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The Role of Commodity Prices in Forecasting U.S. Core Inflation

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Abstract: This note documents a curious finding about the substantial forecast ability of a simple aggregator of three commodity futures prices for U.S. core inflation. The proposed aggregator reduces the out-of-sample root mean squared error for 12-month-ahead inflation forecasts of the benchmark AR(1) model by 28 percent (20 percent) for the PCE (CPI) measure of core inflation. To avoid obfuscation of the sources of forecast ability, the model is intentionally kept simple, although extensions for improving and increasing the robustness of the forecast procedure are also discussed.

JEL classification: C53, E37, G12

Key words: core inflation, commodity futures, convenience yields, forecasting

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1 Introduction

It is a widely accepted fact that U.S. core inflation is notoriously difficult to forecast. Numerous studies have reported the elusive predictability of U.S. inflation over the post-war period using a standard predictive framework and the recent literature has shifted to unobserved component models (Stock and Watson, 2007) and disaggregated data (Stock and Watson, 2015). The lack of robust predictors for trend inflation is rather unfortunate given the importance of core inflation for conducting and communicating monetary policy. In this note, I document some surprising success at forecasting 12-month ahead core inflation by exploiting particular transformations of futures commodity prices. More specifically, I construct (interest-adjusted) spreads of commodity futures prices (convenience yields, CYs) which reflect market expectations about future economic conditions and are believed to contain information about aggregate (excess) demand in the economy. As an added advantage, these CYs tend to purge the noise in raw prices and induce stationarity (with persistence similar to that exhibited by inflation). Given the highly heterogeneous nature of the different commodities, I try to identify individual commodities, not necessarily from the non-food/non-energy category, whose sources of variations appear to have inflationary consequences. I then isolate the common variation in the CYs of these commodities by averaging and smoothing. The resulting series proves to possess systematic predictive power for the annualized core inflation by tracking closely its future movements, especially during the most recent period (since the early 2000s).

As described above, the objective of this note is fairly narrow in scope: to document and characterize the predictive information contained in futures commodity prices. It extends the work in Gospodinov and Ng (2013) by focusing the analysis on specific commodities and core inflation. While the source of the forecasting success of these commodities is believed to be related to their ability to encompass information about future global and domestic excess demand, this conjecture has not been thoroughly investigated. Furthermore, a better aggregation of the information from these commodities and models is also left for future research. Various ways of forecasting improvement and robustification are discussed in the concluding remarks. In what follows, I will provide some motivation for the proposed predictor and present the out-of-sample forecasting results.

2 Data and Heuristics

The sample period for the analysis is January 1988 – December 2015 and is dictated by availability (and sufficient liquidity) of the commodity price data. I focus on two measures of core inflation: (i) CPI (excluding food and energy, source: BLS) and (ii) PCE (excluding food and energy, source: BEA), both of which are seasonally adjusted. In this note, I use only annual (12-month) inflation rates computed as

$$inf_t = 100 \times \frac{(P_t - P_{t-12})}{P_{t-12}},$$

where P_t is either the CPI or PCE index. Similar results are obtained when inflation is constructed as $inf_t = 100 \times [\ln(P_t) - \ln(P_{t-12})]$. The forecasting horizon is also 12-month (1-year) ahead.

Figure 1 plots the core and headline inflation rates based on CPI and PCE indices. By construction, the core inflation is much less volatile than its headline counterpart (the variance ratio of headline to core inflation is 1.7 (1.6) for CPI (PCE) index) while their unconditional means are very similar. In general, core inflation is more persistent than headline inflation with first-order autocorrelation of 0.982 and 0.988 for CPI and PCE, respectively.

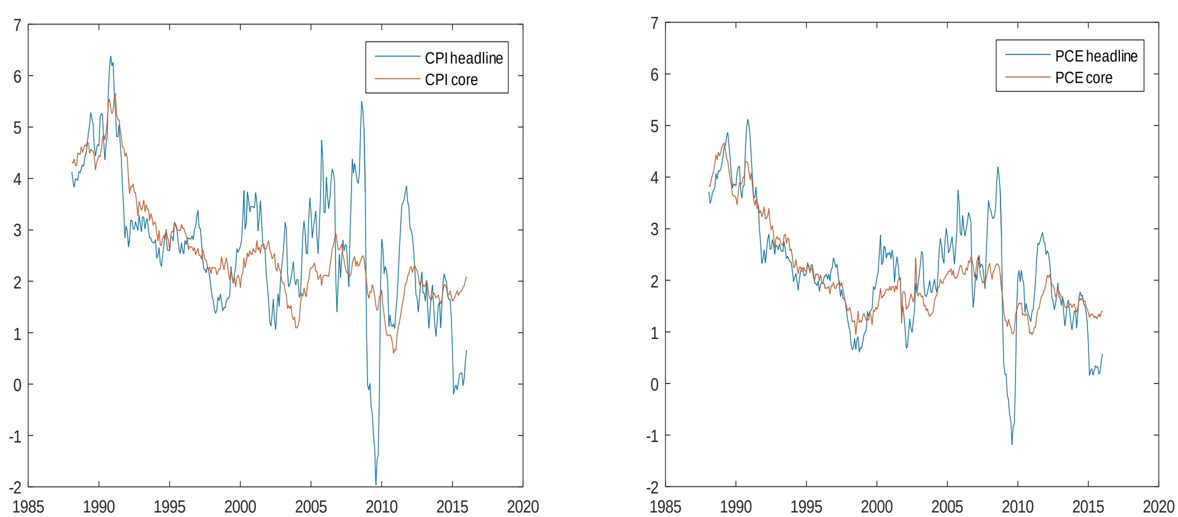

Figure 1. Headline and core annual inflation based on CPI (left) and PCE (right) index.

The commodity (nearest and next-to-nearest) futures price data is from Bloomberg and is sampled at monthly frequency as the last available observation for the month. While data for this sample period is available for 22 commodities, in this note I use data only for 3 commodities: *copper* (standardized (25,000 lbs.) contracts traded on NYMEX with contract months March, May, July, September and December), *live cattle* (standardized (40,000 lbs.) contracts traded on CME with contract months February, April, June, August, October and December) and *orange juice* (standardized (15,000 lbs.) contracts traded on NYBOT with contract months January, March, May, July, September and November).

Since nominal commodity prices are possibly non-stationary and exhibit occasional spikes across all maturities (due to supply, geopolitical or weather disruptions, for example), it is desirable to subject these prices to a transformation that will render them stationary with a dynamics similar to that of annual inflation. It turns out that working with their convenience yield, interpreted as a "dividend flow" to the holder of the commodity, provides both statistical and economic benefits for the data analysis. First, convenience yields, defined below, induce stationarity while they still preserve some persistence of the underlying commodity prices. Second, convenience yields are a forward looking variable that contains information about future excess demand (see Gospodinov and Ng, 2013, and the references therein).

More specifically, let S_{jt} and $F_{jt,n}$ denote the nearest (a proxy for the spot) and next-to-nearest futures price of commodity j for delivery at time $t+n$ and $i_{t,n}$ be the nominal interest earned between period t and $t+n$. The percentage convenience yield (net of insurance and storage costs) for commodity j is computed as

$$cy_{jt} = 100 \times \frac{(1 + i_{t,n})S_{jt} - F_{jt,n}}{S_{jt}}, \qquad (1)$$

using the three-month U.S. Treasury bill as $i_{t,n}$, adjusted for the time that separates the two futures contracts.

Extracting the common variation in the different convenience yields is typically achieved by some type of averaging or principal component analysis. To keep things simple, define the average convenience yield as $\overline{cy}_t = \sum_{j=1}^{3} \widetilde{cy}_{jt}$, where $\widetilde{cy}_{jt}$ denote the standardized (mean 0 and variance 1) convenience yield for commodity j. To further reduce the noise in this aggregator, I smooth the series by a moving average filter over the last k months. In particular, I use a one-sided moving average filter with exponentially decreasing weights $\phi(1-\phi)^i$ for $\phi = 0.2$ and $i = 1, ..., 12$ ($k = 12$) to smooth the series. This smoothing also mimics and summarizes the properties of the empirical predictive model employed in the next section.

Figure 2 presents the dynamics of annual PCE core inflation rate at time $t + 12$ and the smoothed convenience yield factor at time t. Both series are aligned to facilitate direct visual comparison. It is important to emphasize that the convenience yield factor is lagged 12 months; i.e., it is constructed using information in futures commodity prices that is available only up to time t.

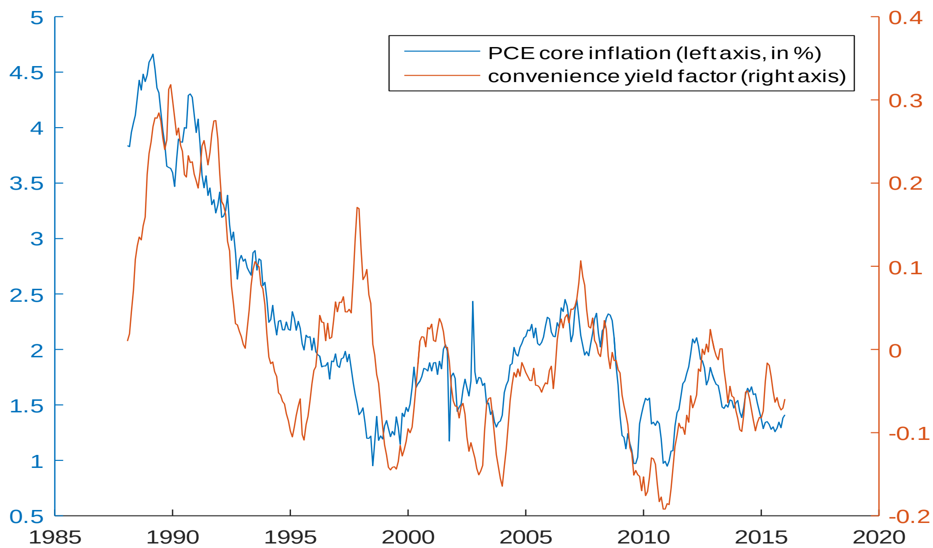

Figure 2. PCE core inflation at time $t+12$ and smoothed convenience yield factor at time t.

While the convenience yield factor is slightly more volatile, it tracks the future movements in core inflation strikingly well. This is especially true for the second half of the sample period when the core inflation process became particularly difficult to forecast. This evidence is suggestive that commodity markets aggregate potentially useful information (possibly a global and domestic demand component) for forecasting the underlying trend in inflation.

3 Main Results

The proposed model for forecasting core inflation is based on the following simple regression

$$inf_{t+12} = \alpha + \sum\nolimits_{i=1}^{p} \beta_i \overline{cy}_{t-i+1} + \varepsilon_t, \tag{2}$$

where $p = 12$ in the results presented below. I refer to the model in (2) as CY model. For the sake of comparison, I also report results from an AR(1) model and a random walk (RW) model for inflation. The in-sample fit of the CY model is very good as evident from Figure 3 below that plots the fitted and actual core inflation based on CPI (left graph) and PCE (right graph). It is worth pointing out that the CY model (2) does not include past values of inflation as predictors. The information about the future level and dynamics of core inflation comes only from the aggregated convenience yields of copper, live cattle and orange juice. In this sense, CY and AR (RW) models are non-nested and the CY model provides independent information.

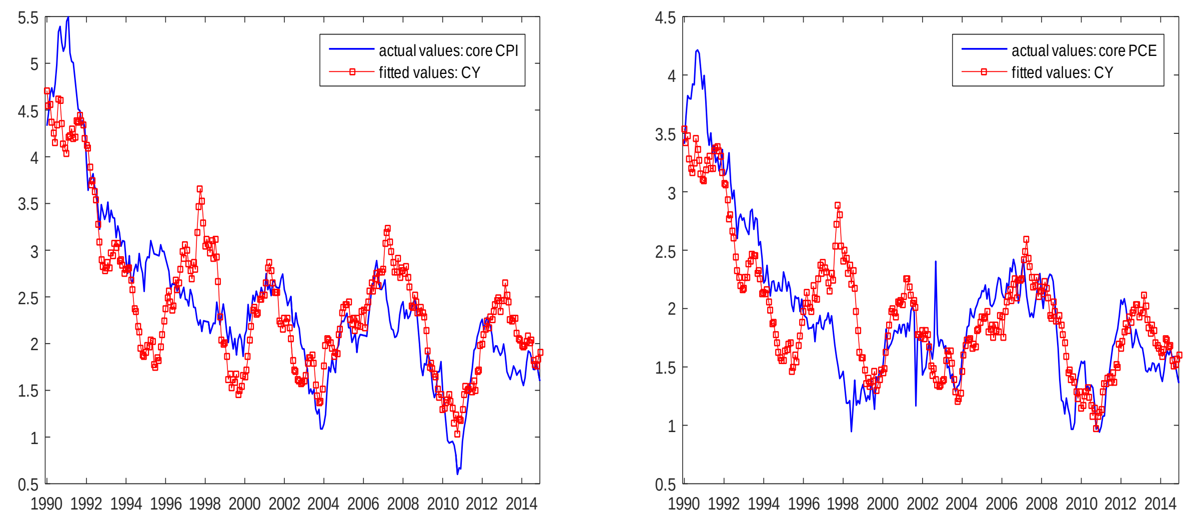

Figure 3. Actual core inflation rates and fitted values from the CY model (2).

While the fit of the CY model is good over the whole period, it markedly improved for the last 15 years of the sample. This is likely due to the increased liquidity of the futures commodity markets. Another possibility is that the underlying fundamentals that determine U.S. core inflation have shifted and since 2000 core inflation is more dependent on factors (say, global demand) that are reflected in the convenience yields.

I now turn to recursive pseudo out-of-sample evaluation of the model. The initial estimation sample is January 1988 – December 1999. This estimation sample is updated recursively by adding one month to the estimation sample. The out-of-sample forecast period is January 2000 – December 2015. The out-of-sample forecasts from the CY and AR(1) models are presented in Figure 4.

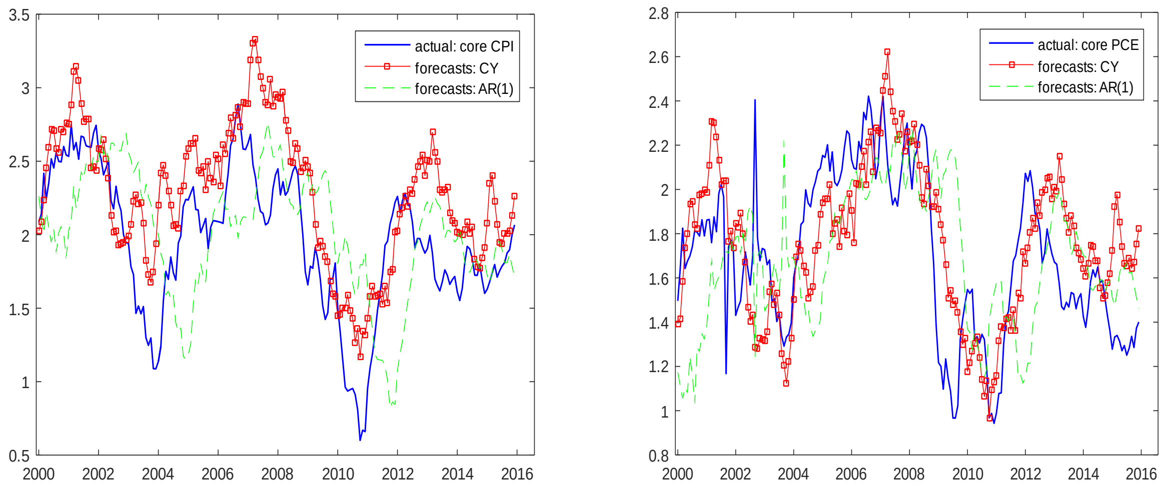

Figure 4. Actual core inflation and out-of-sample forecasts from CY and AR(1) models.

The formal forecast evaluation of the different model is performed using three criteria. First, I compute the root mean squared error (RMSE) as $\sqrt{\frac{1}{n}\sum_{j=1}^{n}\left(inf_j - \widehat{inf}_j\right)^2}$, where inf denotes the actual inflation rate, $\widehat{inf}$ denotes the model forecast and n is the number of out-of-sample observations ($n = 192$). An alternative way of reporting the results is the out-of-sample coefficient of predictive performance OS (Campbell and Thompson, 2008) computed as

$$OS = 1 - \frac{\sum_{j=1}^{n}\left(inf_j - \widehat{inf}_j\right)^2}{\sum_{j=1}^{n}\left(inf_j - \overline{inf}_j\right)^2},$$

where $\overline{inf}$ is the forecast from a benchmark model. I use the AR(1) model as the benchmark. If the value of OS is less than zero, the benchmark performs better than the corresponding (CY or RW) model and if OS is greater than zero, the model dominates the benchmark.

Table 1 reports the RMSE and OS for the different models.

Table 1. Evaluation of out-of-sample forecasting results.

	core CPI		core PCE	
	RMSE	OS	RMSE	OS
AR	0.5561		0.4226	
RW	0.5697	-0.0495	0.4441	-0.1044
CY	0.4448	0.3601	0.3043	0.4816

Consistent with Figure 4 above, Table 1 shows that the CY model outperforms substantially the AR(1) model. The RMSE of the CY model is 28% smaller than that of the AR(1) model for the PCE core inflation. The corresponding RMSE reduction for the CPI core inflation is 20%. The values of the *OS* coefficient are also very large in favor of the CY model. RW model is dominated by both AR(1) and CY models.

Another convenient approach to evaluating forecasts from competing models is the Mincer–Zarnowitz regression (Mincer and Zarnowitz, 1969). The Mincer–Zarnowitz regression has the form

$$inf_j = a_0 + a_1 \widehat{inf}_j + error$$

for $j = 1, \ldots, n$. If the forecasts are unbiased, then $a_0 = 0$ and $a_1 = 1$. Table 2 reports the estimates (along with their Newey-West standard errors) and R^2's from the Mincer–Zarnowitz regressions for the different models.

Table 2. Mincer-Zarnowitz regression results.

	core CPI			core PCE		
	AR	RW	CY	AR	RW	CY
$\hat{a}_0$	1.4254	1.3999	0.1215	1.3109	1.2960	0.5086
	(0.3811)	(0.3454)	(0.2699)	(0.3858)	(0.3272)	(0.1840)
$\hat{a}_1$	0.2674	0.2844	0.8081	0.2339	0.2397	0.6807
	(0.1788)	(0.1607)	(0.1130)	(0.2414)	(0.2017)	(0.1031)
R^2	0.0543	0.0804	0.6014	0.0385	0.0576	0.3935

Notes: Newey-West standard errors are reported in parentheses below the estimates.

The AR(1) and RW forecasts are far from being unbiased as the estimates of both a_0 and a_1 deviate substantially from their values under the null hypothesis. The R^2's for these two models are low and vary between 4% and 8% for the CPI and PCE measures of core inflation. In contrast, the CPI core inflation forecasts from the CY model cannot reject the unbiasedness hypothesis that $a_0 = 0$ and $a_1 = 1$. The R^2 for the CY model forecasts has an impressive value of 60%. While the CY model forecasts for PCE core inflation perform slightly worse, they still significantly outperform the AR(1) and RW model forecasts.

4 Discussion and Concluding Remarks

This note documents and evaluates the substantial forecasting power of three convenience yields for forecasting U.S. core inflation. While the problem of identifying a theoretically sound and empirically successful model for describing and predicting the inflation process is still left largely unresolved, I show that glancing at aggregated information embedded in convenience yields can inform policy makers and market participants about the future dynamics of core inflation. The benefits of this predictive information are further enhanced by the real-time, high-frequency availability of futures commodity prices. This allows for the development of mixed frequency models for nowcasting and forecasting. The documented forecast ability of commodity prices for inflation motivates the integration of futures commodity prices in more structural models such as a term structure model of real yields and inflation derivatives as in Gospodinov and Wei (2016).

Many interesting issues suggested by the empirical regularities between past convenience yields and future core inflation warrant further investigation and analysis. It is conjectured that the reported predictive power is likely due to an underlying demand component that is reflected in convenience yields, where copper plays the role of a global demand proxy while live cattle and orange juice capture domestic demand. More work linking convenience yields to the index of global economic activity of Kilian (2009) and the Chicago Fed national activity index may shed light on this conjecture.

To better elicit the main findings, the predictive model in this paper was intentionally kept simple. More sophisticated models where convenience yields are combined with other predictors are obviously the next natural step in the empirical analysis. Some experimentation showed that level adjustments or intercept corrections (see Clements and Hendry, 1998), that account for possible bias in the past forecasts, to the forecasts from the CY model prove to be beneficial.

Importantly, the selection of convenience yields in this paper is relatively arbitrary. This calls for a more robust and efficient selection of different convenience yields for the purpose of inflation forecasting. One approach to summarizing predictive information for inflation from all commodities is to use an information-theoretic approach to weighted aggregation of forecast models as in Gospodinov and Maasoumi (2016). This method treats all of the CY-based forecasting models as misspecified and assigns weights depending on the model's contribution to the overall reduction of the forecast errors. As a result, this mixing procedure employs information from all models and avoids loss of information from dropping factors or models as in the standard selection procedures.

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