GW | Research Program on Forecasting

Time-series measures of core inflation

Edward N. Gamber
Congressional Budget Office
Washington, DC 20515 USA
Edward.Gamber@cbo.gov
and
Research Program on Forecasting
Center of Economic Research

Julie K Smith
Department of Economics
Lafayette College
Easton, PA 18042 USA
smithjk@lafayette.edu
and
Research Program on Forecasting
Center of Economic Research

RPF Working Paper No. 2016-008
http://www.gwu.edu/~forcpgm/2016-008.pdf

September 16, 2016

RESEARCH PROGRAM ON FORECASTING
Center of Economic Research
Department of Economics
The George Washington University
Washington, DC 20052
http://www.gwu.edu/~forcpgm

Time-series measures of core inflation

Edward N Gamber*
Congressional Budget Office
2nd and D Streets, SW
Washington, DC 20515
(202)-226-2777
ed.gamber@cbo.gov

Julie K Smith**
Department of Economics
Lafayette College
Easton, PA 18042
610-330-5301
smithjk@lafayette.edu
and
Research Program on Forecasting
Center of Economic Research
Department of Economics
The George Washington University
Washington, DC 20052

Abstract

Most papers examining the measurement of core inflation, such as the weighted median, have focused on cross-section information in the disaggregated inflation data. This paper improves on the literature by introducing new measures, based on a definition of core inflation as the best predictor of future inflation that exploits the time-series information in the disaggregated inflation data. Exploiting the time-series information in disaggregated or component inflation data produces better forecasts. Additionally, the best new measure comes from jointly estimating the optimal weights instead of imposing weights based on the persistence of the components or the underlying factors estimated by principal components.

JEL: E31, E37
Keywords: Core inflation, inflation, forecasting, disaggregated components, principal components

*The views expressed in this paper are the author's and should not be interpreted as the Congressional Budget Office's.
**Corresponding author

1. Introduction

The measures of core inflation that many papers examine are either popular ones such as the personal consumption expenditure price index excluding food and energy or measures such as the weighted median or trimmed mean of the personal consumption expenditure price index.[1] This paper inquires whether there are better ways to use disaggregated data to capture core inflation, when core inflation is defined as the measure that forecasts future inflation best. While this is not the only possible definition of core inflation, this definition does appeal to the economic intuition about what core inflation should capture. Core inflation is often called underlying inflation indicating that core inflation is the part of inflation that persists or lasts over time.

There are two main approaches to estimating core inflation. One is the statistical method, which produces measures such as the weighted median. In general, the statistical approach exploits the cross-section properties of the component level inflation data. The other method is the theoretical approach. This method uses economic theory to build a model of inflation from which a measure of core inflation is extracted. Theoretical models tend to use the time-series information in inflation and other relevant economic variables.

According to Vega and Wynne (2003) the approaches differ primarily by the information sets they use. The possible information sets are cross-section information on price changes, time-series information on price changes and other information such as real economic variables. This paper combines the two approaches by using the time-series information of component level inflation data in a statistical manner.

[1] See Bryan and Cecchetti (1994), Johnson (1999), Cutler (2001), Bagliano and Morana (2003), Vega and Wynne (2003), and Smith (2004) for further details.

While others have used the time-series information in the disaggregated data to build a measure of core inflation by developing theoretical models[2], there have been few empirical papers that utilize the time-series data to measure core inflation. Blinder (1997) proposes a measure that takes into account the persistence of each component's inflation rate and each component's covariance with overall inflation. Cutler (2001) builds on his comments and proposes an empirical measure. She suggests a measure that uses the persistence of each component to re-weight the data and aggregates the component inflation rates to obtain forecasts of future inflation. Using the time-series properties of the components is a natural place to begin since it can account for movements in all components of inflation. Previous measures used, such as the trimmed mean, ignore many components across time by construction. Another way to use both time-series and cross-section information is to apply the exponential smoother to measures such as the trimmed mean and weighted median (Cogley, 2002). Thus, the contribution of this paper is to provide a new measure of core inflation built on the statistical properties of time-series data.

There is interest in using disaggregates to forecast aggregates. Hendry and Hubrich (2006) show theoretically that using disaggregated variables in an aggregate model should outperform two alternatives: first, forecasting the disaggregated variables individually then aggregating those forecasts and second, using lagged aggregate variables. They find empirically that for the Euro area and the US that using disaggregate information helps produce better forecasts of aggregate inflation. In addition, Hubrich (2005) finds that aggregating forecasts of

[2] This paper takes a different approach than other papers that use time series information. In particular, we use a statistical approach to evaluate the use of component-level data to forecast inflation. We do not provide a structural interpretation such as Quah and Vahey (1995). We also evaluate inflation forecasts based on principal components derived from the component-level data. That work is similar to Bryan and Cecchetti (1993), Bryan and Pike (1991) and Le Bihan and Sedillot (2002).

disaggregated variables does not help forecast the 12-month Harmonized Index of Consumer Prices inflation rate in the Euro area. Both of these papers provide insight that exploiting the time series information in the disaggregated data may be a better way to get an optimal forecast of aggregate inflation.[3] Hendry and Hubrich (2011) demonstrate that including disaggregated information directly into a forecasting model can result in a smaller MSFEs relative to models that forecast the disaggregated components and then aggregate those forecasts. They also explore combining the disaggregated information using factor analysis. They find that including factors estimated from the disaggregated data into the forecasting model for U.S. inflation results in a lower MSFE compared to the autoregressive model of the inflation. In our analysis below we explore both methods—direct inclusion of disaggregates in the forecasting equation and factor analysis applied to the disaggregated data.

This paper examines the United States since 1984. Specifically, we have disaggregated component level data from the personal consumption expenditure deflator, and we use the time-series properties of the components to find an optimal re-weighting. We compare the predictive power of these new measures to more traditional measures of core inflation. These results demonstrate that disaggregating aggregate inflation and re-weighting based on the time-series properties of the components produces better forecasts than other, more popularly recognized, measures of core inflation. In addition, we find that estimating the weights jointly and not using the persistence of the components or underlying factors (estimated by principal components) produces better forecasts. Blinder (1997), Cutler (2001), Hubrich (2005) and Henry and Hubrich (2006) furthered the literature by suggesting that examining the time-series properties of

[3] Additional papers by Bermingham and D'Agostino (2011), Pedersen (2009). Detmeister (2011) and Crone et al. (2013) further explore the forecasting ability of various core inflation measures.

disaggregated data may be more productive than examining the cross-section properties. This paper extends this research.

The rest of this paper is outlined as follows. Section 2 examines the data. The empirical models and results are examined in Section 3 and 4. Finally, Section 5 concludes.

2. Data

The data are the components of the personal consumption expenditure price index (PCEPI)[4] from January 1959 to December 2015 but given Smith's (2005) results that the monetary regime matters for determining the best forecaster of inflation we analyze the forecasting results starting in 1984. The 50 components used are listed in Appendix A[5]. We forecast the 6-month, 12-month and 24-month ahead inflation rate[6], which is calculated by

$$\pi_{t+k,t} = \left(\left(\frac{P_{t+k}}{P_t} \right) - 1 \right) * (100/(k/12)), \tag{1a}$$

k= 6,12 or 24

where P is the PCEPI. We also compute lagged inflation as the previous 12-month inflation rate of the PCEPI and lagged inflation minus food and energy from the PCEPI minus food and energy in the following manner

$$\pi^{y}_{t,t-12} = \left(\left(\frac{P^{y}_{t}}{P^{y}_{t-12}} \right) - 1 \right) * 100 \tag{1b}$$

y is either PCEPI deflator or PCEPI minus food and energy deflator.

[4] These data are subject to revision and were downloaded on 2/18/2016. We realize using the real-time data may be better however that data is not readily available for the components. Future work will look toward providing a real-time estimate of the PCEPI core inflation measures.
[5] These are the same 50 components used by Bermingham and D'Agostino (2011).
[6] Smith (2004) finds that there is very little difference in the ranking of core inflation measures in forecasts at the 12, 18 or 24 month time horizon.

We find the previous 12-month inflation rates for the components from the monthly price indexes by

$$\pi_{t,t-12}^{j} = \left(\left(\frac{P_t^j}{P_{t-12}^j} \right) - 1 \right) * 100, \tag{1c}$$

where j denotes the component and P^j is the price index for component j.

We also compute the weighted median and trimmed mean from these components. The weighted median is

$$\pi_{t,t-12}^{med} = \frac{1}{N-2m} \sum_{i=m}^{N-m} w^i \pi_{t,t-12}^i$$

$$m = N\alpha$$

where m is the largest integer less than or equal to $N\alpha$, (1d)

w^i is the relative importance weight and i indicates the component.

$N =$ number of components =50.

The trimmed mean[7] is

$$\pi_{t,t-12}^{tm} = \frac{1}{1-\alpha-\beta} \sum_{i=\hat{i}_t(\alpha)}^{\hat{i}_t(1-\beta)} w^i \pi_{t,t-12}^i \tag{1e}$$

$$\alpha = .24, \beta = .31$$

The reason we use smoothed inflation rates as independent variables is to reduce the noise from the monthly inflation rates. Atkeson and Ohanian (2001) use a similar smoothing in their benchmark random walk model of inflation.

3. Empirical Models

We examine several models that re-weight the component inflation rates using the time-series information of the components, and we compare these models to standard measures

[7] The trimming is taken from Dolmas' (2009) technical note from the Federal Reserve Bank of Dallas (http://dallasfed.org/data/pce/tech.pdf).

(lagged inflation, lagged inflation minus food and energy, lagged weighted median and lagged trimmed mean). Theoretically, core inflation is $\pi_{ts}^{c} = \beta_1 \pi_{t-1}^{1} + \beta_2 \pi_{t-1}^{2} + \ldots + \beta_i \pi_{t-1}^{i}$, where π_{ts}^{c} is core inflation based on time-series (*ts*) information and *i* refers to the sub-components of inflation. Lagged inflation is a special case where β_j is equal to the budget shares.

The next question that arises is how to determine the weights (β) using the time-series information. We use three methods to calculate the weights. In the first method we estimate the weights that provide the best fit from a time-series regression. In the second method we impose the weights. When imposing the weights we follow a methodology similar to Cutler and estimate the weights based on the persistence of each component and then impose the weights to forecast headline inflation. We return to discuss the details of Cutler's specification later. In the third method, we combine the information from the disaggregated component data by estimating the underlying factors using principal components. We then use those estimated factors to forecast inflation.

The first model regresses aggregate inflation on the component inflation rates in the following regression:

$$\pi_{t+12,t} = \alpha + \beta_1 \pi_{t,t-12}^{1} + \beta_2 \pi_{t,t-12}^{2} + \ldots + \beta_{50} \pi_{t,t-12}^{50} + \varepsilon_t, \qquad (2)$$

where $\pi_{t+12,t}$ is the 12-month ahead inflation rate and $\pi_{t,t-12}^{j}$ is the previous 12 month component inflation rate. This is the disaggregated regression based model.

Cutler uses an AR(1) to model the persistence of each component's inflation rate.[8] This persistence coefficient then becomes the weight for that component. To obtain forecasts she

[8] Cutler's data are for the United Kingdom and she uses eighty-one components at a monthly frequency.

aggregates the component inflation rates by these estimated persistence weights. She allows the persistence weights to vary annually.

For the United States, we use monthly data for our 50 components. To find the persistence weight for each component we estimate an AR(1) with monthly inflation rates measured as year-over-year inflation rates. The following regression is estimated by OLS for each component.[9]

$$\pi^{j}_{t+12,t} = \alpha + \beta_j \pi^{j}_{t,t-12} + \varepsilon_t , \quad (3)$$

where β_j is the estimated coefficient and t is inflation from period t-12 to period t.[10] If β_j is positive then there is persistence in the component and the persistence coefficient is equal to β_j and if β_j is negative then the persistence coefficient is equal to zero because there is no persistence in that component. The weights are normalized to sum to one. The persistence weights do not vary monthly but annually. After obtaining the persistence weights we transform the data to obtain the persistence-weighted forecast of aggregate inflation. The first model to use persistence weights is named persistence weighted.

The next model uses a combination of persistence weights and the budget shares. The weight on each component equals the persistence weight multiplied by the budget share for each component. This specification prevents a component that is highly persistent but is relatively unimportant from dominating the forecast. This measure may be more useful than the other persistence-weighted measure because it takes account of both factors: the persistence of an

---

[9] We use data either from 1960-1982 or 1978-1982 to find the 1983 persistence weights. After 1983 the persistence weights vary by year.

[10] We use year-over-year inflation rates for the AR model since we use year-over-year inflation in the other regressions.

individual component over time and the importance of an individual component in aggregate inflation.

Another model combines the idea of persistence weights and the regression based model. In this model (disaggregated persistence weighted) we first calculate the persistence weights as described above (equation 3) and then we calculate the persistence weighted component inflation rates. With these inflation rates, we then run a regression based model similar to the one in equation 2.

The next model tested uses both time-series and cross-section information. This measure combines the idea of persistence weighting and the weighted median. We first compute the annual persistence weights as we did for the persistence weighted model. Then, for each month we find the median by using the persistence weights instead of the relative importance weights to rank the component inflation rates.

Finally, following Maria (2004) and Hendry and Hubrich (2011) we combined the information from the component inflation rates by estimating the principal components of our inflation rates of our 50 disaggregated components of the PCEPI. We used the technique proposed by Bai and Ng (2002) to determine the optimal number of factors (which in all cases equaled one).

We compare these regression results to forecasts made with more standard measures. The first uses lagged inflation as the forecaster.

$$\pi_{t+12,t} = \alpha + \beta \pi_{t,t-12} + \varepsilon_t \ , \qquad (4)$$

The second uses either the lagged weighted median, lagged trimmed mean or lagged PCEX as the forecaster.

$$\pi_{t+12,t} = \alpha + \beta x_{t,t-12} + \varepsilon_t \ , \tag{5}$$

where x is the weighted median, trimmed mean or the minus food and energy.

We perform pseudo out-of-sample forecasts[11] at three time horizons (6 months, 12 months and 24 months). We compute the monthly forecasts of the year-over-year inflation rate using Recursive Least Squares (RLS). We limit our forecasting period to 1984 to the end of 2014 for our main set of results that look at forecasting inflation 12 months ahead. We conduct robustness checks by forecasting the 6 month ahead inflation rate and the 24 month ahead inflation rate as well. In addition, we break the sample (1984-2014) down into subsamples as transparency of the Federal Reserve has changed, the Great Recession occurred and possibly the end of the Great Moderation which is where our sample begins.

Our samples are:

Sample	Why break?
1984 - 2014	Great Moderation begins around 1984.
1984 - 1993	Federal Reserve begins making post-FOMC announcements about stance of monetary policy.
1994 - 2007	Period of increased transparency of the Federal Reserve until start of Great Recession.
1984 - 2007	Great Moderation begins and possibly ends at the start of the Great Recession.

4. Results

Tables 1 and 2 both show the results for the 12 month ahead time horizon. In our analysis, we use two benchmarks: a random walk forecast (named lagged headline) on the left hand side of the table and a disaggregated forecast (named disaggregated) on the right hand side. The disaggregated forecast is based on the model specified in equation 2. The four time horizons

[11] We use the last month of data before the month we are forecasting. These data would not have been available to forecasters in real time but this is a common way to evaluate forecasts out-of-sample.

are shown as indicated above. Table 1 outlines the results when the data used are from 1959 to 2015. Estimation is between 1960 and 2014 due to leads and lags needed to transform the price level data into year-over-year inflation rates. Table 2 outlines the results when the data used are from 1977 to 2015. Estimation is then between 1978 and 2014.

We use these two benchmarks for two different reasons. First, one standard benchmark in the inflation forecasting literature is the random walk model particularly after Atkeson and Ohanian (2001) found that this simple model could beat the Phillips curve in forecasting inflation. Second, work by Hendry and Hubrich (2011) suggests that using the components or disaggregates can improve the forecasting of aggregates.

We chose to examine the results from a smaller sample of data because it is well-documented in the inflation literature that the dynamics of inflation have changed over the past 50 years.[12] The end of Bretton Woods, the closing of the gold window, the supply shocks of the 1970s, the shift of the Federal Reserve to focus on interest rates due to the breakdown of the velocity of money and the commitment of the Federal Reserve to low inflation all transformed how inflation responds to supply and demand shocks that the economy encounters. The distant past may not provide as much information about the inflation process as the more recent past; therefore, we may want to disregard the early part of the sample. However, since we need a certain amount of data to estimate our model it is not realistic to just begin with the Great Moderation period if we want to discuss the forecastability of inflation during the Great Moderation. We choose 1978 since it provides 72 observations of data before our forecasting window begins.

[12] See Batini (2006), Beechey and Osterholm (2007), Benati (2008), Mehra and Reilly (2009), and Gamber, Liebner and Smith (2015) for discussion of the change in inflation persistence over different monetary policy regimes.

We have ten forecasting models. We report the RMSE for each model, the ratio of each model to the benchmark and the Diebold-Mariano test statistic which tests if the models provide significantly different forecasts. As one would expect, given the changes in the macroeconomy and monetary policy over the 1984-2014 time period the model that is best forecaster changes over each subsample. We focus our attention on the instances where one model is significantly better than the benchmark.

Considering first the lagged inflation benchmark and the estimation period 1960-2015, we find that both the persistence weighted model and the principal components model consistently outperform the lagged inflation benchmark. When the disaggregated benchmark is used, in most of the samples, there is not a statistical difference. Before greater transparency (at 1%) and over the entire Great Moderation period (at 5%) we do find that the principal components model outperforms the disaggregated benchmark. From these results we can see that the disaggregated model is often as good as any other model at forecasting. By only using the random walk benchmark we might misinterpret these results and think that the principal components model is the model to use when forecasting.

Shortening the estimation period may seem counterintuitive at first, often we are told as econometricians that having more data is better. However, in the case of inflation in the United States we have ample evidence that the persistence or underlying inflation process has changed due to the events in macroeconomy and monetary policy changes[13]. Therefore to capture that change in persistence, we begin an estimation sample in 1978. We continue with our two benchmarks as before.

---

[13] See footnote 13 for relevant articles.

In this estimation period many models outperform the random walk benchmark. In 4 of 5 samples, the disaggregated forecast outperforms the random walk benchmark. These results show the weakness of the random walk model. Looking at the disaggregated benchmark, in the two longest samples (1984-2014 and 1984-2007) the disaggregated model is statistically better at forecasting one year ahead inflation than any other model considered. In the shorter samples, it is never statistically worse than any other model and it is only equivalent to one or two alternative models (disaggregated persistence weighted and persistence weighted).

As a robustness check we forecast both the six month ahead and 24 month ahead inflation rates over the same time horizons.[14] At the six month ahead time horizon, it appears that the principal component is better at picking up shorter term fluctuations in the inflation rate especially compared to the random walk model. The disaggregated benchmark does as well as any other model including the principal components so once again this model seems robust to changes in the implementation of monetary policy and macroeconomic shocks and a shorter forecasting horizon.

The 24 month ahead forecast are very similar to the 12 month ahead. A variety of models including the disaggregated model are better than the random walk. When the disaggregated is the benchmark most models are statistically worse than it and a small fraction of models are equivalent.[15]

Our results are consistent with Hendry and Hubrich (2006) who demonstrated that in population, forecasting an aggregate time series using disaggregated component series should outperform models based on the lagged aggregate or aggregates of the forecasted components. In

[14] For brevity we omit the numerical results for these horizons; however, they are available upon request.
[15] Appendix Tables B1, B2 and B3 show when different models are statistically better than the benchmarks.

finite samples, they find that when the aggregate and component series exhibit “sufficient” variability, using the aggregate components to forecast the aggregate beats the aforementioned alternatives. They demonstrate that these conditions do not hold for euro area inflation, and therefore the forecasting model based on the disaggregated series performs relatively worse than the others. But similar to our findings here, Hendry and Hubrich find that their population results hold for forecasting US CPI inflation using the sample 1980 to 2004. Specifically, they find that the forecasting model based on disaggregated data performs better (has a lower MSFE) than the alternative models.

5. Conclusion

This paper examines whether disaggregating along the time-series dimension can lead to a better forecast of inflation. We find that exploiting the time-series information in disaggregated or component inflation data produces better forecasts than exploiting cross-section information in component inflation data. In addition, this paper explores several different models that utilize the time-series properties of the component inflation rates. The results suggest that the disaggregated model of inflation is as good as or better that the comparison models for the full sample as well as the sub-samples.

References

Bagliano, Fabio C. and Claudio Morana. 2003. "Measuring US core inflation: A common trends approach." *Journal of Macroeconomics*. 25:197-212.

Batini, N. "Euro area inflation persistence," Empirical Economics, vol. 31, 2006, pp. 977-1002.

Beechey, M. and P. Osterholm, "The Rise and Fall of U.S. Inflation Persistence," Finance and Economics Discussion Series Divisions of Research & Statistics and Monetary Affairs. Federal Reserve Board, Washington, D.C., 2007-26.

Benati, L. "Investigating Inflation Persistence Across Monetary Regimes," The Quarterly Journal of Economics, August 2008, pp. 1005-60.

Bermingham, Colin and Antonello D'Agostino. 2011. "Understanding and forecasting aggregate and disaggregate price dynamics," Working Paper Series 1365, European Central Bank.

Blinder, Alan S. 1997. "Commentary" on "Measuring short-run inflation for central bankers." *Review*. Federal Reserve Bank of St. Louis, May/June.

Bryan, Michael F. and Christopher Pike. 1991. "Median price changes: an alternative approach to measuring current monetary inflation." *Economic Commentary.* Federal Reserve Bank of Cleveland. December.

Bryan, Michael F. and Stephen G. Cecchetti. 1993. "Measuring core inflation." *Economic Review.* 29:15-24.

Bryan, Michael F. and Stephen G. Cecchetti. 1994. "Measuring core inflation." In *Monetary Policy*, ed. N. Gregory Mankiw, 195-215. Chicago: University of Chicago Press.

Clark, Todd. 2003. "Disaggregate evidence on the persistence of consumer price inflation." Research Division of the Federal Reserve Bank of Kansas City. RWP 03-11.

Cogley, Timothy. 2002. "A simple adaptive measure of core inflation." *Journal of Money Credit and Banking.* 34:94-113.

Crone, T. M., Khettry, N. N. K., Mester, L. J. And Novak, J. A. 2013. "Core Measures of Inflation as Predictors of Total Inflation." *Journal of Money, Credit and Banking*, 45: 505–519. doi: 10.1111/jmcb.12013

Cutler, Joanne. 2001. "Core inflation in the UK." External MPC Unit Discussion Paper No. 3. London: Bank of England, March.

Detmeister, Alan K. 2011. "The Usefulness of Core PCE Inflation Measures," Finance and Economics Discussion Series 2011-56. Board of Governors of the Federal Reserve System (U.S.).

Gamber, E. N., Liebner, J. P., & Smith, J. K. (2016). Inflation persistence: revisited. *International Journal of Monetary Economics and Finance*, *9*(1), 25-44.

Hendry, David and Kirstin Hubrich. 2006. "Forecasting economic aggregates by disaggregates." European Central Bank Working Paper. No. 589.

Hendry, David F., and Kirstin Hubrich. "Combining disaggregate forecasts or combining disaggregate information to forecast an aggregate." *Journal of Business & Economic Statistics* (2011).

Hubrich, Kirstin. 2005. "Forecasting euro area inflation: Does aggregating forecasts by HICP component improve forecast accuracy?" *International Journal of Forecasting.* 21:119-136

Johnson, Marianne. 1999. "Core inflation: A measure of inflation for policy purposes." In *Measures of Underlying Inflation and their Role in the Conduct of Monetary Policy.* Proceeding of the Workshop of Central Bank Model Builders, Bank of International Settlements, Basel. February.

Le Bihan, Herve and Franck Sedillot. 2002. "Implementing and interpreting indicators of core inflation: the case of France." *Empirical Economics.* 27:473-497.

Maria, Jose Ramos, 2004. "On the Us of the First Principal Component as a Core Inflation Indicator," Economic Research Department Working Paper, No. 3-04 (Lisbon: Banco de Portugal)

Mehra, Yash P. and Devin Reilly. "Short-Term Headline-Core Inflation Dynamics," Economic Quarterly 95(3) 2009, pp. 289-313.

Pedersen, Michael. 2009. "An Alternative Core Inflation Measure," *German Economic Review*, Verein für Socialpolitik, vol. 10, pages 139-164, 05.

Quah, Danny and Shaun Vahey. 1995. "Measuring core inflation." *Economic Journal.* 105:1130-1144.

Rogers, Scott. 1998. "Core inflation: Concepts, uses and measurement." Reserve Bank of New Zealand Discussion paper. G98/9.

Smith, Julie K. 2004. "Weighted median inflation: Is this core inflation?" *Journal of Money Credit and Banking*. 36:253-263.

Stock, James and Mark Watson. 1999. "Forecasting inflation." *Journal of Monetary Economics.* 44:293-335.

Vega, Juan-Luis and Mark A. Wynne. 2003. "An assessment of some measures of core inflation for the euro area." *German Economic Review.* 4:269-306.

Wynne, Mark A. 1999. "Core inflation: A review of some conceptual issues." Research Department: Federal Reserve Bank of Dallas. Working Paper 9903.

Table 1: 12-month ahead forecast RMSE (Estimation period 1960-2014)							
		Benchmark: Random walk			Benchmark: Disaggregated		
	RMSE	Ratio	DM test stat		Ratio	DM test stat	
1984-2014							
Lagged headline (random walk)	1.19				1.161	1.23	
Less food and energy	1.05	0.881	-1.75		1.023	0.26	
Weighted median	1.18	0.989	-0.21		1.148	1.48	
Trimmed mean	1.15	0.967	-0.74		1.123	1.18	
Disaggregated	1.03	0.861	-1.23				
Persistence weighted	1.09	0.911	-4.35	**	1.057	0.45	
Persistence weighted* budget shares	1.21	1.015	0.95		1.179	1.25	
Median weighted by persistence	1.10	0.926	-1.93		1.075	0.71	
Disaggregated persistence weighted	1.03	0.868	-1.21		1.008	0.61	
Principal components	1.02	0.856	-6.40	**	0.993	-0.13	
1984-1993							
Lagged headline (random walk)	1.05				0.905	-0.86	
Less food and energy	1.15	1.094	1.12		0.990	-0.07	
Weighted median	1.14	1.083	1.45		0.980	-0.16	
Trimmed mean	1.09	1.036	0.74		0.938	-0.51	
Disaggregated	1.16	1.105	0.86				
Persistence weighted	0.87	0.824	-3.47	**	0.746	-2.67	**
Persistence weighted* budget shares	1.06	1.004	0.19		0.909	-0.76	
Median weighted by persistence	1.01	0.958	-0.86		0.867	-1.18	
Disaggregated persistence weighted	1.15	1.092	0.79		0.989	-0.53	
Principal components	0.92	0.875	-3.39	**	0.792	-2.79	**
1994-2007							
Lagged headline (random walk)	0.93				1.201	1.64	
Less food and energy	0.79	0.850	-2.44	**	1.020	0.20	
Weighted median	1.05	1.122	1.51		1.347	2.18	*
Trimmed mean	0.99	1.058	0.87		1.271	1.80	
Disaggregated	0.78	0.833	-1.64				
Persistence weighted	0.86	0.922	-2.19	*	1.107	0.92	
Persistence weighted* budget shares	0.96	1.027	1.84		1.233	1.78	
Median weighted by persistence	0.92	0.990	-0.25		1.189	1.37	
Disaggregated persistence weighted	0.79	0.845	-1.65		1.015	0.65	
Principal components	0.79	0.847	-3.55	**	1.017	0.27	

1984-2007							
Lagged headline (random walk)	0.98				1.029	0.34	
Less food and energy	0.96	0.974	-0.46		1.002	0.02	
Weighted median	1.09	1.104	1.93		1.136	1.28	
Trimmed mean	1.03	1.048	1.07		1.078	0.77	
Disaggregated	0.96	0.972	-0.34				
Persistence weighted	0.86	0.877	-3.74	**	0.902	-1.21	
Persistence weighted* budget shares	1.00	1.016	1.13		1.046	0.49	
Median weighted by persistence	0.96	0.975	-0.77		1.003	0.04	
Disaggregated persistence weighted	0.96	0.971	-0.37		0.999	-0.07	
Principal components	0.85	0.863739	-4.9	**	0.89	-2.14	*

Table 2: 12-month ahead forecast RMSE (Estimation period 1978-2014)							
		Benchmark: Random walk			Benchmark: Disaggregated		
	RMSE	Ratio	DM test stat		Ratio	DM test stat	
1984-2014							
Lagged headline (random walk)	1.13				1.720	2.92	**
Less food and energy	0.97	0.860	-1.86		1.479	3.40	**
Weighted median	0.96	0.845	-2.18	*	1.453	2.94	**
Trimmed mean	0.97	0.853	-2.45	**	1.466	2.67	**
Disaggregated	0.66	0.581	-2.92	**			
Persistence weighted	1.07	0.946	-2.58	**	1.626	2.52	**
Persistence weighted* budget shares	1.12	0.992	-0.48		1.706	2.67	**
Median weighted by persistence	0.99	0.873	-2.63	**	1.502	2.68	**
Disaggregated persistence weighted	0.71	0.629	-2.74	**	1.082	2.85	**
Principal components	0.99	0.874	-3.28	**	1.503	5.26	**
1984-1993							
Lagged headline (random walk)	0.98				1.494	2.72	**
Less food and energy	0.95	0.839	-0.370		1.443	2.97	**
Weighted median	0.82	0.724	-1.80		1.245	2.01	*
Trimmed mean	0.83	0.736	-1.65		1.266	2.05	*
Disaggregated	0.56	0.495	-2.72	**			
Persistence weighted	0.84	0.742	-2.50	**	1.276	1.87	
Persistence weighted* budget shares	0.95	0.841	-0.99		1.447	2.52	**
Median weighted by persistence	0.88	0.779	-1.41		1.340	2.41	**
Disaggregated persistence weighted	0.61	0.541	-2.70	**	0.931	1.44	
Principal components	0.87	0.884	-2.45	**	1.552	4.28	**
1994-2007							
Lagged headline (random walk)	0.88				1.342	3.58	**
Less food and energy	0.83	0.780	-0.70		1.268	3.00	**
Weighted median	0.84	0.737	-0.87		1.269	2.87	**
Trimmed mean	0.80	0.738	-1.89		1.212	2.45	**
Disaggregated	0.59	0.705	-3.58	**			
Persistence weighted	0.87	0.525	-0.51		1.318	3.27	**
Persistence weighted* budget shares	0.89	0.767	0.44		1.349	3.48	**
Median weighted by persistence	0.82	0.785	-1.75		1.252	3.02	**
Disaggregated persistence weighted	0.63	0.728	-3.44	**	0.963	1.81	
Principal components	0.81	0.917	-1.69		1.364	5.12	**

1984-2007							
Lagged headline (random walk)	0.93				1.407	4.04	**
Less food and energy	0.88	0.781	-0.71		1.344	3.93	**
Weighted median	0.83	0.732	-1.82		1.259	3.26	**
Trimmed mean	0.81	0.718	-2.26	*	1.235	2.99	**
Disaggregated	0.58	0.512	-4.04	**			
Persistence weighted	0.86	0.756	-2.12	*	1.301	3.38	**
Persistence weighted* budget shares	0.92	0.809	-0.67		1.391	3.90	**
Median weighted by persistence	0.85	0.750	-2.00	*	1.289	3.58	**
Disaggregated persistence weighted	0.63	0.552	-3.97	**	0.950	2.30	*
Principal components	0.84	0.906	-2.89	**	1.448	6.55	**

Appendix A: List of 50 Components

New motor vehicles
Used autos
Motor vehicle parts and accessories
Furniture and furnishings
Household appliances
Glassware, tableware, and household utensils
Tools and equipment for house and garden
Video, audio, photographic, and information processing equipment and media
Sporting equipment, supplies, guns, and ammunition
Sports and recreational vehicles
Recreational books
Musical instruments
Other durable goods
Food and nonalcoholic beverages purchased for off-premises consumption
Alcoholic beverages purchased for off-premises consumption
Food produced and consumed on farms
Garments
Other clothing materials and footwear
Gasoline and other energy goods
Pharmaceutical and other medical products
Recreational items
Household supplies
Personal care products
Tobacco
Magazines, newspapers, and stationery
Expenditures abroad by U.S. residents
Less: Personal remittances in kind to nonresidents
Housing
Household utilities
Outpatient services
Hospital and nursing home services
Motor vehicle services
Public transportation
Membership clubs, sports centers, parks, theaters, and museums
Audio-video, photographic, and information processing equipment services
Gambling (91)
Other recreational services
Food services
Accommodations
Financial services
Insurance
Communication
Education services
Professional and other services
Personal care and clothing services
Social services and religious activities
Household maintenance
Foreign travel by U.S. residents
Less: Expenditures in the United States by nonresidents
Final consumption expenditures of nonprofit institutions serving households

Appendix Table B1: Summary of model performance--12 month ahead forecast horizon
Each cell reports the model(s) that produced significantly smaller forecast errors relative to the benchmark

Samples	1984-2014	1984-1993	1994-2007	1984-2007
Estimation period 1960-2015				
Random walk benchmark	Persistence weighted Principal components	Persistence weighted Principal components	Less food and energy Persistence weighted Principal components	Persistence weighted Principal components
Disaggregated benchmark	None – all statistically equivalent	Persistence weighted Principal components	None – 8 of 9 statistically equivalent	Principal components
Estimation period 1978-2015				
Random walk benchmark	Weighted median Trimmed mean Disaggregated Persistence weighted Median persistence weighted Disaggregated persistence weighted Principal components	Disaggregated Persistence weighted Disaggregated persistence weighted Principal components	Disaggregated Disaggregated persistence weighted	Weighted median Trimmed mean Disaggregated Persistence weighted Median persistence weighted Disaggregated persistence weighted Principal components
Disaggregated benchmark	None – all statistically worse	None – 2 of 9 statistically equivalent and remainder worse	None – 1 of 9 statistically equivalent and remainder worse	None – all statistically worse

Appendix Table B2: Summary of model performance--6 month ahead forecast horizon
Each cell reports the model(s) that produced significantly smaller forecast errors relative to the benchmark

Samples	1984-2014	1984-1993	1994-2007	1984-2007
Estimation period 1960-2015				
Random walk benchmark	Persistence weighted Median persistence weighted Principal components	Persistence weighted Principal components	Principal components	Persistence weighted Principal components
Disaggregated benchmark	None – all statistically equivalent	Principal components	None – all statistically equivalent	Principal components
Estimation period 1978-2015				
Random walk benchmark	Trimmed mean Median persistence weighted Principal components	Principal components	None- all statistically equivalent	Trimmed mean Median persistence weighted Principal components
Disaggregated benchmark	None- all statistically equivalent	None- all statistically equivalent	None- all statistically equivalent	None – 1 of 9 statistically worse and remainder equivalent

Appendix Table B3: Summary of model performance--24 month ahead forecast horizon
Each cell reports the model(s) that produced significantly smaller forecast errors relative to the benchmark

Samples	1984-2013	1984-1993	1994-2007	1984-2007
Estimation period 1960-2015				
Random walk benchmark	Less food and energy Persistence weighted Principal components	Weighted median Persistence weighted Principal components	Less food and energy Persistence weighted Principal components	Persistence weighted Principal components
Disaggregated benchmark	None – all statistically equivalent	Persistence weighted	None – all statistically equivalent	Principal components
Estimation period 1978-2015				
Random walk benchmark	Less food and energy Weighted median Trimmed mean Disaggregated Persistence weighted Median persistence weighted Disaggregated persistence weighted Principal components	Weighted median Trimmed mean Disaggregated Persistence weighted Disaggregated persistence weighted	Disaggregated Disaggregated persistence weighted Principal components	Trimmed mean Disaggregated Persistence weighted Disaggregated persistence weighted
Disaggregated benchmark	None – 1 of 9 statistically equivalent and remainder worse	None – 1 of 9 statistically equivalent and remainder worse	None –2 of 9 statistically equivalent and remainder worse	None – 1 of 9 statistically equivalent and remainder worse