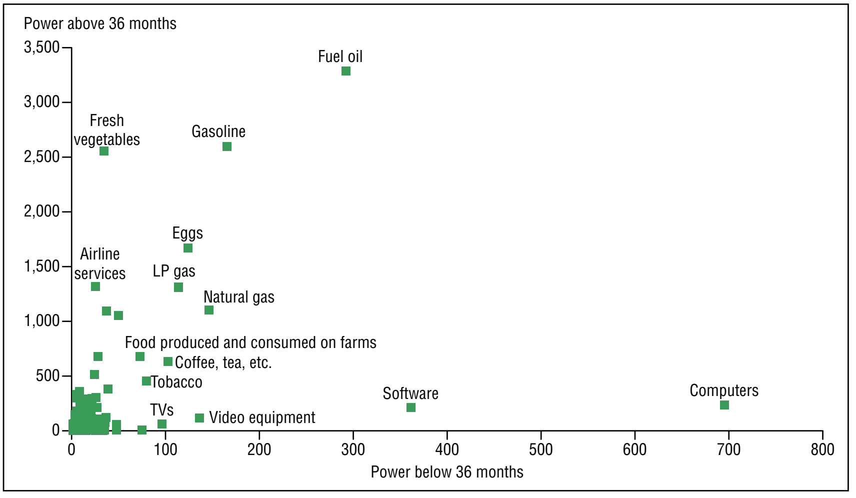
Gasoline obviously has more higher-frequency power than computers (or the median), but its lower-frequency power is not inconsequential. The opposite is true for computers, which dominate in terms of lower-frequency power but nonetheless possess substantial power (relative to the median PSD) at higher frequencies. Are there other items with these properties and, if so, what are they? To answer this question—without showing the reader 186 power spectral densities—I exploit integrals of the PSDs as a means of decomposing a series' overall variance by frequencies. In particular, for each of the 186 PCE components, I calculate the component's average power—the integral of its PSD $f_i(\omega)$—above and below a frequency of $2\pi/36$, or a period of 36 months.

I find that while fresh vegetables, gasoline (together with fuel oil), and computers (together with software) are the most extreme outliers in terms of high- and low-frequency average power, a number of other items also stand out. Figure 3 presents a scatter plot of low-frequency average

[11] This is the median by frequency—i.e., the median of $\{10\log_{10} f_i(\omega) | i = 1,2,\ldots186\}$ at each frequency ω.

power (on the x axis) versus high-frequency average power (on the y axis) for each of the 186 components. Since the integral under a series' spectral density is proportional to its variance, the units on both axes have the interpretation of annualized percentage points squared.

Figure 3: Average Low-Frequency Power vs. Average High-Frequency Power for 186 PCE Components



NOTE: The cut-off frequency is 36 months.

In all, about 20 items stand out from the rest; several of them are highlighted. The remaining 160 or so items form a dense cloud near the origin. Supposing that one's aim is to minimize high-frequency volatility, items that hug the vertical axis—airline services or fresh vegetables, for example—would seem to be natural candidates for exclusion. If preserving low-frequency power is also good, the items along the vertical axis would represent efficient exclusions in the sense that, while there may be other items with more high-frequency power, such items also possess more low-frequency power.[12] The opposite is true with the locus of consumer electronics products highlighted along the horizontal axis: For any one of those items, there are many more with the same or greater high-frequency power but with less low-frequency power.

The other highlighted items occupy a middle ground, distinguished from the vast majority of items along both dimensions. Excluding them might reduce high-frequency volatility, but only at a cost of lost low-frequency signal.

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[12] That is, the direction of preference for making exclusions is toward the northwest of the graph.

3. THE LONGER-TERM EFFECTS OF EXCLUSIONS

Given that many of the most volatile items in the PCE have relatively high power across lower as well as higher frequencies, it seems worthwhile to consider the impact that excluding various items has on the longer-term behavior of measured inflation. The objects of analysis in this section will be a set of price indexes obtained by excluding each of the 186 PCE components—indexes of the form "PCE ex item j" for all 186 js.

The impact of excluding a particular item depends on both the item's time series properties and its weight in the PCE. The expenditure weights discussed thus far have been calculated at a particular point in time (the last month of the sample). The PCE price index is, in fact, a chain aggregate, with weights that vary from month to month. Precisely, the PCE price index evolves over time according to:

$$P_{t+1} = P_t \sqrt{\left(\frac{\sum_{i=1}^{N} Q_t^i P_{t+1}^i}{\sum_{i=1}^{N} Q_t^i P_t^i}\right)\left(\frac{\sum_{i=1}^{N} Q_{t+1}^i P_{t+1}^i}{\sum_{i=1}^{N} Q_{t+1}^i P_t^i}\right)},$$

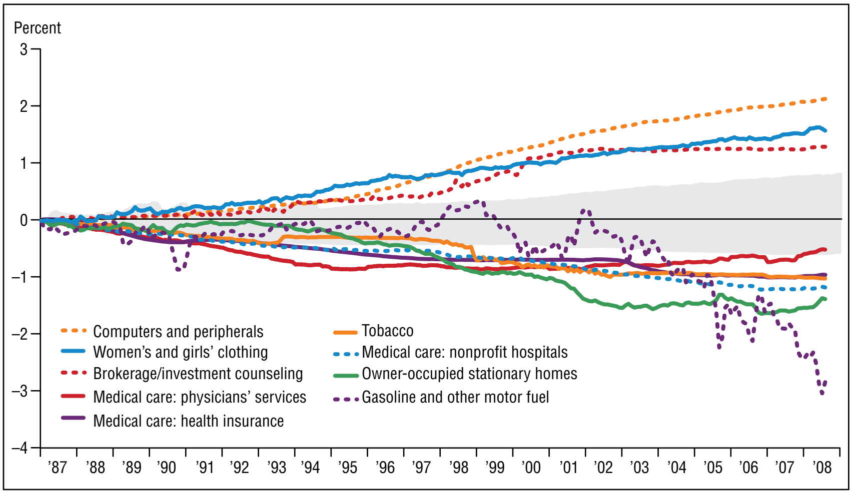
where Q_t^i denotes the real quantity of component i consumed at date t. Our calculations of "PCE ex item j"— denoted $P_t^{\text{ex } j}$—use the above formula, with the summations running over all $i \neq j$. I normalize all the $P_t^{\text{ex } j} = 1$. Given that price index, log monthly price changes are then calculated exactly as described in the section "Data and Notation."

Figure 4 plots $100(\log P_t^{\text{ex } j} - \log P_t)$, where P_1 has also been normalized to equal 1. The values of the 186 series at the end of the sample thus have the interpretation of both the percentage difference between the headline and "PCE ex item j" indexes and the percentage point change, caused by excluding item j, in the total amount of inflation over the sample. Nine series with unusual behavior have been highlighted, while the location of the other 177 series is represented by the gray shaded area. Subsequent figures will have a similar organization.

The $P_t^{\text{ex } j}$ series for most of the 186 items remains in the range of ± 1 percent of P_t through much of the sample. There are, though, a few exceptions. Three series are notably higher than the others, indicating that excluding those items increases measured inflation over the whole sample by an outsized amount. Those series are PCE ex computers, PCE ex women's and girls' clothing, and PCE ex "personal business services: brokerage/investment counseling." These are items that combine substantial relative price declines over the whole sample with relatively large weights in PCE. From Table 1, we know that all three of the excluded items also rank high in terms overall volatility (22nd, 50th, and 11th, respectively).

Several series are notably lower than the rest, indicating that the exclusion of those items decreases measured inflation over the whole sample by an outsized amount. The most prominent of these series is PCE ex gasoline, which stays within the middle cluster of series until about 2004, at which point it falls sharply. The other series are PCE ex "medical care services: health insurance," ex tobacco, ex "medical care services: nonprofit hospitals," and ex owner-occupied stationary homes (aka "owners' equivalent rent"). These items combine relatively large weights with substantial relative price increases (over the whole sample). Only two, however, are among items with very high overall volatility: gasoline (second on Table 1) and tobacco (16th).

Figure 4: Full-Sample Inflation Effects of Excluding j from PCE: Values $100(\text{Log}(P_t^{\text{ex } j}/P_1^{\text{ex } j}) - \text{Log}\,(P_t/P_1))$ for $j = 1,2, \ldots, 186$



NOTE: The shaded area represents the location of all series not explicitly indicated.

Items that combine high overall volatility with outsized impacts on full-sample inflation—computers, women's clothing, brokerage services, gasoline, and tobacco—are items for which one needs to exercise caution when choosing exclusions with an aim of reducing volatility. For these items, the data suggest a trade-off between reducing volatility and distorting the long-run inflation picture. It may well be that the trade-off should be decided in favor of volatility reduction, given the size of the long-run impact. Even a 3 percentage point effect on total inflation over the full sample (about 22 years) only amounts to about a 0.1 percentage point impact on the average annualized rate of inflation over the full sample.

Table 3 shows the impact of excluding computers, women's clothing, brokerage services, gasoline, and tobacco on total inflation and on the average annualized rate of inflation over the sample period. The effect on total inflation is simply the five series' endpoints in Figure 4, which are translated into annualized percentage points to obtain the effect on the average inflation rate.

Perhaps, though, the impact of an item's exclusion on total inflation over the full sample is not the appropriate—or only appropriate—metric for judging the longer-term impact of various exclusions. A small impact over 22 years may mask a larger impact over periods that are shorter—three to five years, for example—but nevertheless extend beyond the horizon of "transitory effects" that we imagine we're excluding (or wish to exclude) in constructing a "PCE ex…" measure of inflation. The series "medical care: physicians' services" in Figure 4 illustrates this point: Through most of the 1990s, it was the item whose exclusion had the largest negative impact on cumulative inflation, though the price index excluding physicians' services found its way back into the pack of less-extreme series by the end of the sample.

Table 3: Values of 100 (Log($P_T^{\text{ex } j}/P_1^{\text{ex } j}$) – Log ($P_T/P_1$)) for Five Items That Combine High Volatility with a Large Impact on Total Inflation Over the Full Sample

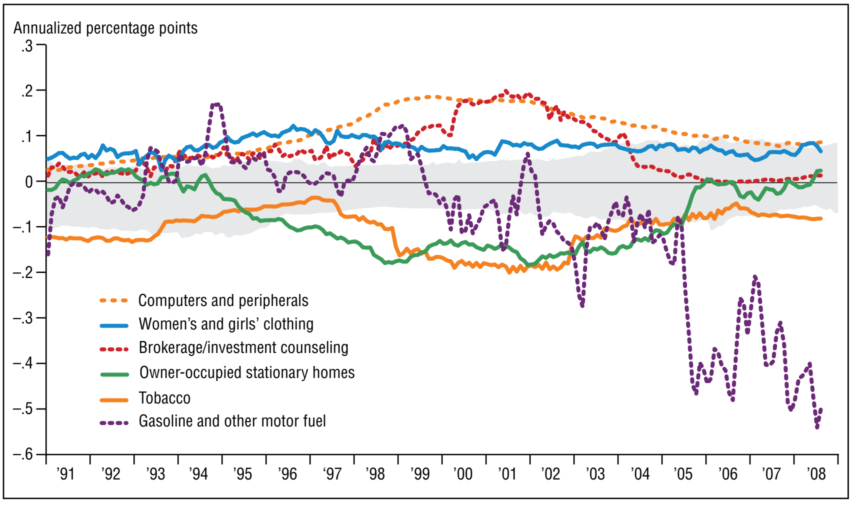
Item excluded	Full sample inflation effect	Effect on average annualized inflation rate
Computers and peripherals	2.16	.10
Women's and girls' clothing	1.59	.07
Personal business services: brokerage/ investment counseling	1.31	.06
Tobacco	–1.02	–.05
Gasoline and other motor fuel	–2.86	–.13

To analyze these medium-term effects, I again examine the behavior of $P_t^{\text{ex } j}$ for each of the 186 PCE components. In this case, I calculate average annual inflation rates over periods of four years (48 months) and compare these rates with the series of four-year inflation rates in headline PCE. In the notation described in the introduction, what I examine is the behavior of $\pi_{t,48}^{\text{ex } j} - \pi_{t,48}$ from month 49 of the sample (January 1991) to the end (August 2008).

The results are shown in Figure 5, which is analogous in form to Figure 4. The usual suspects—the items from Table 3—are again implicated as outliers along with owner-occupied stationary homes. As Figure 5 makes clear, though, each of these items has gone through periods in which its medium-term impact has been larger than the full-sample effect captured in Figure 4. In the second half of the 1990s, for example, the rate of decline in computer prices accelerated; during that period, annualized four-year inflation rates in PCE ex computers exceeded four year-inflation rates in headline PCE by about 0.2 percentage point. The same is true in the early 2000s for PCE ex brokerage/investment counseling. The exclusion of women's and girls' clothing has less extreme medium-term effects, raising the four-year average inflation rate by at most about 0.12 percentage point early in the sample.

Excluding either gasoline or tobacco was shown to have a relatively large downward impact on total inflation over the full sample—at least relative to other highly volatile items and relative to all items except owner-occupied housing and some components of medical care. The same is true to a greater degree with the medium-term impact of excluding gasoline and tobacco. Price increases for gasoline, in particular, over the past several years have been large enough and sustained enough that excluding gasoline from the PCE results in a decrease in the average four-year inflation rate of 0.5 percentage point at the end of the sample period. For tobacco, examining the medium term shows that its full-sample effect given in Table 3 owes much to a few years in the late 1990s and early 2000s when the exclusion of tobacco reduces the four-year average inflation rate by over 0.1 percentage point.

Figure 5: Medium-Term Effects of Excluding Item j from PCE: Values of $\pi^{\text{ex } j}_{t,48} - \pi_{t,48}$ for $j = 1,2, \ldots, 186$



NOTE: The shaded area represents the location of all series not explicitly indicated.

What we also see in Figure 5 is that gasoline has had periods—the mid-1990s and again in the late 1990s—in which inflation in PCE ex gasoline exceeded inflation in headline PCE. Even though PCE ex gasoline departs significantly from headline PCE for sustained periods, one could, prior to around 2005, point to the mix of periods in which this departure was alternately positive and negative to support the view that over the very long term, the exclusion had little impact. How much weight we should give to the experience of the past three years is unclear. Over the last half of 2008, gasoline prices fell to a level last seen in 2004—so perhaps we are entering a period in which the rate of increase in PCE ex gasoline will again exceed the headline rate.

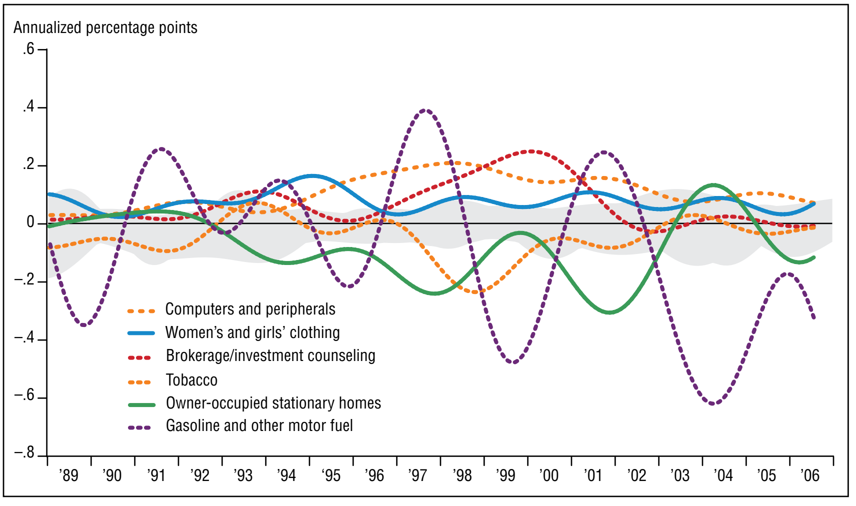
I now turn to a final measure of the longer-term impact of an item's exclusion, motivated by the considerations of power across frequencies in section 3. In this analysis, I filter monthly headline PCE inflation $\{\pi_t\}$ and each of the log monthly price change series $\{\pi^{\text{ex } j}_t\}$ into trend and cyclical components, using a band-pass filter.[13] The pass band is 2–36 months, so

[13] See Baxter and King (1999) or Christiano and Fitzgerald (2003).

the resulting trend captures movements with periods below three years. Given trend estimates for headline PCE and each of the 186 “PCE ex…” indexes, I can then ask which exclusions, if any, produce indexes with trends that differ significantly from the trend in headline inflation.

The results are shown in Figure 6. Analogous to the last two figures, the typical series plotted in Figure 6 is the difference between the trend in $\{\pi_t^{\text{ex } j}\}$ and the trend in $\{\pi_t\}$, so a positive (negative) value over some interval of time indicates that excluding item j results in an inflation measure with higher (lower) trend inflation compared with the headline index over that interval. The gray shaded area again represents the location of all series other than those highlighted.

Figure 6: Trend Effects of Excluding Item j from PCE: Band-Pass Filtered Trend in $\{\pi_t^{\text{ex } j}\}$ Minus Band-Pass Filtered Trend in $\{\pi_t\}$ for j = 1,2, …, 186



NOTES: The pass band is 2–36 months. The shaded area represents the location of all series not explicitly indicated.

The message is, perhaps not surprisingly, similar to that of Figure 5. Computers, women’s and girls’ clothing, brokerage/investment services, gasoline, and tobacco (as well as owner-occupied housing) have the largest impact. The periods over which excluding women’s clothing, brokerage services or tobacco have large trend effects are relatively short, lasting a few years each. The impact of excluding computers is persistent and one-sided. The trend effect of excluding gasoline is the most substantial, though it is neither consistently positive or negative, except at the very end of the sample.[14]

[14] Note that, consistent with the recommendation of Christiano and Fitzgerald, I drop the first and last 24 months of data in Figure 6 based on the imprecision of trend estimates at the endpoints of the sample.

4. EXCLUSIONS THAT REDUCE HIGH-FREQUENCY VOLATILITY

In the previous section, I focused on the longer-term impact of excluding certain items from the PCE. In some ways, the longer-term impact measures a cost associated with exclusion-based indexes—the possible alteration of our view of the medium- or long-term behavior of inflation. The benefit is, hopefully, a reduction in transitory volatility, resulting in a core inflation series whose short-run movements are more likely to be durable relative to those in headline inflation. Or, in the words of Mishkin (2007), "[R]elative to changes in headline inflation measures, changes in core measures are much less likely to be reversed, provide a clearer picture of the underlying inflation pressures, and so serve as a better guide to where headline inflation itself is heading."

Decomposing the various price-change series into trend and cyclical components, as we did in the last section, suggests a natural gauge of the efficacy of individual exclusions in reducing transitory volatility—namely, a comparison of the volatilities of the higher-frequency, cyclical components of each of the $\{\pi_t^{\text{ex }j}\}$ with the cyclical volatility of $\{\pi_t\}$.

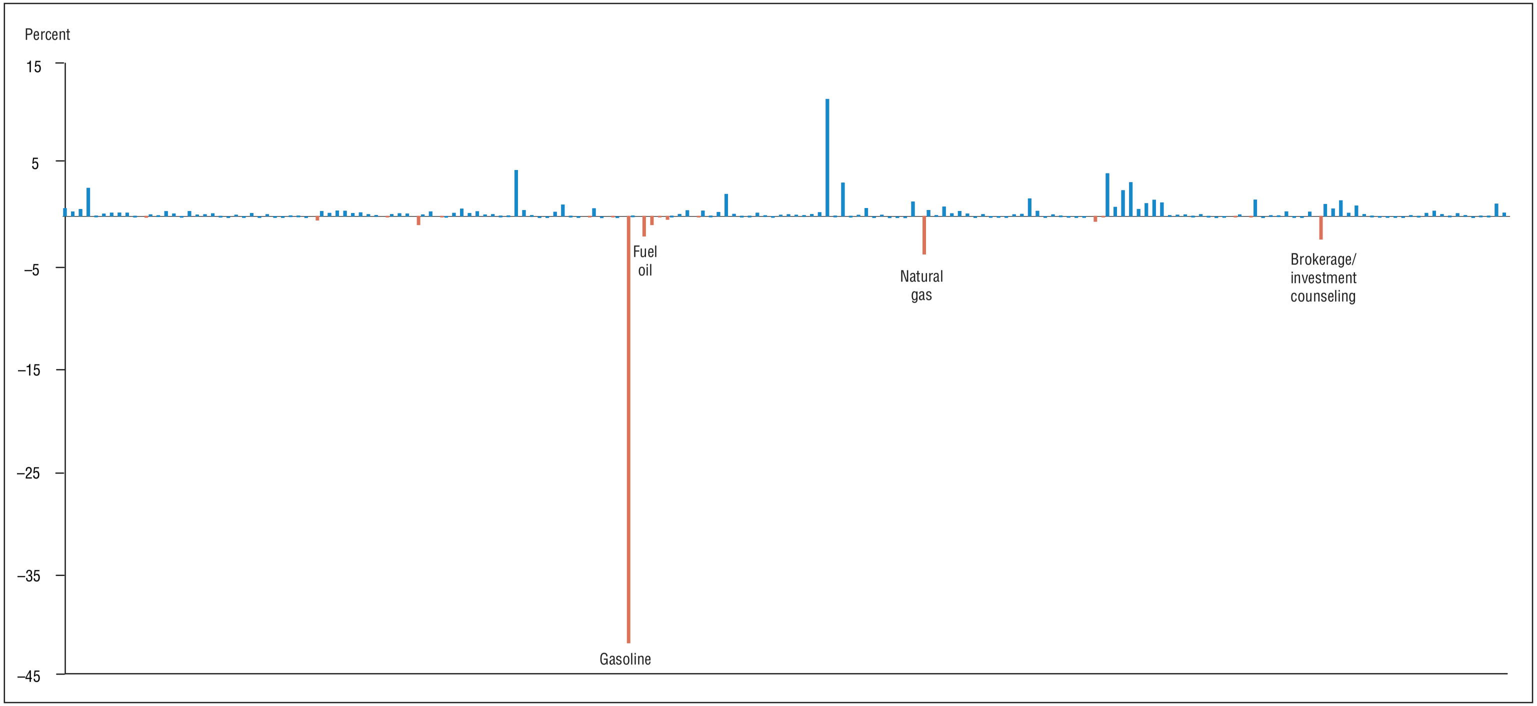
Recall that the filtering exercise from the last section employed a band-pass filter with a pass band of 2–36 months. In this section, we apply the same filter but focus on the cyclical component—corresponding to movements with a period less than three years—rather than the trend. For each $\{\pi_t^{\text{ex }j}\}$, I calculate the standard deviation of the cyclical component minus the standard deviation of the cyclical component of the headline series $\{\pi_t\}$. Negative values indicate that excluding item j produces a series with less cyclical volatility, while positive values indicate the opposite. To facilitate interpretation of the magnitudes, I express all changes in cyclical volatility as a percentage of the cyclical volatility of the headline series $\{\pi_t\}$.[15] These percent changes in cyclical volatility are shown by the bars in Figure 7.

Gasoline, of course, is the extreme outlier in this picture. Surprisingly, though, the number of items for which exclusion reduces cyclical volatility is quite small—only 19, in fact. Excluding any of the remaining 168 items results in an inflation series with higher cyclical volatility than the headline index. The 19 items, together with their percentage reductions in cyclical volatility and their expenditure weights, are presented in Table 4.

Three familiar items are on the list—gasoline, brokerage counseling, and tobacco. This is not surprising given the spectral shapes of the log monthly price changes for these series. (Brokerage counseling and tobacco have PSDs similar to that of gasoline, which we saw in Figure 2. In particular, all three have very high power across all frequencies outside of the very lowest.) Note, too, that the focus on cyclical volatility eliminates computers from the discussion.

[15] The standard deviation of the cyclical component of $\{\pi_t\}$ is 1.83 annualized percentage points.

Figure 7: Changes in Cyclical Volatility from Excluding Each of 186 PCE Components



NOTE: Each bar represents the standard deviation of the cyclical component of $\{\pi_t^{\text{ex } j}\}$ minus the standard deviation of the cyclical component of $\{\pi_t\}$, expressed as a percent of the latter.

Table 4: 19 Items for Which $\{\pi_t^{ex\ j}\}$ Has Lower Cyclical Volatility than $\{\pi_t\}$

Rank	Item excluded	Change in cyclical volatility (percent)	Expenditure weight (percent)
2	Gasoline and other motor fuel	–42.04	4.32
10	Household operation services: natural gas	–3.80	.79
11	Personal business services: brokerage/ investment counseling	–2.34	1.13
1	Purchased fuel oil	–2.04	.16
8	Purchased LP gas and other fuel	–.92	.13
3	Food: fresh vegetables	–.92	.40
7	Transportation services: airlines	–.59	.37
26	Jewelry and watches	–.46	.66
16	Tobacco	–.39	.96
37	China, glassware, tableware, and utensils	–.19	.40
25	Semidurable house furnishings	–.16	.46
172	Recreation services: casino gambling	–.15	.82
4	Food: eggs	–.13	.10
27	Other transportation services	–.05	.10
14	Coffee, tea, and beverage materials	–.05	.20
125	Recreation services: pari-mutuel net receipts	–.02	.07
5	Women's luggage	–.02	.04
6	Men's luggage	–.01	.02
9	Farm fuel	.00	.00

NOTE: The third column gives the change in cyclical volatility as a percentage of the standard deviation of the cyclical component of $\{\pi_t\}$. Rank indicates the item's overall volatility ranking.

Only three food items are on the list—meaning 26 food items, accounting for 95 percent of spending on food, are not. Among energy goods and services, all but lubricants and electricity are on the list. Lubricants and electricity amounted to roughly 23 percent of spending on energy in August 2008 (most of which was electricity).

All but two of the items in Table 4 were also present on the list of the 20 percent most volatile items given in Table 1. Those two items—pari-mutuel betting and casino gambling—actually rank quite low in terms of their overall volatility (i.e., the sample standard deviations of their log monthly price changes).

The top 11 items from Table 1 are on the list, as are the items ranked nos. 14, 16, 25–27, and 37. Those items ranked in the top 37 in Table 1 but absent from Table 4 (i.e., nos. 12–13, 15, 17–24, and 28–36) have aggregate weight of about 4.8 percent of PCE. The aggregate expenditure weight of the 19 items on the Table 4 is 11.1 percent, compared with 20.9 percent for food and energy (or 20.9 percent for the 52 items listed in Table 1).

Notwithstanding the presence on the list of gasoline, brokerage/investment counseling services, and tobacco, one might nevertheless imagine constructing a "PCE ex…" index that excludes the 19 items listed in Table 4. Such an index, compared with PCE ex food and energy, would exclude a much smaller share of expenditures and be more narrowly focused on the aim of reducing transitory volatility. If such an index proved superior to PCE ex food and energy according to standard criteria—for example, ability to the track the trend in headline PCE inflation or forecast headline PCE inflation—the index might be preferable to PCE ex food and energy.

The reductions in cyclical volatility given in Table 4 represent the effect of excluding items one at a time from PCE. It's possible, depending on the covariance structure between the components, that excluding items as a group could have a much different effect. Ideally, one would solve for the group of items which, when excluded, would yield the largest decline in cyclical volatility—subject, of course, to some constraint on the maximum size of the group, measured by expenditure weight.[16] Unfortunately, such an optimization problem is unmanageable: The set of all subsets of $\{1, 2, \ldots, 186\}$, obeying anything other than a very tight constraint on the sizes of the subsets, is massive.

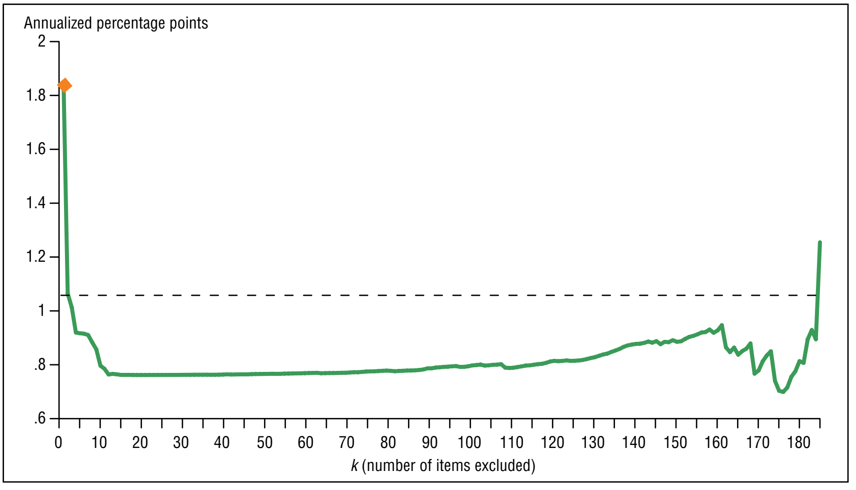
As an alternative, consider the following exercise: Order all 186 PCE components from largest reduction in cyclical volatility to largest gain in cyclical volatility (i.e., extend Table 4 to cover all 186 components). Now, imagine excluding the first k items, as k ranges from 0 to 185 ($k = 0$ corresponds to the headline PCE index, while $k = 185$ is the index consisting solely of the component at the bottom of the list, which happens to be owner-occupied housing). For each value of k, we calculate the standard deviation of the cyclical component of the log monthly price changes for the index excluding items 1 through k.

Figure 8 plots the resulting cyclical standard deviations at each value of k. Note the large reduction one obtains from excluding the first several items. The point where the curve first flattens out is near $k = 19$—i.e., when all the items from Table 4 have been excluded. The cyclical standard deviations remain basically flat until around $k = 60$, then rise until only a handful of items remain in the index. At that point—well past any plausible cutoff for the total size of the exclusions—the behavior of the standard deviation becomes highly erratic.

[16] Without this constraint, the solution might very well exclude all but one item.

The horizontal line plotted along with the series of cyclical standard deviations is the standard deviation of the cyclical component of inflation in PCE ex food and energy. Thus, excluding just the 19 items on Table 4 gives a substantial reduction in cyclical volatility even relative to PCE ex food energy, which represents exclusions amounting to twice the expenditure weight as the items from Table 4.

Figure 8: Standard Deviations of the Cyclical Component of Annualized Log Monthly Changes in PCE Excluding the *k* Items Giving the Largest Reductions in Cyclical Volatility, $k = 0, 1, \ldots, 185$



NOTE: The dotted line is the standard deviation of the cyclical component of PCE ex food and energy, the diamond that of headline PCE.

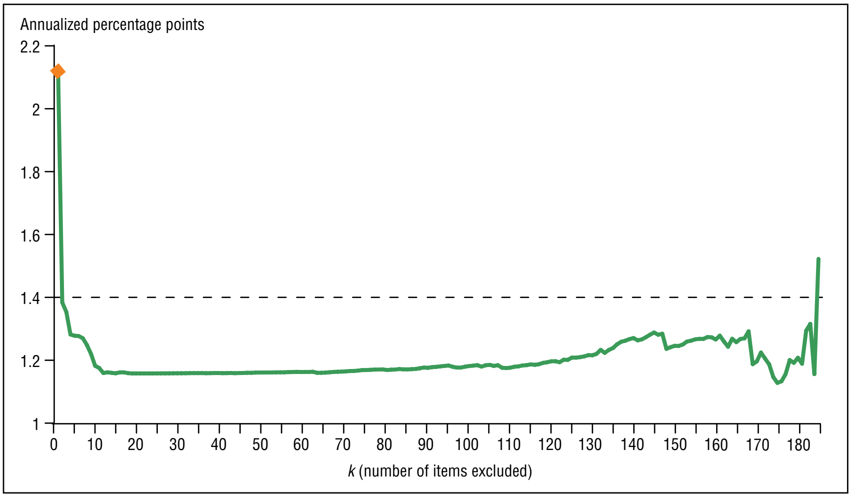
Excluding those items yielding the largest reductions in cyclical volatility also produces an inflation rate with less overall volatility than either the headline index or PCE ex food and energy. “Overall volatility” here denotes the standard deviation of the log monthly price changes coming from the various indexes, calculated over the full sample. This is illustrated in Figure 9, which has a similar structure to Figure 8, except that I plot overall volatilities rather than cyclical volatilities.

Clearly, our price index obtained by excluding the items on Table 4—call it “PCE ex 19”—has some advantages over PCE ex food and energy, achieving lower cyclical and overall volatility, while excluding about half as many items by expenditure weight. How does this index compare with ex food and energy along other dimensions? Two common metrics for evaluating a core inflation index are the index’s ability to track the trend in headline inflation and forecast future headline inflation.

To implement the first metric, I again utilize the band-pass filter, with the same 2–36-month pass band. Let $\{\pi_t^{\mathrm{Tr}}\}$ denote the trend in log monthly headline PCE inflation, and let $\{\pi_t^{\mathrm{ex\ 19}}\}$ denote log monthly inflation in PCE ex 19. As a measure of distance between $\{\pi_t^{\mathrm{Tr}}\}$ and $\{\pi_t^{\mathrm{ex\ 19}}\}$, I compute the mean absolute deviation, or MAD:

$$\frac{1}{T}\sum_{t=1}^{T}\left|\pi_t^{\mathrm{Tr}} - \pi_t^{\mathrm{ex\ 19}}\right|.$$

Figure 9: Standard Deviations of Annualized Log Monthly Changes in PCE Excluding the *k* Items Giving the Largest Reductions in Cyclical Volatility, *k* = 0, 1, ..., 185



NOTE: The dotted line is the standard deviation of PCE ex food and energy, the diamond that of headline PCE.

I also perform the same calculation using either $\{\pi_t^{\mathrm{ex\ F\&E}}\}$, the log monthly inflation rates from PCE ex food and energy, or $\{\pi_t\}$, the log monthly inflation rates for headline PCE, instead of $\{\pi_t^{\mathrm{ex\ 19}}\}$. Table 5 shows the results of these calculations. Among the three indexes—headline PCE, PCE ex food and energy, and PCE ex 19—PCE ex 19 has the smallest MAD with respect to the trend in headline inflation. As shown in the third column, the MAD of PCE ex food and energy is 1.4 times as large as the MAD of PCE ex 19, while the MAD of headline PCE is over two times as large.

Given that the items excluded from PCE ex 19 were chosen on the basis of reductions in the cyclical volatility of inflation, it's not that surprising that the index's inflation rate hews more closely to trend inflation than does inflation in PCE ex food and energy. Whether PCE ex 19 should have superior forecasting ability or not is less obvious.

With regard to the evaluation of an index's forecasting ability, one approach would be to use the index's average rate of inflation over the recent past—the last one, six, or 12 months, for example—as one of several variables on the right-hand side of a forecasting equation, with average headline inflation over some horizon—the next 12, 24, or 36 months, say—as the object being forecast. The other right-hand-side variables might be measures of resource utilization, such as the unemployment rate or capacity utilization rate. This is not the approach I take here. Instead, I evaluate the ability of each index's recent past, alone, to forecast future headline inflation. While forecasts of this type ignore potentially useful nonprice information, I think they better reflect the use to which core inflation measures are typically put. Knowing which core index performs best in this restricted forecasting framework is useful, even if the winner would be dominated by a more sophisticated forecasting equation.

Table 5: Mean Absolute Deviations from the Trend in Headline Inflation

Index	MAD, in percentage points	MAD/minimum MAD
Headline PCE	1.35	2.15
PCE ex food and energy	.90	1.43
PCE ex 19	.63	1.00

To evaluate the three inflation indexes—headline, ex food and energy, and ex 19—in a manner consistent with the practice described above, I calculate annualized log inflation rates over various differencing horizons (through 12 months) for each of the three indexes, then calculate the mean absolute deviation between those inflation rates and annualized headline inflation over the coming 12, 18, 24, and 36 months. For example, using the subscript notation described in the introduction,

$$\frac{1}{T}\sum_{t=1}^{T}\left|\pi_{t+24,24} - \pi_{t,12}^{\text{ex F\&E}}\right|$$

measures the accuracy of inflation in PCE ex food and energy over the past 12 months in predicting inflation in headline PCE over the next 24 months. More generally,

$$\frac{1}{T}\sum_{t=1}^{T}\left|\pi_{t+h,h} - \pi_{t,d}^{\text{ex F\&E}}\right|$$

measures the accuracy of d-month inflation in PCE ex food and energy in predicting h-month inflation in headline PCE.

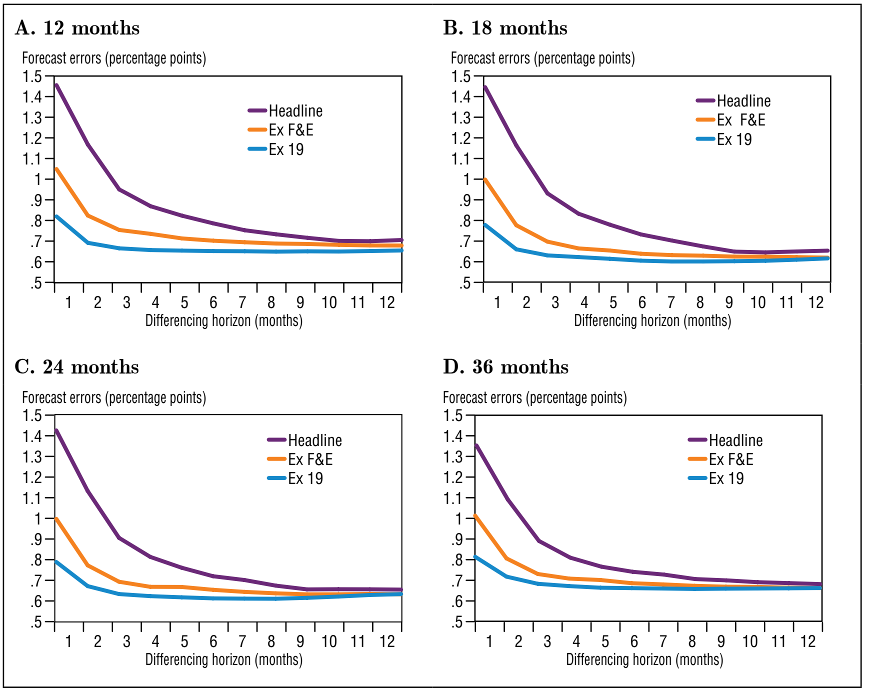
The four panels of Figure 10 show the results for forecast horizons of $h = 12$, 18, 24, and 36 months. The horizontal axes measure the differencing horizon ($d = 1$ to 12 months), and the vertical axes are in annualized percentage points. Each panel contains three series, one each for headline PCE, PCE ex food and energy, and PCE ex 19.[17]

With one exception, the mean absolute forecast errors for PCE ex 19 are the smallest of the three at each forecast and differencing horizon.

[17] In each panel, the sample period is the largest subset of the full sample that is consistent with the forecasting horizon and the longest differencing horizon.

The one exception is at a forecast horizon of 24 months and a differencing horizon of 12 months (the right edge of panel C of the figure), where PCE ex food and energy has a slightly smaller error (0.62 percentage points versus 0.63 percentage points). Of course, when the differencing horizon is 12 months, the errors for PCE ex 19 and PCE ex food and energy differ only negligibly in at least three of the four panels.

Figure 10: Mean Absolute Forecast Errors $(1/\mathrm{T})\Sigma^{\mathrm{T}}_{t=1}|\pi_{t+h,h} - \pi^{f}_{t,d}|$ for f = Headline PCE, PCE ex Food and Energy, and PCE ex 19; d = 1, 2, ..., 12; and h = 12, 18, 24, and 36



Thus, for this particular test of predictive ability, the PCE ex 19 index performs better (or at least no worse) than PCE ex food and energy, though in some cases, the difference in performance of the two indexes is negligible.

One issue that immediately comes to mind, given these results, is robustness. The time-series volatilities of PCE items can change over time, owing to changes in market structure or changes in BLS/BEA methodology, so the items listed in some future version Table 4 might not be the 19 items listed here. Also, the identification of those items relied on filtering the various inflation series into trend and cyclical components, and the accumulation of additional data may alter that trend–cycle decomposition, especially in the later part of the sample.

As a robustness check, I repeated the exercises of this section for a shorter, more recent sample period, August 1997 to August 2008.[18] This is roughly the second half of the full sample period. What I find, not surprisingly, is that the analogue of Table 4 (the set of items that, excluded individually, reduce cyclical volatility) is different, though only slightly. The set consists of 18 items. Three items from Table 4 do not appear on the analogous list for the more recent sample period: "coffee, tea, and beverage materials," "transportation services: airlines," and "other transportation services." Two items that would be excluded using the shorter sample do not appear on Table 4: "food: fats and oils" and "food produced and consumed on farms."

As I did with PCE ex 19, I also constructed a "PCE ex…" index excluding the 18 items drawn from the more recent sample period—Table 4 plus "food: fats and oils" and "food produced and consumed on farms" and less "coffee, tea, and beverage materials," "transportation services: airlines," and "other transportation services." Using data for the more recent sample period, I repeated the exercises above, comparing the performance of the "PCE ex…" measure (call it PCE ex 18) to both headline PCE and PCE ex food and energy, in terms of volatility (cyclical and overall), ability to track the trend in headline inflation, and ability to forecast headline inflation.

Table 6 summarizes the results with respect to volatility and adherence to trend inflation. The volatility numbers are standard deviations of annualized log percent changes, constructed in the same manner as the series shown in Figures 8 and 9. The units are in annualized percentage points. Adherence to trend inflation is measured as the mean absolute deviation between each listed series and the band-pass filtered trend in headline PCE inflation.

Table 6: Results for the Subsample, August 1997 to August 2008

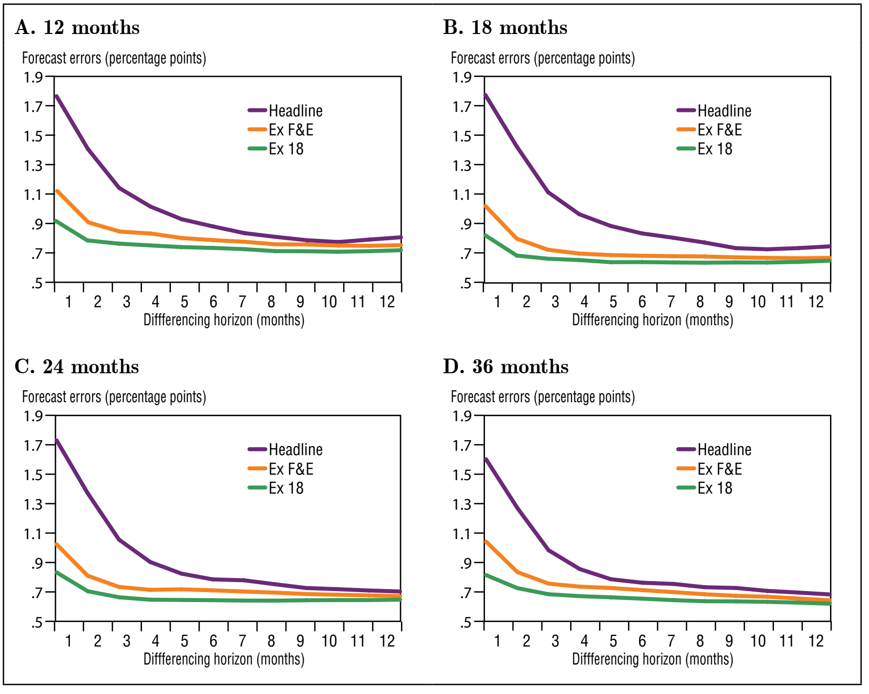
Index	Cyclical volatility	Overall volatility	MAD with respect to trend, in percentage points
Headline PCE	2.17	2.41	1.63
PCE ex food and energy	1.00	1.03	.93
PCE ex 18	.72	.87	.64

NOTES: Cyclical volatility and overall volatility are analogous to the numbers shown in Figures 8 and 9; MAD is analogous to the data given in Table 5.

[18] I use the full sample, though, for the band-pass filtering, eliminating the need to discard observations from the early part of the shorter sample.

The four panels of Figure 11—analogous to Figure 10—summarize the results for forecasting ability. Note that in all cases, PCE ex 18 over the more recent sample period performs as well relative to headline PCE and PCE ex food and energy as PCE ex 19 does over the full sample period.

Figure 11: Forecasting Results for the Subsample August 1997 to August 2008; Mean Absolute Forecast Errors $(1/T)\Sigma_{t=1}^{T}|\pi_{t+h,h} - \pi_{t,d}^{f}|$ for f = Headline PCE, PCE ex Food and Energy, and PCE ex 18; d = 1,2, ..., 12; and h = 12, 18, 24, and 36



None of the results, though, should be viewed as sidestepping the implications of Rich and Steindel's 2007 analysis—no one core measure is apt to dominate all alternative measures across every performance metric and sample period. The results do suggest that core measures derived by excluding items that contribute to cyclical volatility in headline inflation may be useful additions to the set of alternative measures.

5. CONCLUSIONS

A handful of items in the PCE are “special” in the sense of having outsized impact on either the high-frequency volatility of PCE inflation or its longer-term behavior. These items include gasoline and other motor fuel, tobacco, fresh vegetables, women’s and girls’ apparel, brokerage/investment services, computers, software, owner-occupied housing, and a few others. The behavior of price changes for these series—or price changes for PCE excluding them—differs sharply from the behavior of comparable quantities for the vast majority of items making up the PCE. The very different behavior of these items makes them a natural focus of any exclusion-based measure of core PCE inflation, but the results also suggest caution in dealing with some of them.

We can identify exclusions that produce outsized effects on the measurement of longer-term inflation. We can also identify exclusions that produce improvements in the higher-frequency volatility of inflation. It would be nice if there were no intersection between the items on the two lists. Unfortunately, the lists do overlap—the consequence of several items that display high volatility across a wide range of frequencies. Excluding these “problematic” items—in particular gasoline, brokerage/investment services, and tobacco—produces price indexes with less higher-frequency volatility than headline PCE but also with longer-term behavior that departs from the longer-term behavior of headline PCE to a much greater extent than is the case with the typical PCE item.

I thus highlight a trade-off, or tension, in the exclusion of certain items from PCE, though I do not propose a resolution to that tension. That is both a failing of the present paper and a direction for future work.

Trade-offs notwithstanding, in the penultimate section of the paper, I consider a “PCE ex…” index that excludes only those items that contribute to higher-frequency volatility in inflation—that is, items which, when excluded, lower the volatility of the cyclical component of log price changes in PCE. This index includes some energy and almost all food items. By expenditure weight, it excludes about half as many items as the PCE ex food and energy index, which it dominates in terms of overall volatility, cyclical volatility, proximity to the trend in headline inflation, and ability to forecast future headline inflation. Any index with these properties would seem to be an obvious object for further study.

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